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Subjective risk belief function in the field: Evidence from cooking fuel choices and health in India

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Abstract

We investigate the accuracy of the perceptions of health risks in India. The context of our study is the risk of developing physical symptoms related to household air pollution caused by cooking. Using field data collected from 588 respondents in 17 villages in West Bengal, we regress the probability of symptoms on fuel choices to predict respondent-specific health risk changes. The estimated risks, which we treat as objective risks, are then compared with the corresponding subjective probabilistic beliefs, which are elicited by an interactive method with visual aids. Our results show that, on average, the respondents slightly underestimate the change in risk when switching from cooking with firewood to cooking with liquefied petroleum gas, even though their beliefs are qualitatively correct. The results further show that risk misperception is associated only with religion among individuals' observed characteristics, suggesting that their unobserved characteristics play a substantial role in risk misperception.

Keywords: Belief, Cooking fuel choice, Health risk, India, Risk misperception, Subjective probabilistic expectation
JEL classification: D83, D84, I12, O13, Q53

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1. Introduction

In developing countries, the levels of investment in both preventive health and environmental quality improvement remain low (Dupas, 2011; Greenstone and Jack, 2015). One plausible reason for this situation is that people may not correctly perceive the related health risks. If people underestimate the expected costs of the status quo, they may not demand health-seeking products. Therefore, the presence or absence of risk misperceptions needs to be identified to improve health and the environment in low-income countries.

Moreover, investigating whether systematic risk misperceptions exist is crucial for understanding the nature of risk attitudes. Preferences and subjective beliefs are considered two potential sources of variation in attitudes toward risk. For example, Savage (1954) extends expected utility (EU) theory to allow decision-makers to maximize EU based on their preferences and the subjective probabilities of different states. More recently, several non-EU models of risk preferences have been proposed.[1] Among these models, both rank-dependent EU theory and cumulative prospect theory use a two-step framework of preferences and beliefs to understand decision-making (Barberis, 2013; Fox and Tversky, 1998). A number of empirical studies have estimated risk preferences from field data by using one or more of these models and assuming that subjective beliefs correspond to objective probabilities (for a review, see Barseghyan et al., 2018). However, if this assumption does not hold, a basic identification problem will occur because many preference and belief combinations can lead to the same choice (Manski, 2004), meaning that a quantitative study on the accuracy of risk perception is required.[2]

There is a longstanding literature on risk misperception in many areas, such as smoking, food, terrorism, healthcare, and air pollution.[3] For example, Breyer (1993) finds that experts believe that hazardous waste sites pose *medium-to-low* risks to the public, while household air pollution poses a *high* risk, even though public perceptions have driven policies to focus on hazardous waste sites rather than air quality within houses. Note that earlier studies—including Breyer (1993)—elicit subjective *nonprobabilistic* beliefs using ordered categories such as a Likert scale. Several recent studies differ

[1] Examples include rank-dependent EU theory, developed by Kahneman and Tversky (1979) and Quiggin (1982); cumulative prospect theory, developed by Tversky and Kahneman (1992); and the model of reference-dependent preferences, developed by Köszegi and Rabin (2006).

[2] For example, Barseghyan et al. (2013b) find evidence of a probability distortion characterized by the substantial overweighting of small risks and only mild insensitivity to risk changes. Furthermore, they argue that neither Gul's (1991) model of disappointment aversion nor Kőszegi and Rabin's (2006) model alone can explain probability distortions. However, they cannot determine whether probability distortions occur because individuals engage in probability weighting or whether they misperceive risks at the beginning.

[3] Wright and Ayton (1994) provide a comprehensive review of early studies on subjective risk beliefs.

from earlier contributions by eliciting subjective *probabilistic* beliefs.[4] A seminal work by Viscusi (1990), for example, examines whether smokers underestimate the risk of lung cancer by eliciting subjective *probabilistic* beliefs. Using a national telephone survey in the US, he finds that the average value of subjective beliefs about the risk to smokers is approximately 0.4, while the *true* value is estimated to range from 0.05 to 0.1, suggesting a high overestimation on average.[5]

Several other studies further compare elicited beliefs and estimated risks at the individual level. Oster et al. (2013) examine the beliefs of US citizens on their probability of having Huntington disease and compare them with an evaluation performed by a doctor based on the results of clinical tests for each individual enrolled in the study. Carman and Kooreman (2014) elicit the beliefs of Dutch citizens on their probability of having influenza, heart disease and breast cancer with and without preventive care. They also compare beliefs with individual-specific risk levels, which are calculated by using epidemiological models. Khwaja et al. (2007) assess the accuracy of subjective probabilistic beliefs about the 10-year mortality hazard collected in the Health and Retirement Study in the US by comparing the survey results with econometrically estimated hazards for individuals in the same sample. Relatedly, Khwaja et al. (2009) compare smokers' subjective beliefs about future survival with corresponding individual-specific probabilities, which are estimated from regression analyses.

This paper extends the above line of research to the developing world, where imperfect information regarding health risks is more pronounced. In quantifying individual-specific misperception in regions such as rural India, there are at least two challenges: the elicitation of subjective beliefs of individuals with a low level of education and the estimation of objective probabilities without high-skilled doctors. To address the first problem, we adopt an interactive method developed by Delavande et al. (2011b) and Delavande (2014). This method utilizes visual aids to elicit subjective probability since simply asking the percentage chance of the occurrence of an event is too abstract and complex for some respondents, especially in the developing world.[6] To overcome the second problem, we use econometric analyses following Khwaja et al. (2007) and Khwaja et al. (2009).[7] We conduct regression analyses and calculate respondent-specific risk changes using

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[4] To the best of our knowledge, Viscusi and O'Connor's (1984) study is the first to elicit a continuous risk belief measure and create a probabilistic variable.

[5] In Viscusi (1990), subjective probabilistic beliefs are elicited by using the following question: "Among 100 cigarette smokers, how many of them do you think will get lung cancer because they smoke?" The individual's response to this question is divided by 100 to obtain the lung cancer belief. The average is 0.426 for a sample of 3,119 respondents. The estimate of the *true* probability is calculated using information from reports by the US surgeon general.

[6] Okeke et al. (2013) elicit subjective probabilistic beliefs on cervical cancer risk in Nigeria but without using visual aids.

[7] Similarly, Brown et al. (2017) study the effect of beliefs regarding water safety on avoidance behavior in Cambodia

estimated coefficients. To address potential endogeneity concerns, we adopt an instrumental variable (IV) method. Since we rely on recall data, we further address possible mismeasurement (measurement error) by using a parametric method.

To compare subjective beliefs and objective probabilities, we adopt a concept that we call the "subjective risk belief function" (SRBF), which is originally proposed by Johansson-Stenman (2008). The SRBF represents subjective risk beliefs as a function of objective risk. Note that the SRBF becomes flatter (steeper) than a slope of one if the individual overestimates small (large) risks and underestimates large (small) risks. According to Johansson-Stenman (2008), the degree of bias in the belief about the change in risk, i.e., the slope coefficient of the SRBF, is crucial to designing efficient information provision policies. By considering our econometrically estimated risks as *true* objective risks, our research framework enables us to estimate the SRBF, which has been considered theoretically (Barseghyan et al., 2013a; Johansson-Stenman, 2008).[8]

The specific context of risk examined in this paper is the risk of physical symptoms potentially related to household air pollution caused by cooking with solid fuels (for a review of this topic, see Jeuland et al., 2015). In various developing countries, household air pollution from primitive household cooking fires is considered the leading environmental cause of death (Hanna et al., 2016). Estimates of the burden in India alone show that approximately 1.04 million premature deaths and 31.4 million disability-adjusted life years are attributable to household air pollution (Balakrishnan et al., 2014). Currently, in the majority of India, it is possible to switch to cleaner cooking fuel, such as liquefied petroleum gas (LPG), by paying additional fixed and variable costs. However, a substantial proportion of households continue to use dirty fuel (for example, firewood). One possible reason for this choice is their underestimation of the change in health risk (Mobarak et al., 2012); hence, we quantitatively examine whether misperceptions of the change in risk exist.

From our elicitation of subjective risk beliefs, we find that all 588 respondents believe that the risk of experiencing symptoms when using solid fuel is higher than that when using LPG. This finding suggests that the entire sample qualitatively correctly recognizes the health risks of using solid fuel. Then, we estimate the slope coefficient of the SRBF, which informs us of the accuracy of subjective beliefs in risk change by its deviation from the reference value: a coefficient of one. The estimated slope coefficient is 0.7, which is statistically significantly smaller than one. This result

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and utilize the method of Delavande et al. (2011b). They elicit subjective beliefs and create a dummy variable for being "optimistic," using the sample mean as the reference point. In contrast to Brown et al. (2017), the present study estimates the objective risk for each respondent by using econometric analyses and compares it with beliefs to incorporate the possible variation in objective risks.

[8] One exception is Khwaja et al. (2007), who present a local linear smooth plot of subjective and objective mortality hazard that corresponds to the SRBF.

implies that, on average, our sample slightly overestimates small risks and slightly underestimates large risks, meaning a slight underestimation of the change in risk.

We further add characteristic variables and their interaction terms with estimated objective risk to the SRBF. The estimation results show that Muslim (Hindu) respondents are more likely to underestimate (overestimate) the risk change, implying an association between religious faith and risk beliefs. In summary, this paper shows that it is possible to quantitatively examine the accuracy of beliefs about health risk, even in the less developed world. Furthermore, our research framework allows us to empirically examine the source of biased beliefs.

In Section 2, we present the conceptual framework of the SRBF. In Section 3, we describe our data. We conducted household surveys in 17 villages in West Bengal to create a dataset on cooking fuel choices, physical symptoms, and subjective beliefs related to fuel use and health status. In Section 4, we econometrically estimate the health function and calculate two respondent-specific probabilities of experiencing symptoms. In Section 5, we present the results of the elicitation and calculation of the two subjective probabilistic beliefs for each respondent. In Section 6, we compare the subjective beliefs with the objective probabilities and estimate the SRBF. Furthermore, we study the association between individuals' observed characteristics and the individual-specific coefficient of the SRBF. Section 7 discusses the policy implications and the limitations of the study, and Section 8 concludes the paper.

2. Conceptual framework

Consider a health risk $r_i \in [0,1]$ of individual *i* associated with a certain action taken by the individual. Health risk can be, for example, the probability that an individual will have a symptom of a respiratory infection. Let s_i be the subjective belief of individual *i* regarding this probability. Johansson-Stenman (2008) assumes that this subjective belief is a function of the objective risk, that is, $s_i = \psi(r_i)$.[9] We refer to this function, ψ, as the SRBF.

Johansson-Stenman (2008) extends EU theory and presents a model in which risk misperceptions are allowed. Note that the model provides an important implication regarding the effectiveness of an information provision policy. Specifically, the misperception of risk levels ($s_i - r_i > 0$ or $r_i - s_i > 0$) is not a necessary condition for information provision to be effective; what matters is whether there is a misperception regarding the change from a risky choice to a relatively

[9] Barseghyan et al. (2013a) also propose a utility function that includes $\psi(r_i)$. They develop a strategy to distinguish the model of rank-dependent probability weighting from systematic risk misperceptions in field data without directly measuring subjective beliefs.

safe alternative.

Importantly, the steepness of the SRBF can succinctly express a signal of the misperception of risk changes that relates to policymaking. Assume a linear SRBF to simplify the analyses:

$$s_i = \psi(r_i) = \rho_0 + \rho_1 r_i. \tag{1}$$

If an individual correctly perceives the change in risk, then $\frac{\partial\psi}{\partial r} = 1$. However, if the SRBF is flat (steep) such that $\frac{\partial\psi}{\partial r} < 1 (> 1)$, then the change in risk is underestimated (overestimated); therefore, information provision may improve the efficiency of choice.[10]

3. Data

3.1. Background

Approximately 60% of the world's population currently uses either gas or electricity for cooking, while the remaining 40% uses solid fuels (Smith et al., 2014). Solid fuels include coal, charcoal, animal dung, agricultural residue, and firewood. Burning such fuels for cooking produces carbon monoxide, PM2.5, and other toxic chemicals. Many epidemiological studies provide evidence linking cooking-related household air pollution with various diseases (reviews include Smith and Pillarisetti, 2017). Such diseases include acute lower respiratory infections (ALRIs), lung cancer, cataracts, and chronic obstructive pulmonary disease (COPD). Smith et al. (2014) estimate that household air pollution caused 3.9 million premature deaths worldwide in 2010 and as much as a 4.8% reduction in disability-adjusted life years. Among those who cook using solid fuels, one-fourth live in India.

There are several ways to reduce the health risks related to household air pollution. A traditional approach is to improve the cooking stoves used to burn solid fuels. For example, a chimney could be attached to stoves to let the polluted air out of the room. However, several studies suggest that improving stoves may not reduce health risks (Anenberg et al., 2013; Hanna et al., 2016). For this reason, gas and electricity, which are cleaner, are widely promoted (Smith and Pillarisetti, 2017). Since 2015, the Indian government (along with the world's three largest oil companies) has been phasing in several measures to promote LPG, such as the provision of subsidies and the free distribution of LPG

[10] Johansson-Stenman (2008) models information provision as a costly public policy that reduces the discrepancy between subjective beliefs and objective risks both in levels and changes. He regards $\frac{\partial\psi}{\partial r}$ as an important parameter when examining the optimal information provision in the second-best world, where taxing risky goods is not allowed. Another notable feature of the model is the fear (or mental suffering) associated with risk beliefs, which is directly included in the utility function. Despite its potential importance in modeling utility, fear is excluded from the present study since it is unrelated to the existence (or nonexistence) of a systematic bias in risk beliefs.

gas stoves (Gould and Urpelainen, 2018).[11] Nevertheless, the use of LPG remains limited.

3.2. Sample construction

We use a dataset collected for our concurrent work (Chattopadhyay et al., 2021).[12] In addition to the dataset used in the concurrent work, we collected subjective risk belief data for the present paper. We selected Dhapdhapi-II gram panchayat (GP)[13] in the state of West Bengal as our research site since the use of dirty cooking fuels is prevalent there. There are seventeen villages in this GP, and the majority of residents still use traditional solid fuels for cooking, even though LPG distribution networks are already established. Switching from solid fuels to LPG incurs both fixed and variable costs. At the time of our field research, the average cost of switching, including the cost of purchasing an LPG stove, was approximately 5,000 Indian rupees (INR), which was approximately 75% of the average monthly income of our sample households.[14] In addition, households have to purchase LPG cylinders distributed by traders.[15] These costs may make switching from solid fuels to LPG less attractive since households can collect their own firewood.

Following a preliminary survey, we conducted two rounds of field surveys. The first round was conducted from December 2016 to January 2017. We used a stratified random sampling method to choose 600 household heads among the 13,024 adults listed on the voter list of Dhapdhapi-II GP, which was published online. A *part* was our stratification unit.[16] In the first round, our enumerators visited the selected 600 households, and 596 participated (four declined to participate). The second round was conducted from December 2017 to January 2018. Our enumerators visited the same 596 households that had participated in the first round and obtained responses from 588 (a further eight

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[11] One of the most important programs is the *Pradhan Mantri Ujjwala Yojana* (PMUY), which aims to provide LPG connections to adult woman members of socioeconomically weaker households (see Jain et al., 2018a; Kar et al., 2019).

[12] Chattopadhyay et al. (2021) examine the impact of subjective risk beliefs on fuel choice and health. They find that beliefs with regard to becoming sick from dirty fuel usage reduce the fraction of days with dirty fuel usage that degrades the health of the respondent.

[13] A GP is village-level unit of self-government in India. A typical GP consists of several villages.

[14] According to Kar et al. (2019), a PMUY beneficiary needs to pay, for example, only 1,990 INR for the upfront cost of switching to LPG.

[15] Usually, one LPG cylinder (14.2 kg) is considered a unit of LPG consumed for domestic purposes. In the 2016-2017 period, in this region, the average price of one LPG cylinder was 640 INR, and the subsidized cost was 420 INR. Kar et al. (2019) provide more detailed information on the LPG market in India. Gupta and Köhlin (2006) and Gould and Urpelainen (2018) present a more comprehensive explanation of cooking fuel markets in India.

[16] There are 15 *parts* in Dhapdhapi-II GP. A *part* is a stratification unit within each electoral constituency and imperfectly corresponds to a *village*. As the size of the population in each part was not uniform, we sampled proportionally based on the population size of each part.

households declined to participate in the second round). This paper uses data on subjective beliefs and the self-reported experience of symptoms as well as fuel usage collected from these 588 households in the second round.[17] We define our respondent as the primary cook in the household.

3.3. Definition of the variables

Smith and Pillarisetti (2017) discuss lung function, eye opacity, blood pressure, and the electrocardiogram ST-segment as biomarkers of the effects of household air pollution. Thus, in the current study, we would ideally collect data on these biomarkers for each respondent to evaluate objective health risks. For example, Hanna et al. (2016) conducted spirometry tests with approximately 2,500 subjects to evaluate the impact of improved cooking stoves on lung function. However, it is costly to conduct such clinical tests in all visits with the cooperation of, for example, doctors. Hanna et al. (2016) further conducted recall surveys on physical symptoms to complement the results of the spirometry tests. From the questionnaire used in their study, we selected ten physical symptoms and conducted a preliminary survey to examine the prevalence of the symptoms at our research site. From the results of our survey, we defined the three most frequently observed symptoms as signals of diseases potentially caused by household air pollution, namely, *dry cough*, *sore or runny eyes*, and *difficulty breathing*. In the second round of our survey, for each symptom "Y," we asked, "Did you experience Y in the last 30 days?" We then created an indicator variable to denote the self-reported experience of symptoms ($Symp_i$), which took the value of 1 if the respondent had experienced at least one of the three symptoms in the past 30 days and 0 otherwise.[18]

Next, we surveyed each household's cooking fuel usage patterns. As noted above, both firewood and LPG, as well as other cooking fuels, are used in this area. Furthermore, some households use different cooking fuels within a month or even within a day. Such fuel stacking is well known in the literature (Gould and Urpelainen, 2018; Kar et al., 2019). We asked the respondents, "In the last 30 days before the previous month, how many days did you use X for cooking?" For fuel "X," we asked about seven types of fuels: electricity, LPG, kerosene, coal/charcoal, solid fuels such as cow dung cakes/straw, firewood, and others.[19] While most of the sample households used either firewood or LPG, we considered two categories of fuels to include minor options and to simplify the questions

[17] Of the variables collected in the first round, this paper uses the individual and household characteristic variables.
[18] A selection of "30 days" is common in the literature. See, for example, Edwards and Langpap (2012), Hanna and Oliva (2015), and Heltberg (2005).
[19] We asked the respondents to allocate 30 days to these seven types of fuels. As a result, our variable for the number of days of clean or dirty fuel usage captures fuel stacking over the course of a month. However, it does not explicitly capture fuel stacking within a day, which is a limitation of our data.

on risk beliefs. Following Gupta and Köhlin (2006) and Heltberg (2005), we define the sum of the days of LPG, kerosene, and electricity usage as the number of days of *clean* fuel usage and the sum of the days of coal/charcoal, solid fuels, firewood, and others usage as the number of days of *dirty* fuel usage. By dividing the number of days of dirty fuel usage by 30, we create a variable of the fraction of days of dirty fuel usage by household i, denoted as $Dirty_i \in [0,1]$, which is our variable of interest. The English versions of the questionnaires used in our surveys are shown in Appendices C, D and E.

In Section 4, we estimate an objective probability that respondent *i* will have one of the three symptoms in the next month if she or he uses dirty fuel for all 30 days in this month:

$$r_i(Dirty_i = 1) = \Pr_i(Symp_i = 1|Dirty_i = 1).$$

We also elicit respondent i's subjective belief about this probability:

$$s_i(Dirty_i = 1) = \psi\big(\Pr_i(Symp_i = 1|Dirty_i = 1)\big).$$

In Section 5, we report the methods and results of our elicitation of subjective risk beliefs. A comparison of the two enables us to identify misperceptions regarding the level of risk of dirty fuel. To identify misperceptions of the level of risk of clean fuels and the change in risk, we estimate an objective probability that respondent i will have one of the three symptoms in the next month if the respondent uses clean fuel for all 30 days in this month:

$$r_i(Dirty_i = 0) = \Pr_i(Symp_i = 1|Dirty_i = 0).$$

Additionally, we elicit a subjective belief about it:

$$s_i(Dirty_i = 0) = \psi\big(\Pr_i(Symp_i = 1|Dirty_i = 0)\big).$$

3.4. Summary statistics

[Table 1]

Table 1, Panel A reports the summary statistics of the variables. Seventy-six percent of the respondents reported that they had experienced at least one of the three symptoms in the last month. Online Appendix Figure A1 shows the distribution of the fraction of days of dirty fuel usage ($Dirty_i$), which shows two pileups at the values 0 and 1. Approximately half of the respondents (45.2%) indicated that they used only dirty fuel for all 30 days before the previous month, while 13.1% used clean fuel only.[20] Other respondents used both clean and dirty cooking fuel within the same month. As a result, the mean of $Dirty_i$ is 0.68. Almost all of our respondents are women; there is only one household in which a

[20] Among those who used dirty fuels for all 30 days, 82.1% used only firewood, while the remainder also used other solid fuels, such as cow dung cakes. Among those who used clean fuels for all 30 days, 96.1% used only LPG. According to Jain et al. (2018b), who report the summary statistics of ACCESS 2018, that is, India's largest energy access survey, which covered more than 9,000 households from 756 villages in 54 districts, the proportion of rural households in West Bengal that use LPG as their exclusive cooking fuel was 40% in 2018.

man is the primary cook.

The average age of our respondents is 38.5 years, while the average number of years of education is 4.7. In our sample, 69.4% of households follow the Hindu religion, while the others follow the Muslim religion. To control for the long-term and/or cumulative impact of household air pollution, we create the variable "cumulative years of clean fuel usage until the first round" (CY). For this variable, 78.6% of our sample has a zero value since these respondents used only dirty fuel until the first round. The remaining 21.4% of the sample has a value larger than zero, and the average of those who have a value larger than zero is 6.8 years.

4. Estimation of objective risks

4.1. Probit model

To quantitatively identify risk misperception in the field, we first estimate the respondent-specific risk of symptoms using data collected in the survey. As a benchmark, we consider a probit model by assuming that $Dirty_i$ is exogenous:

$$E[Symp_i = 1 | Dirty_i, \boldsymbol{X}_i] = \Phi(\beta_0 + \beta_1 Dirty_i + \boldsymbol{X}_i{}'\delta_1), \tag{2}$$

where $\boldsymbol{X}_i$ is the vector of individual and household characteristics and $\Phi(\cdot)$ is the cumulative distribution function (CDF) for the standard normal distribution. These characteristics include the age of the respondent (Age_i), household size, the years of education of the respondent, an indicator of whether the respondent's household follows the Hindu religion, monthly household income ($Income_i$), an indicator of whether the respondent is a housewife, the number of cooks in the household, an indicator of whether the kitchen is located outside the dwelling space, an indicator of whether the household owns a personal computer, and two binary variables defined using CY. These two binary variables control for the possible nonlinearity in the impacts of the years of clean fuel usage until the first round.[21]

Using the results of the regression, the objective probability that respondent i will have one of three symptoms in the next month if the respondent uses dirty fuel for all 30 days in this month is calculated as follows:

$$r_i(Dirty_i = 1) = \Phi\left(\hat{\beta}_0 + \hat{\beta}_1 + \boldsymbol{X}_i{}'\hat{\delta}_1\right),$$

where $\hat{\beta}_0$, $\hat{\beta}_1$ and $\hat{\delta}$ are the estimates of the probit model. Similarly, the probability of the

[21] The two indicator variables are $CY5$ and $CY15$. Let $CY5 = 1$ if $5 < CY \leq 15$ and $CY5 = 0$ otherwise; and let $CY15 = 1$ if $15 < CY$ and $CY15 = 0$ otherwise. The omitted category takes the value of $0 \leq CY \leq 5$. Table 1 reports the summary statistics of $CY5$ and $CY15$.

respondent using clean fuel for all 30 days in the month is calculated as follows:

$$r_i(Dirty_i = 0) = \Phi\left(\hat{\beta}_0 + \boldsymbol{X}_i{}'\hat{\delta}_1\right).$$

We refer to the two probabilities above as *estimated risks*. Estimated risks generally vary across individuals since they depend on observed characteristics $\boldsymbol{X}_i$.

In early epidemiological studies of household air pollution, the health impacts on particular age groups were of primary interest (see, for example, Smith, 2000; Ezzati and Kammen, 2001). Accordingly, the WHO (2006) reports significant heterogeneity in health impacts by age. Subsequently, the interest of researchers has shifted to the impact of differences in income (for a review, see Smith and Ezzati, 2005).[22] To capture the possible heterogeneity in the impacts of dirty fuels, in our second specification, we add two interaction terms to equation (2): $(Dirty_i \times Age_i)$ and $(Dirty_i \times Income_i)$.

There are two primary concerns regarding the model above. First, there is a possibility of endogeneity problems. For example, those who are more likely to have symptoms may be less likely to use dirty fuel. Second, there may be a case in which a respondent misreports the experience of symptoms since we rely on recall data. We address these two concerns as detailed in the subsections below.

4.2. Two-stage residual inclusion (2SRI) model

To address the possible endogeneity of $Dirty_i$, we adopt IV methods. As our instrument, we construct a variable based on the following question: "How much time (in minutes) does one have to spend to reach the nearest motorable road from your house by walking?"[23] We interpret the response to this question ($Time\ to\ (a\ motorable)\ road_i$) as representing the household's distance from motorable roads or, conversely, its proximity to trees and bush. As most households collect firewood from those places by themselves, our instrument is expected to be relevant in that it is positively and significantly correlated with $Dirty_i$. See Online Appendix Figures A2–4 that present pictures of motorable and non-motorable roads in our research site.

The exclusion restriction requires that $Time\ to\ road_i$ is uncorrelated with the unobserved individual-specific component of $Symp_i$ while affecting it only through $Dirty_i$. A potential threat to this exogeneity assumption is that the time to the nearest motorable road may be associated with the

[22] Another issue was the heterogeneity in health impacts by gender. However, we do not consider this heterogeneity since 99.5% of our respondents are women and our sample lacks variation by gender.

[23] To be more precise, we asked, "How much time does one have to spend to reach the nearest main road by walking?" (see the Online Appendix D for the English version). Then, we further explained that a "main road" meant a road that motor vehicles were able to use. In this context, a "motorable road" differs among the respondents.

level of traffic-related air pollution, which in turn influences the symptoms. This association is consistent with epidemiological evidence obtained in developed countries; specifically, living near busy streets is associated with asthmatic and bronchitic symptoms (Bayer-Oglesby et al, 2006; Brauer et al., 2002; Garshick et al., 2003; Venn, 2001).[24] A similar relationship is likely to hold in Kolkata (i.e., the capital of West Bengal, in which the research site is located), given that 70% of all individuals in Kolkata suffer from respiratory disorders caused by air pollution (Mukhopadhyay, 2009), which is mainly attributed to motor vehicles (Haque and Singh, 2017).

Nonetheless, these findings are not directly applicable to our research site (17 villages), which is approximately 40 kilometers away from Kolkata, for several reasons. First, the quality of air at the research site is likely to be far better than the national ambient air quality standards (NAAQS). According to the Indian Institute of Social Welfare and Business Management (2020), the concentrations of air pollutants such as PM2.5, NOx, and ozone are likely to be well within the permissible NAAQS at the selected stations in Baruipur town, that is, the stations nearest to our research site.[25] Moreover, the research site is approximately 6 kilometers further away from and more rural than Baruipur town, suggesting that ambient air pollution is not an issue of concern in it. Second and equally importantly, there is almost no traffic congestion, if any, at the research site. Our preliminary survey shows that only 1.4% of households own cars, indicating a very low rate of car ownership.[26] In addition, our main survey shows that the motorcycle/scooter ownership rate is 18.5% in our sample. As shown by these survey results, the main modes of transportation are walking, bicycles, motorcycles, and cycle/auto rickshaws. Furthermore, when commuting to inner urban areas, most individuals use public transportation (mainly trains).[27] For these reasons, we assume that traffic-related air pollution from motorable roads at the research site is not at the level that influences the symptoms.

Another potential threat to the exogeneity assumption is that which relates to crop residue

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[24] Using data from a Swiss cohort study on air pollution and lung diseases in adults, Bayer-Oglesby et al. (2006) find that living near busy streets is associated with asthmatic and bronchitic symptoms, with attacks of breathlessness, wheezing with breathing problems, and wheezing without a cold. Examining a sample of US male veterans, Garshick et al. (2003) provide evidence that exposure to vehicular emissions from living near busy roadways might contribute to persistent wheeze and bronchitic symptoms. Similar findings are obtained for children in the Netherlands (Brauer et al., 2002) and in the UK (Venn, 2001).

[25] Baruipur town is a semiurban town having special hospitals, a police station, and a college. It is a relatively developed area compared to our research site, which is rural. In terms of traffic, the traffic congestion in Baruipur town is quite high, while that in the research site is quite low.

[26] In the preliminary survey, we found that only 1 out of 70 households owned a car. For this reason, we dropped the car ownership question from the survey questionnaire.

[27] According to our survey results, approximately 40% of the respondents' husbands commute to urban areas to work in informal sectors.

burning. In India, the seasonal emission of air pollutants from the burning of agricultural waste is becoming a serious health issue. However, crop burning is not very common in West Bengal, and this issue is emerging mostly in northern India (Sakar et al., 2018a).[28] A recent study has found that the air pollutants from crop burning in northern India are spreading to the far eastern parts, including West Bengal (Sakar et al., 2018a). However, importantly, most air pollutants from crop burning come from other states in northern India and are not necessarily correlated with the distance from motorable roads or bush. In Section 4.5, we will further examine the concern over the exclusion restriction to address the robustness of our results.

Due to the nonlinearity of equation (2), we use the two-stage residual inclusion (2SRI) approach. Note that 2SRI is consistent but the two-stage least squares estimator is not if the model is nonlinear (Terza et al., 2008). Furthermore, we adopt the fractional response variable framework (Papke and Wooldridge, 1996) in the first stage since $Dirty_i$ is a proportion that ranges from zero to one.

The first stage of our model is a fractional probit where the conditional mean function is specified as follows:

$$E[Dirty_i|z_i, \boldsymbol{X}_i] = \Phi(\beta_2 + \beta_3 z_i + \boldsymbol{X}_i'\gamma), \tag{3}$$

where z_i is the instrument. We obtain the Bernoulli quasi-maximum likelihood estimators of β_2, β_3 and γ ($\hat{\beta}_2$, $\hat{\beta}_3$ and $\hat{\gamma}$, respectively). For the second stage, we use the nonlinear least squares method for the following regression model:

$$Symp_i = \Phi(\beta_4 + \beta_5 Dirty_i + \boldsymbol{X}_i{}'\delta_2 + \beta_u \hat{u}_i) + e_i^{2SRI}, \tag{4}$$

where e_i^{2SRI} is the regression error term and $\hat{u}_i$ is the residual, defined as $\hat{u}_i = Dirty_i - \Phi\left(\hat{\beta}_2 + \hat{\beta}_3 z_i + \boldsymbol{X}_i'\hat{\gamma}\right)$. The two estimated risks of this model are calculated using the estimates $\hat{\beta}_4$, $\hat{\beta}_5$, $\hat{\delta}_2$ and $\hat{\beta}_u$.

4.3. Hausman, Abrevaya and Scott-Morton (HAS) model

Another econometric concern is the misclassification of $Symp_i$. It is possible that although an individual responded that she or he had one of the three symptoms in the last month, the response was incorrect. The opposite might also have happened, where there was a response of no symptoms while

[28] Crop residue burning started in the late 1980s with the start of mechanized harvesting in Punjab and spread to the other states in northern India (Sakar et al., 2018b). According to the estimation by Sahu et al. (2021), in 2018, the crop residue burned over the entire Indian subcontinent was amounted to 151.6 MT, of which 6.4 MT (4.2%) was estimated to have been burned in West Bengal.

the respondent actually had a symptom. Since we asked about the experience of symptoms that were minor and common for the past several weeks, these misclassifications might have occurred.

The misclassification may be more of a possibility. The majority of existing studies in the literature provide evidence that self-reports of diseases tend to understate the corresponding clinical diagnoses, even though the former is positively correlated with the latter. For example, using a health survey of England collected through a questionnaire and a medical examination by a trained nurse, Johnston et al. (2009) find that 28% of self-reports understate the actual status, with a correlation of 0.17. Similar results are reported for lung disease and hypertension by Onur and Velamuri (2018), who use data from the Longitudinal Aging Study of India survey, which includes blood pressure readings and vision, lung function, and physical functioning tests. Baker et al. (2004) examine the Canadian National Population Health Survey matched with diagnosis information from the Ontario Health Insurance Plan (OHIP). According to their statistics, for each of the 13 diseases examined, there is a positive correlation between the self-report measures and OHIP records (ranging from 0.13 to 0.71), and the frequency of false negatives dominates that of false positives.

These studies have two implications for our analysis. The evidence of a positive correlation suggests that our self-reported data on the symptoms have predictive content for the actual symptoms, providing some justification for using self-reported data in the current study. On the other hand, the evidence of the tendency toward false negatives suggests that our self-reported data may contain measurement errors. This implication raises a concern regarding the estimation of equation (2) since the estimators of nonlinear models can be made inconsistent by measurement error in the dependent variables (Hausman, 2001).

To address this issue, we rely on the study by Hausman et al. (1998), who develop a parametric method for estimating a binary outcome model with misclassification, the Hausman, Abrevaya and Scott-Morton (HAS) model. We define the probabilities of false positives and false negatives conditional on the true status of symptoms as follows:

$$\Pr(Symp_i = 1 \big| Symp_i^T = 0) = \alpha_{0i},$$

$$\Pr(Symp_i = 0 \big| Symp_i^T = 1) = \alpha_{1i},$$

where $Symp_i^T$ is the true indicator for $Symp_i$. Hausman et al. (1998) assume that these probabilities are constants for all individuals, that is, $\alpha_{0i} = \alpha_0$ and $\alpha_{1i} = \alpha_1$ for all i. They therefore propose the following regression model that allows for misclassification:

$$Symp_i = \alpha_0 + (1 - \alpha_0 - \alpha_1)\,\Phi\,(\beta_6 + \beta_7 Dirty_i + \boldsymbol{X}_i{}'\delta_3) + e_i^{HAS}, \tag{5}$$

where e_i^{HAS} is the error term.[29] Again, we adopt the probit model. Hausman et al. (1998) show that parameters ($\alpha_0, \alpha_1, \beta_6, \beta_7,$ and δ_3) are identified due to the nonlinearity of the normal CDF as long as $\alpha_0 + \alpha_1 < 1$.[30] They further demonstrate that the maximum likelihood estimation of this equation is straightforward and provides consistent estimators.[31] Note that the estimated coefficients of α_0 and α_1 provide a specification test for whether misclassification is a problem. The two estimated risks of this model are calculated using the estimates $\hat{\beta}_6$, $\hat{\beta}_7$, and $\hat{\delta}_3$ to obtain reasonable results, even allowing for the possibility of misclassification.

4.4. Results of the estimation of objective risks

[Table 2]

Table 2 reports the estimation results of the five models: the probit model, probit model with interaction terms, 2SRI model, 2SRI model with interaction terms, and HAS-probit model. Panel A reports the estimated coefficients. Appendix Table A1 reports the average marginal effects for all the variables included in the models. The results of the five models consistently show that $Dirty_i$ is positively associated with the experience of symptoms in the subsequent month.

Column 3 of Appendix Table A1 presents the first-stage estimates of the 2SRI model. Our instrument is positively and statistically significantly associated with $Dirty_i$ (the average marginal effect is 0.004, p-value = 0.001). Based on this result, we argue that our instrument is plausibly strong.[32] Columns 3 and 4 of Table 2 report the results of the 2SRI models. The residual of the first stage ($\hat{u}_i$) is not statistically significant. Therefore, there is no endogeneity of $Dirty_i$ given that our instrument is exogenous.

Column 5 of Table 2 reports the results of the HAS-probit model. The estimated probability of a false positive (α_0) is 0.10, while that of a false negative (α_1) is 0.03. These results suggest that

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[29] With no misclassification, $\alpha_0 = \alpha_1 = 0$, and this equation becomes equation (2).

[30] Note that this condition is relatively weak since it states that the combined probability of misclassification is not so high that, on average, one cannot tell which result actually occurred (Hausman, 2001). Furthermore, note that knowledge of or an assumption on the error distribution is necessary to obtain consistent estimators in the HAS model.

[31] Meyer and Mittag (2017) refer to this estimator as the HAS-probit.

[32] To further examine the strength of our instrument, we conduct the weak instrument test proposed by Montiel Olea and Pflueger (2013), which is designed for linear models. Assuming our model is linear, we conduct an IV regression; Column 1 of Online Appendix Table A2 reports the results. The estimate of the first-stage least squares coefficient is 0.004 (p-value = 0.001), which is consistent with the result using the fractional probit model. The effective first-stage F-statistic is 14.3, which exceeds the critical value of 12 (significance level of 5% and threshold of 30% of worst-case bias). This result supports our argument on the strength of our instrument, although the test may not be valid in binary models.

some respondents who answered “yes” to the symptom question may not have suffered from it.[33] Note that the coefficient of $Dirty_i$ in the HAS-probit model (Column 5) is larger than that in the standard probit model (Column 1), meaning that the health risk of dirty fuels can be underevaluated if the possibility of misclassification is ignored. This attenuation effect due to misclassification is consistent with a previous study (Meyer and Mittag, 2017).

The result is unchanged even if we change the classification of kerosene from a clean fuel category to a dirty fuel category. This sensitivity analysis is motivated by a recent change in the classification of kerosene as a dirty fuel (for example, WHO 2018). Online Appendix Table A3 reports the results of the analysis that correspond to Table 2.[34] The results in the two tables are similar. To further examine the sensitivity of our main results, we omit households that use kerosene or electricity for at least one day in the month (23 households). Again, the results are almost the same (see Online Appendix Table A4). In summary, we conclude that a positive and significant impact of dirty fuels exists and that the results are robust to model choices and the definition of the dirty fuel category.

To quantitatively evaluate the health risk of dirty fuels, we estimate the average adjusted predictions (AAPs) at specific values of $Dirty_i$. Panel B reports the results of the five models. Column 1 reports the results of the probit model. If all the respondents use dirty fuels for all 30 days ($Dirty_i = 1$), then the average of the probabilities that each respondent will have the symptoms in the next month is 0.98. All five models show quantitatively similar results, meaning that using dirty fuels for all 30 days almost certainly results in experiencing the symptoms. This average probability decreases to 0.90 if $Dirty_i$ is decreased to 0.75. The probability becomes 0.70 (0.40) if the fraction of dirty fuel usage becomes half (a quarter) of a month.

Note that the probability of the symptoms may not be zero even if an individual uses clean fuels for all 30 days since the symptoms examined in this study are quite common and can be caused by factors other than cooking. The estimated average probability at $Dirty_i = 0$ shows a larger variation than that at $Dirty_i = 1$. The AAP for the 2SRI model is 0.19, while the AAP for the HAS model is 0.04. Due to this sensitivity regarding the choice of health risk models, we estimate the SRBF for each of the five models and compare them in the next section. Using the estimated coefficients, we calculate two probabilities, $r_i(Dirty_i = 0)$ and $r_i(Dirty_i = 1)$, for each model for each respondent. We consider these estimated risks as objective probabilities.

[33] This result differs from that of Baker et al. (2004), who report larger rates of false negatives compared to those of false positives. However, the result of Baker et al. (2004) shows that the rates of false positives are larger for conditions that individuals tend to self-diagnose (such as migraines). Note that our symptoms of interest (dry cough, sore or runny eyes, and difficulty breathing) are also conditions that individuals tend to self-diagnose.

[34] The mean of the new dirty variable is 0.686, while that of $Dirty_i$ is 0.679 (see Table 1).

4.5. Robustness checks

The results in Table 2 are highly robust to a series of robustness checks and alternative specifications. In this section, we present the overview of our robustness checks; see Tables A5–9 in the Online Appendix for details.

The estimates of the 2SRI models imply no endogeneity of $Dirty_i$; however, this implication may be because of the low validity of our instrument. There could be a concern that our instrument directly affects whether a respondent experiences symptoms through, for example, the possible variation in ambient air pollution, even though our research site is rural and relatively small. Thus, we check the robustness of our results using an alternative instrument that is less likely to affect whether a respondent experiences symptoms other than through $Dirty_i$.

We construct an alternative IV termed "$Time\ to\ the\ market_i$" based on the following question: "How much time does one have to spend to reach the nearest market by walking?"[35] Similar to $Time\ to\ road_i$, we interpret the response to this question as the inverse of the distance to bush. Importantly, this alternative instrument is more likely to satisfy the exclusion restriction since, compared to $Time\ to\ road_i$, it is less likely to be correlated with traffic-related air pollution. Thus, we expect that it is positively correlated with $Dirty_i$ but affects $Symp_i$ only through fuel usage.

Online Appendix Tables A5 and A6 report the IV estimates using the alternative instrument. The results of the first-stage regression show that the instrument is positively and statistically significantly associated with $Dirty_i$ (the average marginal effect is 0.003, p-value = 0.051).[36] The result of the second-stage regression shows that the estimated coefficients and AAPs are very similar even when using $Time\ to\ the\ market_i$ as the instrument. Again, the residual of the first stage is not statistically significant, which confirms our result that $Dirty_i$ is not endogenous.

Next, we change from a probit model to a logit model. For the 2SRI model, we use $Time\ to\ road_i$ as the instrument, adopt a fractional logit model in the first stage, and adopt a logit model in the second stage. The estimates are similar when using these logit models (Table A6). Finally, the estimates are similar even when dropping outliers in CY (Table A7) or controlling for the impact of CY by using alternative indicator variables and a simple linear control (Tables A8 and A9). These

[35] The market here is referred to as Dhapdhapi Bazaar.

[36] This alternative instrument is relatively weak. We again conduct the weak instrument test, as in the previous subsection. Column 2 of Online Appendix Table A2 shows that the effective first-stage F-statistic is 10.7, which is below the critical value of 12 (significance level of 5% and threshold of 30% of worst-case bias). However, the Kleibergen–Paap rk Wald statistic is 7.41 (p-value = 0.007), which rejects the null hypothesis that the model is underidentified.

results suggest that our estimates are not driven by specific outliers.

5. Elicitation and aggregation of subjective risk beliefs

5.1. Methods for eliciting subjective probabilistic beliefs

The elicitation of subjective probabilities began in developed countries. Manski (2004) and Hurd (2009) review the literature on elicitation methods. More recently, economists have begun to elicit subjective probabilities in less developed countries. Delavande (2014) summarizes the challenges and methods of eliciting subjective probabilities in developing countries. Delavande et al. (2011b) conclude that even in developing countries, survey respondents can generally understand and answer probabilistic questions.

Several notable designs that differ from those for developed countries have been proposed. First, using visual aids and physical objects is encouraged in developing countries since simply asking for a percentage chance is too abstract.[37] Asking respondents to allocate stones, marbles, or beans helps them to express probabilistic concepts, even if they are less literate. The use of 10 or 20 physical objects is now quite standard in the literature.[38] Second, asking about a binary event is easier for respondents than asking about the distribution of a continuous outcome. Third, asking respondents to imagine an event that will be experienced by "people like you" is commonly adopted. This type of wording is appealing since it helps respondents formulate expectations separately for idiosyncratic and aggregated risks. Delavande (2014) provides more detailed and other related discussions.

5.2. Subjective beliefs about the risk of the three symptoms

Prior to the first round, we conducted a pilot test in our preliminary survey targeting 70 households in August 2016. In this test, we attempted to elicit people's beliefs regarding several physical symptoms, including the three that are considered in this paper.[39] Unlike the main survey, which focuses on the health risks that may appear in the next month, we also elicited beliefs about risks in the subsequent three-month, six-month, one-year, and two-year periods.

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[37] In developing countries, the collection of subjective probabilistic expectations in the course of a one-on-one interview is common, unlike in developed countries, where the use of mail, phone, or online surveys is common (Delavande et al., 2011b).

[38] Delavande et al. (2011a) examine the sensitivity of elicited subjective probabilities to variations in elicitation designs such as the number of beans. They conduct a methodological randomized experiment with boat owners in India and elicit expectations about future fish catches.

[39] Furthermore, we elicited subjective beliefs about the risks of symptoms in the respondents' spouses and children, in addition to themselves.

From the pilot test, we obtained two intriguing findings. First, many respondents believed that the probability that they would have symptoms in the future depended on whether they had any symptoms currently. They believed that future symptoms depended on their current health condition and the type of fuel they used. Thus, in the main surveys, we decided to elicit people's subjective beliefs conditional on their current symptom status.

Second, regarding the three symptoms (dry cough, sore or runny eyes, and difficulty breathing), most of the respondents believed that the probability of having these symptoms in the following month was less than one, even if they had the symptoms currently. In other words, they believed that they could be healed naturally.[40] This belief is different from beliefs about HIV/AIDS elicited in other work (for example, Delavande and Kohler, 2016). In the case of such a disease, once a person has HIV, it is not worth considering probabilistic beliefs that the person will not become infected with HIV.

Based on these observations, we assume that the individuals at our research site separately form the following two beliefs conditional on their fuel usage patterns:

$$\psi\left(\Pr_i\left(Symp_{i,t+1} = 1 \middle| Dirty_{i,t} = a, Symp_{i,t} = 0\right)\right) = \psi_{ia0}, \tag{6}$$

$$\psi\left(\Pr_i\left(Symp_{i,t+1} = 1 \middle| Dirty_{i,t} = a, Symp_{i,t} = 1\right)\right) = \psi_{ia1}, \tag{7}$$

where t denotes the time period, with a 30-day period constituting one period, and $a \in [0,1]$.

Two remarks are worth noting. First, it is not an *a priori* hypothesis that individuals believe that the experience of symptoms in the next period depends on the experience of symptoms in the current period. Rather, this model is based on the observations of our pilot test.[41] Second, as a result of our modeling, an individual's belief becomes a two-state Markov chain conditional on a given fuel usage pattern $a \in [0,1]$.

[40] Many respondents expressed their belief that the probability of developing any symptoms in six months would be lower than the probability of having symptoms in three months and that the probability of having symptoms in one year would be lower than the probability of having symptoms in six months. We also elicited subjective risk beliefs by proposing hypothetical situations regarding treatment, such as a situation in which they would receive medications from a physician and a situation in which they would make their own remedies using homemade medicines. See Online Appendix E for details on the preliminary survey questionnaire.

[41] We acknowledge that a different argument can be made about individuals' beliefs. Specifically, individuals may believe that the probability of experiencing symptoms in the next period depends not only on symptoms in the current period but also on symptoms in the previous n (>1) periods. However, if we assume that an individual's beliefs depend on symptoms in the past n periods (and fuel usage pattern), the beliefs that must be elicited would increase exponentially. This would impose a greater burden on the survey respondents, and the survey would then become unwieldy, making the respondents more likely to skip questions, leading to biases. We therefore sought a compromise by assuming that individuals believe that the probability of having symptoms in the next period depends only on their present symptoms.

Following Delavande (2014) and other previous studies, we elicited the subjective risk beliefs of our respondents using ten candies, allowing them to express probabilities in units of 0.1.[42] Our enumerators explicitly asked the respondents to link the number of candies allocated to the perceived likelihood of experiencing the three symptoms.[43] In the survey, the term *sick* was used if a respondent had one of three symptoms and *healthy* if not. The following question was used to elicit subjective risk beliefs:

> *Consider a hypothetical individual who is identical to you. Imagine that there are options regarding the primary fuel for cooking. In each health status situation H, please answer how likely you think it is that she (or he) will become (remain) sick in the next 30 days if she (or he) used fuels X in all the previous 30 days.*

where X has two options, "LPG, kerosene, or electricity" and "firewood, cow dung cakes, or coal." Note that we did not use the term *dirty* or *clean*. For the health status situation, "H," the options were "she is *healthy*" and "she is *sick*." The instructions used in the elicitation are shown in Appendix C. The above questions enabled us to elicit the four subjective risk beliefs of individual *i*: ψ_{i00}, ψ_{i01}, ψ_{i10}, and ψ_{i11}.

Since we model individual subjective beliefs as a Markov process, it is possible to calculate a stationary distribution conditional on each fuel choice $a = \{0,1\}$ using the following equation:

$$\psi\big(r_i(Dirty_i = a)\big) = \frac{\psi_{ia0}}{1+\psi_{ia0}-\psi_{ia1}}. \tag{8}$$

To compare the estimated risks and elicited beliefs, we use this concept of a stationary distribution of the subjective probabilities. The aggregation of four beliefs into two using this concept makes it possible for us to compare the two estimated risks obtained in the previous section. In Section 7, we will discuss the robustness of our results regarding this approach by estimating the SRBF without using this concept.

5.3. Results of the elicitation of subjective risk beliefs

[Figure 1]

[42] While several previous studies elicit subjective probabilistic beliefs by simply asking people to rate the risk from zero to 10 (for example, Khwaja et al., 2007), Viscusi and Hakes (2003) raise the concern that this scale does not succeed as a probability metric, and they recommend the use of visual aids.

[43] Before the question on the risks of cooking, our enumerators elicited the respondents' subjective beliefs on the likelihood of rainfall on that particular day to check whether the respondents had understood how to express their beliefs.

Table 1, Panel B reports the means and standard deviations of the four elicited risk beliefs, while Figure 1 shows the histogram of the four beliefs. The left panels of Figure 1 show the distributions of the subjective belief that an individual will experience one of the three symptoms in the next month ($Symp_i = 1$) when she or he uses clean cooking fuel and if she or he currently has symptoms or is healthy. The right panels of Figure 1 show the distributions of the subjective belief that an individual will become sick in the next month when she or he uses dirty cooking fuel and if she or he is currently sick or healthy. Although the subjective beliefs range from zero to one, the distribution of the subjective belief that a healthy individual will have a symptom in the next month if she or he uses clean fuel is concentrated at a very low value (approximately 0.1), while the distribution of the subjective belief that a sick individual will have symptoms in the next month if she or he uses clean fuel is concentrated at a moderately low value. The distribution of the subjective belief that a healthy individual will have symptoms in the next month if she or he uses dirty fuel is concentrated at moderately high values (approximately 0.6), while the distribution of the subjective belief that a sick individual will have symptoms in the next month if she or he uses dirty fuel is concentrated at high values (approximately 0.9). The comparison between Panels A and C (similarly, B and D) suggests that, on average, the respondents believe that the probability of experiencing symptoms is high if one experiences symptoms currently compared to the case in which one is currently healthy.

[Figure 2]

Figure 2 shows the histograms of the two subjective beliefs, which are the stationary distributions of the two Markov chains. This figure shows that the histogram for the case in which one uses clean fuel (Panel A) is skewed to the left, while the case in which one uses dirty fuel (Panel B) is skewed to the right. These findings suggest that, on average, our respondents believe that using LPG (or kerosene or electricity) leads to a lower probability of symptoms than using firewood (or cow dung cakes or coal).

6. Estimation of the subjective risk belief function

6.1. Estimation of the average SRBF

[Figure 3]

Figure 3 plots the two elicited subjective beliefs (see Figure 2) on the y-axis and the two estimated risks on the x-axis for the 588 respondents. Panels A, B, C, D, and E correspond to the estimated risks obtained by the probit, probit with interaction terms, 2SRI, 2SRI with interaction terms, and HAS models, respectively. The red X depicts $s_i = \psi(r_i(Dirty_i = 0))$, and the blue cross depicts $s_i =$

$\psi(r_i(Dirty_i = 1))$. The green line (the 45-degree line) shows $s_i = r_i$, which indicates that the respondent has a correct belief in terms of risk levels.

Similar patterns emerge across the panels. First, the blue crosses are plotted to the upper-right side of the red Xs, suggesting that dirty fuels are worse than clean fuels in terms of objective health risks, which is qualitatively correctly perceived by the respondents. Second, a fraction of the red Xs are concentrated at the bottom of the graphs and scattered on the x-axis. These respondents believe that there is no risk from clean fuels, even though they face nonzero objective risks. The majority of the respondents, however, seem to overestimate the risk from clean fuels, as shown by the many red crosses located above the 45-degree line. Third, the majority of blue crosses are located below the 45-degree line, implying that the respondents tend to underestimate the risk from dirty fuels, while a small fraction of the respondents (concentrated at the top of the graphs) believe that dirty fuel usage will surely result in experiencing the symptoms. Lastly, the variation in subjective beliefs is larger than that in estimated risks, suggesting that while our respondents qualitatively correctly perceive the risks, both under- and overestimation of risk levels exist.[44]

To investigate the misperception of risk changes on average, we examine the steepness of the SRBF. We model the linear SRBF and estimate $\frac{\partial \psi}{\partial r}$ using the following regression equation:

$$s_i = \rho_0 + \rho_1 r_i + \sigma_i + u_i, \tag{9}$$

where σ_i represents the individual fixed effects, u_i is the error term, and ρ_1 corresponds to $\frac{\partial \psi}{\partial r}$.

[Table 3]

Table 3 reports the results for each pair of estimated risks obtained by the five models. When the probit model is used, the slope is found to be 0.68 and significantly different from both zero and one at the one percent level. The estimated intercept is 0.09 and significantly different from zero at the one percent level. These estimates suggest that, on average, our respondents almost accurately perceive the risk of clean fuel but underestimate the risk of dirty fuel, leading to a slight underestimation of the change in risk. Similar results are obtained from the probit with interactions model and the 2SRI without/with interactions model (Columns 2, 3, and 4). Among the models, the HAS model yields the smallest slope (0.59) and the largest intercept (0.17) (Column 5). The estimates reflect Panel E of Figure 3; red crosses are clustered on the left side, and blue crosses are clustered on the right side of the graph, which is attributed to the AAP at $Dirty_i = 0$ ($Dirty_i = 1$) being smaller (larger) in the

[44] See Online Appendix Figures A5–10 for the results using the estimated risks calculated from sensitivity analyses and robustness checks conducted in Section 4. All the figures are qualitatively similar to those in Figure 3.

HAS model than those in the other models (Table 2, Panel B). These results are highly robust to alternative specifications in the estimation of objective risks, which are examined in Section 4. See Online Appendix Table A11 for details.

As we obtained two plots for each respondent, we can consider the respondent-specific SRBF and examine its slope coefficient for each respondent. We begin by visually depicting the respondent-level heterogeneity in the SRBF. We calculate the two differences as follows:

$$\Delta s_i = \psi\big(r_i(Dirty_i = 1)\big) - \psi\big(r_i(Dirty_i = 0)\big),\ \Delta r_i = r_i(Dirty_i = 1) - r_i(Dirty_i = 0), \quad (10)$$

where $\frac{\Delta s_i}{\Delta r_i}$ yields the slope of individual i's linear SRBF. Again, Δr_i is calculated using the five models of health risk.

[Figure 4]

Figure 4 plots $(\Delta s_i, \Delta r_i)$ with the 45-degree (red) line on which $\Delta s_i = \Delta r_i$. The figure shows that there is no observation with $\Delta s_i < 0$, indicating that all 588 respondents believe that firewood (and other solid fuels) entails a higher risk of the three symptoms than LPG (and kerosene). The figure also demonstrates that the variation in Δs_i is greater than the differences in our estimated risks (Δr_i). These patterns are observed in all five panels. In other words, the patterns of variation in the individual-specific SRBF are very similar across the five models, despite the differences in the estimates of the average SRBF coefficients across the models.

[Table 4]

Table 4 reports the matrix of correlation coefficients among $\frac{\partial \psi_i}{\partial r}$, which is calculated by using the estimated risks obtained from the five models. The results show that each individual's SRBF slope coefficients are extremely highly correlated among the five models of health risk. The correlations are virtually the same when the Spearman rank correlation is used instead. These results imply that we can focus on one model among the five to investigate where the variation in risk perception—the SRBF slope coefficient—is coming from.

6.2. Individual-specific SRBFs and characteristics

To investigate whether the individual-specific SRBF slope coefficient is associated with individuals' observed characteristics and how, we divide our sample into three groups (low, middle, and high) based on the level of continuous characteristic variables. For example, based on their age, the sample is divided into the younger third, middle third, and older third. We then compare the means and standard deviations of the SRBF slope coefficient by group to identify systematic differences and trends among groups. For binary characteristic variables, we calculate the means and standard deviations by events. We select the SRBF slope coefficients calculated using the health risk model (A): the probit model without interaction terms.

[Table 5]

Table 5 presents the results. We do not find significant differences in most of the continuous characteristic variables. Additionally, no linear trend among the three groups is observed. Among the binary variables, we find significant differences in religion. Note that the variable takes a value of one if the respondent's household follows the Hindu religion and zero otherwise: those who take a value of zero follow the Muslim religion based on the results of our survey. The results show that the average SRBF coefficient is 0.71 for Hindu respondents and 0.61 for Muslim respondents; this difference is statistically significant at the one percent level. These results are robust across different health risk models (results available upon request).

To further investigate the characteristics that are correlated with a misperception of risk levels and changes, we estimate the following equation:

$$s_i = \rho_0 + \rho_1 r_i + \sum_{x \in \boldsymbol{X}} \big(\rho_x x_i + \rho_{rx}(r_i \times x_i)\big) + u_i, \tag{11}$$

where $\boldsymbol{X}$ is the set of characteristic variables x. If ρ_x is positive (negative), an individual with a larger (smaller) x_i tends to perceive a *level* of risk to be higher (lower). If ρ_{rx} is positive (negative), an individual tends to perceive a *change* in risk to be larger (smaller).

[Table 6]

Table 6 reports the ordinary least squares (OLS) estimates. In Columns 1 and 2, we include plausibly exogeneous variables and those with interaction terms, respectively. Column 2 shows that the coefficient on $r_i \times Hindu_i$ is positive and significant, suggesting that, on average, the Hindu respondents' belief in risk change is larger than that of Muslim respondents. The point estimates indicate that the difference is approximately 0.1 points. In Columns 3 and 4, we add the remaining characteristic variables used in Section 4 and their interaction terms, even though these characteristics may be endogenous. For $r_i \times Hindu_i$, the coefficient remains almost the same even when other characteristics are controlled for. For other characteristics and interaction terms, only the indicator "kitchen is located outside the dwelling space" is negative and significant, implying that these respondents have a relatively low risk perception in terms of the risk level.

Columns 5 and 6 present the results of the subgroup analyses to examine whether there is heterogeneity in the association of risk perceptions and characteristics by religion. The estimated SRBF slope coefficients are 0.71 for Hindu respondents and 0.61 for Muslim respondents, which are in line with the previous descriptive results in Table 5. The results for Hindu respondents show that their risk level perceptions are negatively associated with being a housewife and having a kitchen located outside the dwelling space. The results for Muslim respondents show that their risk level perceptions are negatively associated with monthly household income.

These results, however, do not necessarily indicate that Hindu respondents' beliefs are more accurate. Part of the difference between the two groups can be explained by the high number of "extreme responses." Some of the respondents present very extreme answers to the subjective belief questions: zero risk from using clean fuel ($s_i(Dirty_i = 0) = 0$) and ten candies for using dirty fuel for 30 days ($s_i(Dirty_i = 1) = 1$), which results in $\Delta s_i = 1$. These responses account for 10.5% of all samples. In Figure 4, these samples are plotted as the upper limit of the graphs. Evidently, most of them overestimate their objective risks because they are plotted above the red line. In Online Appendix Table A12, we present the share of samples with "extreme responses" by groups of characteristics, as we did in Table 5. While we do not find differences in most of the characteristic variables, we again find a significant difference in religion, with 12.7% for Hindu respondents and 5.5% for Muslim respondents. If we exclude these "extreme responses," then the difference in the SRBF slope coefficient becomes smaller, although the average for Hindu respondents $\left(\frac{\partial\psi}{\partial r} = 0.64\right)$ remains larger than that for Muslim respondents $\left(\frac{\partial\psi}{\partial r} = 0.57\right)$. In summary, Muslims tend to underestimate risk change, and Hindus tend to provide more extreme answers; as a result, there is a significant difference in risk misperceptions between Hindus and Muslims.

7. Discussion

7.1. Policy implications

The results of the previous section imply an association between risk perceptions and religious beliefs. According to our results of the first stage of the 2SRI model in Section 4, Muslim respondents are more likely to use dirty fuels (see Appendix Table A1), which is consistent with the findings of previous studies (see the review by Lewis and Pattanayak, 2012). If their preference for solid fuels is the result of cultural practices and taste associated with meals (Gupta and Köhlin, 2006), then our results may be interpreted as an association between preferences and beliefs.

However, this interpretation requires caution because religious identity can be confounded by contextual factors that influence an individual's perceptions (Gupta et al., 2018). In West Bengal, for example, Muslims constitute the minority and Hindus the majority. In addition, Muslims are considered a major disadvantaged group in India (Asher et al., 2021). Indeed, using a lab-in-the-field experiment in West Bengal and Bangladesh, Gupta et al. (2018) find that behavior is not driven by religious identity *per se* but is highly influenced by the relative status it generates within the population.

Nevertheless, we can say that the SRBF slope coefficient is associated with at least some observable variables. From this finding, we can draw the policy implications of this study. A recent study by Jeuland et al. (2020) finds that preference heterogeneity has important implications for the effectiveness of interventions in the context of household air pollution from cooking. Similarly, the heterogeneity in subjective risk beliefs could influence the effectiveness of interventions. We find that there is significant heterogeneity associated with religion—a variable that is easy to observe—implying that it can be used to differentiate interventions, such as information provision, by the two religious groups. Specifically, our findings imply that policies aimed at addressing Muslims' misperception of risk are especially needed to encourage clean cooking. Furthermore, providing correct information to Hindus may lead to an unintended result because a nonnegligible portion of the group overestimates the risk of dirty cooking.

7.2. On the assumption of a stationary distribution of a Markov process

In this study, to compare estimated risks and elicited beliefs, we combined four elicited beliefs into two using the concept of a stationary distribution of a Markov process (see Sections 5.2 and 5.3). This operationalization is used for analytical tractability, given that the estimation of four objective risks would require dealing with a selection in the initial health status. However, the Markov assumption may not hold in reality. Furthermore, even if the Markov assumption is satisfied, the stationary distribution may not well represent the true risks faced by the respondents. One might therefore be concerned that our main results are artifacts of the assumptions.

To completely address this concern, one would need to estimate objective risks conditional on the status of $Symp_{i,t}$ and compare the four estimated risks with the corresponding four beliefs (i.e., ψ_{i00}, ψ_{i01}, ψ_{i10}, and ψ_{i11} in equations (6) and (7)). This analysis would require data on symptom status 60 days prior to our survey as well as data on instruments for the initial health status. The former data correspond to $Symp_{i,t}$ in equations (6) and (7), while the latter could be used to control for endogeneity arising from $Symp_{i,t}$. Unfortunately, however, we do not have these data.

As a compromise, we make two simplifying assumptions. First, we assume that the symptom status 60 days prior to our survey (i.e., the second round) is the same as that in the first round, that is, one year prior to the second round. Second, we assume that a selection in the initial health status is exogenous. These two assumptions allow us to simply divide the sample into two groups based on health status in the first round and thus estimate the objective risks for each group in the same manner as in Section 4.

The estimation results for objective risks conditional on *sick* (*healthy*) are presented in Online Appendix Tables A13 and A14 (A15 and A16). The results again show that the usage of dirty fuel for 30 days ($Dirty_i$) is positively associated with the experience of symptoms in the subsequent 30 days. Online Appendix Figures A11 and A12 present the four elicited beliefs on the y-axis and the four estimated risks on the x-axis. The patterns exhibited in these figures are broadly similar to those in Figure 3. Online Appendix Table A17 reports the results of the SRBF based on the plots in Figures A8 and A9. The estimated slope coefficients range from 0.28 to 0.34, which is even smaller than those obtained earlier, suggesting that the respondents tend to underestimate the risk change. Overall, these results do not seem to contradict our main results.

7.3. Limitations

This study has several limitations. First, our research subject is not necessarily a serious disease. In general, a study on the risk of serious diseases, such as ALRIs or COPD, would have greater policy implications. However, it is more difficult to evaluate the objective risk of such serious diseases since they occur less frequently. For this reason, we targeted three minor symptoms; hence, a careful interpretation of the results is required. If the respondents misperceive the risk of serious symptoms, their fuel choice becomes less efficient, even if they accurately perceive the risk of minor symptoms. We admit that there is a tradeoff between the policy implications of the research subject and the feasibility of objective risk estimation. Furthermore, this study focuses on short-term effects, that is, the impact of the use of fuel for one month on health in the following month. The SRBF for long-term risks is a noteworthy topic for further research. Another limitation of this study is that it examined the health impacts only on individuals who are actually involved in cooking, while the health risks for children are also an important policy issue. Whether parents or other decision-makers in the household correctly perceive the health risks of their fuel choices for their children is an extremely important question.

Second, this study does not consider confidence in the respondents' subjective beliefs. In the survey, we asked the respondents about their beliefs about the parameter, say $p \in [0,1]$, of the binomial random variable for the occurrence of the symptom. However, it is possible that an individual forms a series of subjective beliefs over the parameter space (for example, 20% chance for $p = 0.4$, 70% chance for $p = 0.5$, and 10% chance for $p = 0.6$), the variance (or, more generally, the distribution) of which reflects the level of the individual's confidence. Moreover, an individual may hold a set of subjective distributions (Manski, 2004). Thus, it would be worthwhile to examine who is confident.

Third, the sensitivity of the regression analysis used to estimate objective risks should be addressed. The SRBF estimates were sensitive to the selection of the econometric model, indicating the difficulty in estimating objective risks. Nevertheless, we believe that previous studies that use the average value obtained from epidemiological predictions have similar limitations. The quality of data collection and econometric analysis must be improved to obtain better estimates of the SRBF.

Fourth, it is not clear whether actual risk or subjective belief affects individuals' behavior. While many previous studies show that subjective belief affects behavior (for example, Chattopadhyay et al., 2021; Delavande and Kohler, 2016), it is worth investigating this issue further to identify the relative importance of the effect of actual risk or subjective belief on behavior.

8. Conclusion

This paper proposes a research framework for quantifying individuals' misperceptions regarding changes in risk, presents the SRBF concept, and estimates it in West Bengal. From our elicitation of subjective beliefs, we find evidence that people who are involved in cooking in West Bengal believe that firewood has higher health risks than LPG. This perception is qualitatively correct. The Indian government is already implementing several programs, such as providing subsidies for the initial upfront cost of an LPG connection (see Kar et al., 2019 for further details). In fact, some households at our research site had already received subsidies to cover this upfront cost, which implies that the superiority of LPG with respect to health may now be widely known. This finding implies that there must be foundational obstacles to the widespread adoption of clean fuels, other than biased perception, as is widely discussed in the literature (Lewis and Pattanayak, 2012; Jeuland et al., 2021).

On the other hand, when estimated risks are quantitatively considered, we find slight misperceptions of the health risk regarding switching from firewood to LPG. The coefficient of the average linear SRBF is estimated to be between 0.59 and 0.71, which is statistically significantly smaller than one (though it is also statistically significantly larger than zero). For this reason, it can be expected that the effects of additional information provision policies on behavioral change may exist, but they may not be significant.

There is another finding on the association between misperception and a characteristic variable. The SRBF estimates, which include interaction terms, show no significant correlations in terms of age, educational levels, household income, or other characteristics. The only observed variable for which we find a significant correlation with risk misperception is religion. This finding implies that the variations in unobserved characteristics play a substantial role in determining the degree of risk misperception. In other words, it is essential to investigate risk perceptions themselves to understand the risk attitudes of individuals since they cannot be explained by most observable characteristics.

The evidence above leads to at least three important directions for future research. First, investigating further correlations between observables and misperceptions would make it possible to target information provision by the observables and to identify the source of biased perceptions. Second, examining the accuracy of the risk perceptions of household heads who are not the primary cook in the household is required. The reason is that previous studies find that households with a female head of household are more likely to use cleaner fuels (Lewis and Pattanayak, 2012), implying the importance of intrahousehold bargaining and gender politics. Third, further empirical studies on belief formation using our framework are possible.

The potential impact of our results on the literature on risk attitudes is worth noting. Previous studies show that risk preference is biased toward overweighting (underweighting) to extremely small (large) probabilities or shows an inverted S shape (Barseghyan et al., 2018). Our results suggest that risk beliefs are also biased in a similar way. Further studies on risk attitudes that incorporate both preferences and beliefs, possibly extending our research framework, are required.

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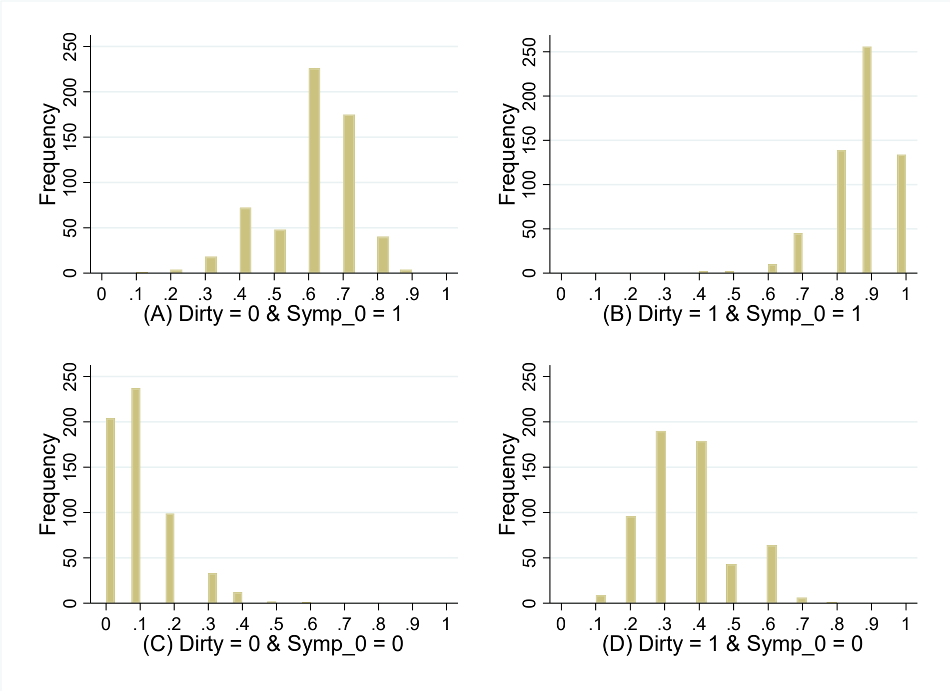


Figure 1. Distribution of four elicited subjective beliefs

Notes: This figure shows the distribution of the elicited subjective beliefs. Ten candies were used in our field survey, allowing the respondents to express probabilities in units of 0.10. Panels A, B, C, and D show the elicited ψ_{i01}, ψ_{i11}, ψ_{i00}, and ψ_{i10}, respectively.

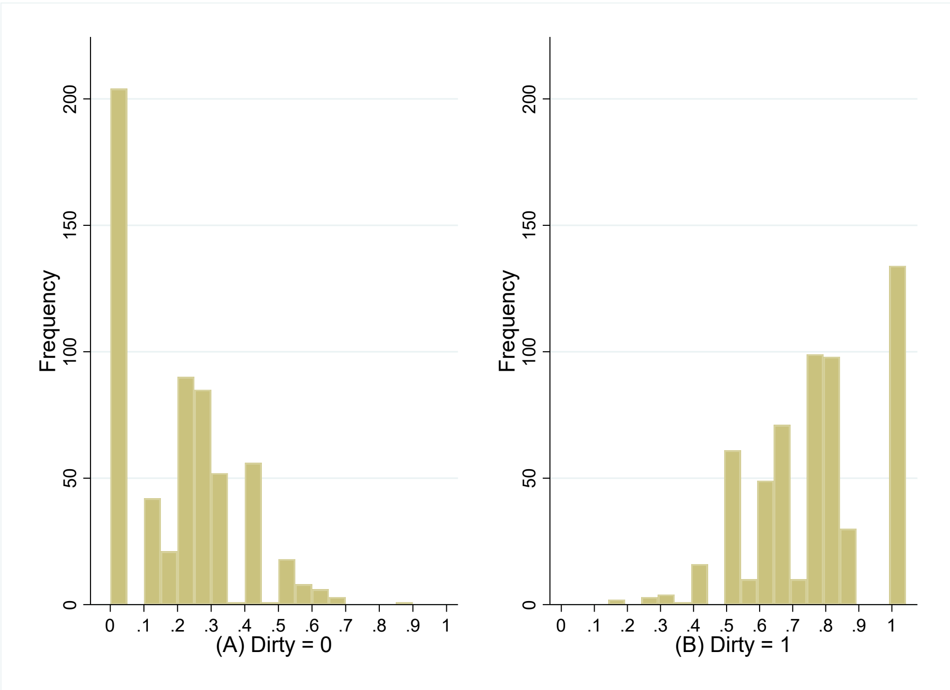
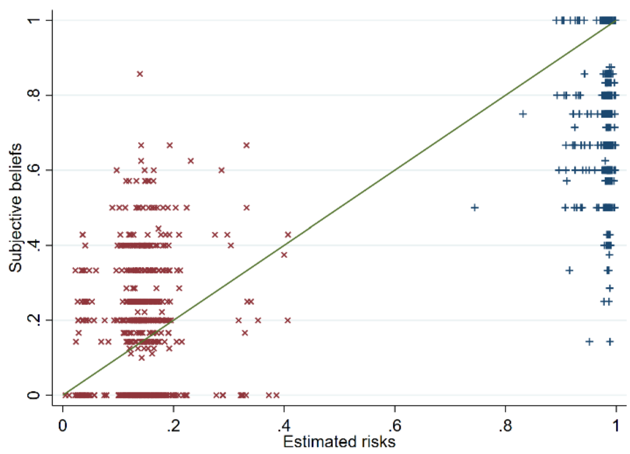
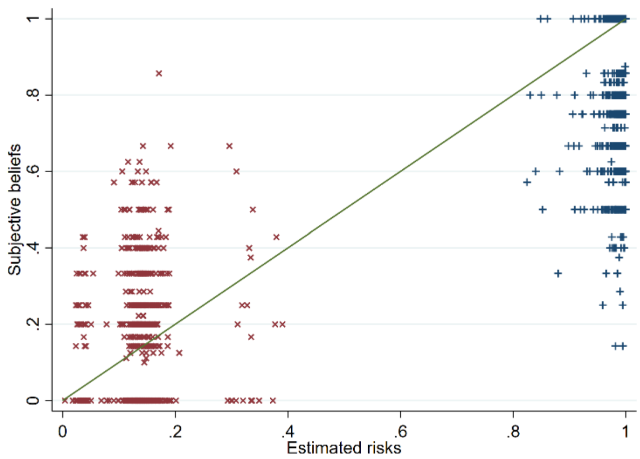


Figure 2. Distribution of the two subjective beliefs

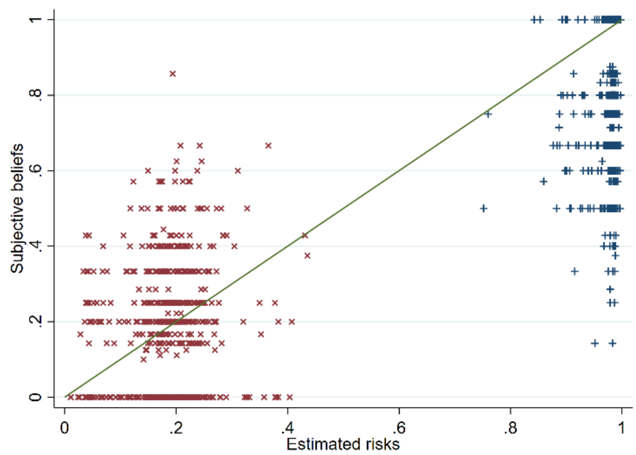
Notes: This figure shows the stationary distribution of subjective probabilities conditional on each fuel choice. Panel A shows $\psi(r_i(Dirty_i = 0))$, and Panel B shows $\psi(r_i(Dirty_i = 1))$.



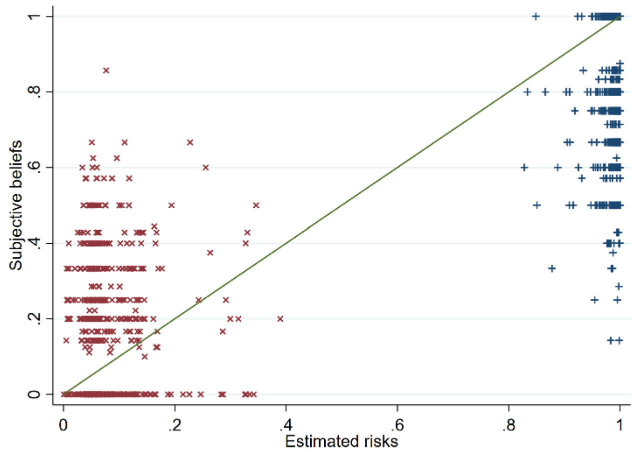
(A) Probit



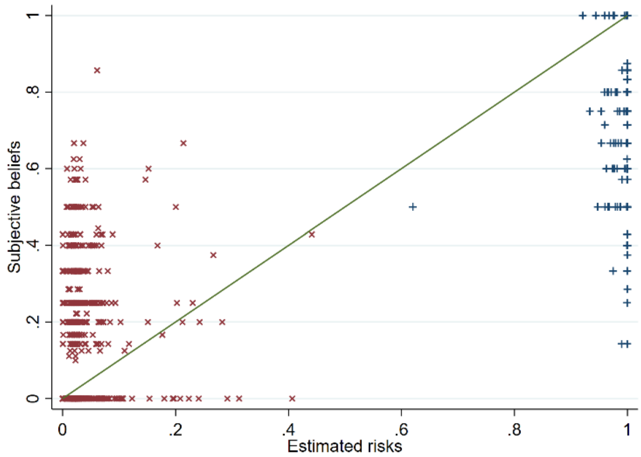
(B) Probit with interaction terms



(C) 2SRI



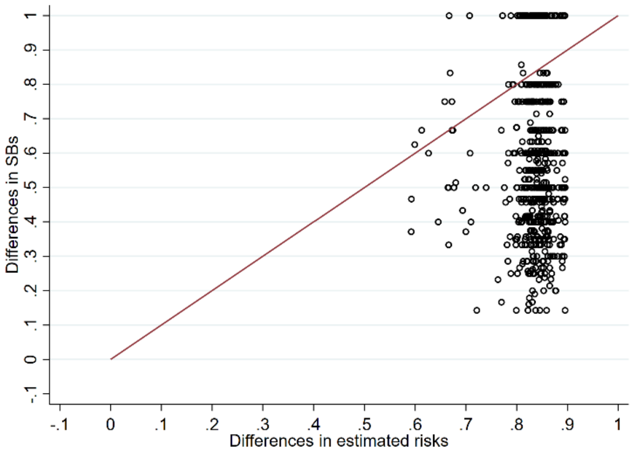
(D) 2SRI with interaction terms



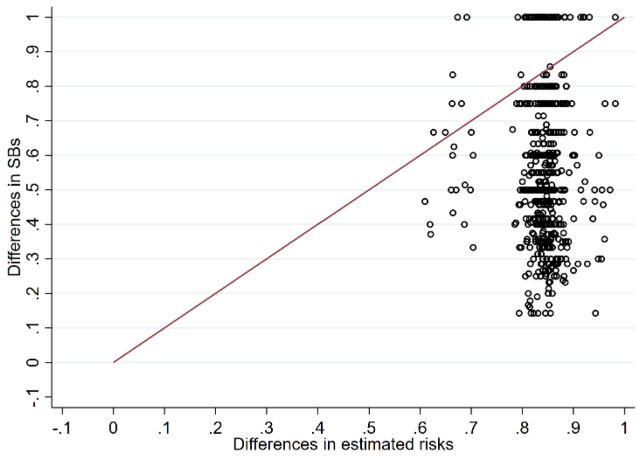
(E) HAS-probit

Figure 3. Subjective beliefs and estimated risks

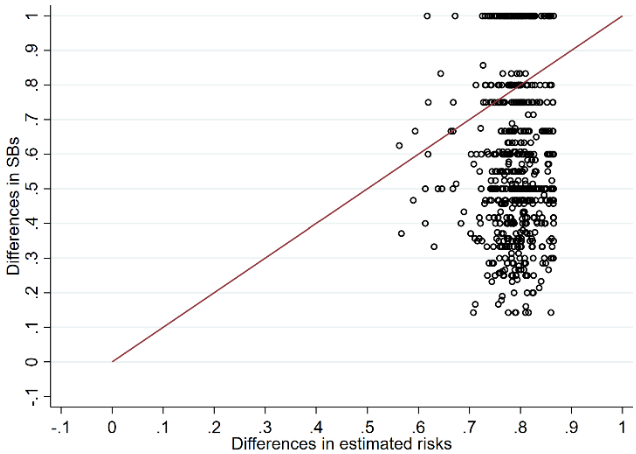
Notes: This figure shows the empirical results of the relationship between subjective beliefs and objective estimated risks of the 588 respondents. Panels A, B, C, D, and E correspond to estimated risks calculated using probit, probit with interaction terms, 2SRI, 2SRI with interaction terms, and HAS models, respectively. The red X depicts $s_i = \psi\big(r_i(Dirty_i = 0)\big)$, and the blue cross depicts $s_i = \psi\big(r_i(Dirty_i = 1)\big)$. The green line shows $s_i = r_i$.



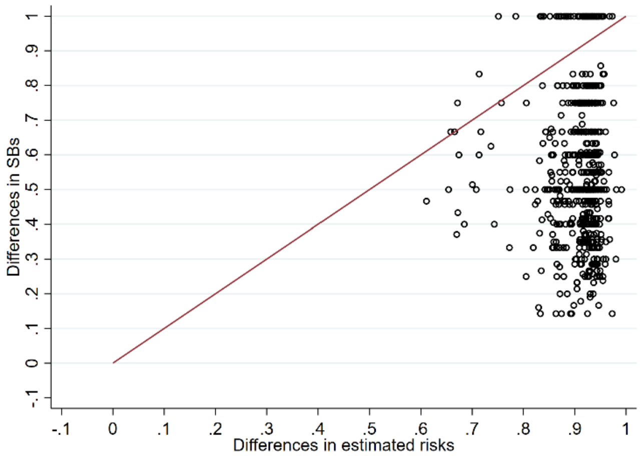
(A) Probit



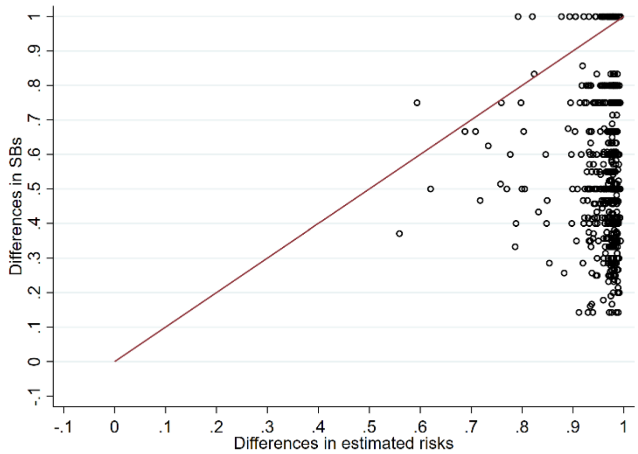
(B) Probit with interaction terms



(C) 2SRI



(D) 2SRI with interaction terms



(E) HAS-probit

Figure 4. Subjective beliefs and estimated risks in risk changes

Notes: This figure plots $(\Delta s_i, \Delta r_i)$. Panels A, B, C, D, and E correspond to the estimated risks calculated using probit, probit with interaction terms, 2SRI, 2SRI with interaction terms, and HAS models, respectively. The red line illustrates $\Delta s_i = \Delta r_i$.

Table 1. Summary statistics

	Mean	Standard deviation
Panel A: Characteristic variables		
Symptoms in the past 30 days ($Symp_i$) (binary)	0.755	0.430
Fraction of days of dirty fuel usage ($Dirty_i$) before the previous month	0.679	0.379
Female (binary)	0.995	0.071
Age of the respondent	38.548	11.221
Respondent's household follows the Hindu religion (binary)	0.694	0.461
Years of education of the respondent	4.713	4.141
Monthly household income (*1000 INR)	7.428	3.690
Household size	4.612	2.054
Respondent is a housewife (binary)	0.952	0.213
Number of cooks in the household	1.128	0.403
Kitchen is located outside the dwelling space (binary)	0.158	0.365
Cumulative years of clean fuel usage until the first round (CY)	1.466	4.167
$5 < CY \leq 15$ (CY5) (binary)	0.060	0.237
$15 < CY$ (CY15) (binary)	0.022	0.147
Household owns a personal computer (binary)	0.065	0.246
$Dirty_i$ × Age of the respondent	26.151	17.071
$Dirty_i$ × Monthly household income	4.608	2.987
Panel B: Instrumental variables		
Time to reach the nearest motorable road ($Time\ to\ road_i$)	13.170	13.187
Time to reach the nearest market ($Time\ to\ the\ market_i$)	17.653	13.740
Panel C: Four elicited subjective beliefs		
$\psi(\Pr(Symp_{i,t=1} = 1 \mid Dirty_i = 1 \text{ and } Symp_{i,t=0} = 0))$	0.363	0.127
$\psi(\Pr(Symp_{i,t=1} = 1 \mid Dirty_i = 1 \text{ and } Symp_{i,t=0} = 1))$	0.876	0.100
$\psi(\Pr(Symp_{i,t=1} = 1 \mid Dirty_i = 0 \text{ and } Symp_{i,t=0} = 0))$	0.102	0.101
$\psi(\Pr(Symp_{i,t=1} = 1 \mid Dirty_i = 0 \text{ and } Symp_{i,t=0} = 1))$	0.600	0.128

Notes: The number of observations is 588.

Table 2. Risk of dirty fuel for physical symptoms (probit, 2SRI, and HAS)

Dependent variable: $Symp_i$	(1)	(2)	(3)	(4)	(5)
Probit models:	Standard	Standard	2SRI	2SRI	HAS
Panel A: Coefficients					
$Dirty_i$	3.247***	1.977***	2.989**	2.481	5.439***
	(0.331)	(0.622)	(1.298)	(1.829)	(0.990)
$Dirty_i$ × Age of the respondent		0.008		0.008	
		(0.018)		(0.022)	
$Dirty_i$ × Monthly household income		0.152**		0.164	
		(0.063)		(0.102)	
First-stage residual ($\hat{u}_i$)			0.267	-0.586	
			(1.366)	(1.676)	
Misclassificationα_0					0.103**
					(0.049)
Misclassificationα_1					0.026***
					(0.010)
Other control variables	Yes	Yes	Yes	Yes	Yes
Panel B: Average Adjusted Predictions					
AAP at $Dirty_i = 0$	0.145	0.139	0.187	0.078	0.037
	(0.044)	(0.047)	(0.233)	(0.126)	(0.029)
AAP at $Dirty_i = 0.25$	0.393	0.399	0.434	0.317	0.286
	(0.045)	(0.045)	(0.210)	(0.212)	(0.073)
AAP at $Dirty_i = 0.5$	0.695	0.710	0.710	0.670	0.741
	(0.027)	(0.024)	(0.071)	(0.129)	(0.053)
AAP at $Dirty_i = 0.75$	0.901	0.907	0.897	0.907	0.961
	(0.020)	(0.019)	(0.036)	(0.027)	(0.020)
AAP at $Dirty_i = 1$	0.980	0.980	0.976	0.985	0.997
	(0.009)	(0.009)	(0.030)	(0.011)	(0.003)
Observations	588	588	588	588	588
Log likelihood	-163.400	-161.338	-163.370	-161.233	-159.198
AIC	352.800	350.675	354.740	354.467	348.396
BIC	409.697	411.949	416.014	424.494	414.046

Notes: Panel A reports the estimated coefficients for each model. The results for the constant term and control variables are not reported. Appendix Table A1 reports the results of all the control variables. The numbers in parentheses are standard errors clustered at the *part* level in Columns 1 and 2, the bootstrap estimate of the standard errors clustered at the *part* level for Columns 3 and 4, and standard errors in Column 5. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Panel B reports the average adjusted predictions (AAPs) at each value of $Dirty_i$. The numbers in parentheses are delta-method standard errors.

Table 3. Estimation of the subjective risk belief function (fixed effects)

Dependent variable: s_i	(1)	(2)	(3)	(4)	(5)
Model of the health risk	Probit	Probit	2SRI	2SRI	HAS
Interaction terms	No	Yes	No	Yes	No
Estimated risk (r_i)	0.675***	0.670***	0.714***	0.621***	0.587***
	(0.011)	(0.011)	(0.012)	(0.010)	(0.009)
Constant	0.090***	0.095***	0.054***	0.140***	0.166***
	(0.006)	(0.006)	(0.007)	(0.005)	(0.005)
p-value (H_0: $\frac{\partial\psi}{\partial r} = 1$)	0.000	0.000	0.000	0.000	0.000
Fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1176	1176	1176	1176	1176
R squared	0.868	0.868	0.867	0.868	0.867

Notes: This table reports the results of the estimation of the subjective risk belief function. The numbers in parentheses are standard errors clustered at the respondent level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Correlation and Spearman rank correlation coefficients among the five models

	(1)	(2)	(3)	(4)	(5)
Variable: $\Delta s_i / \Delta r_i$	(A) Probit	(B) Probit	(C) 2SRI	(D) 2SRI	(E) HAS-probit
(A) Probit	1.000				
	(1.000)				
(B) Probit with interaction terms	0.995	1.000			
	(0.993)	(1.000)			
(C) 2SRI	0.997	0.992	1.000		
	(0.997)	(0.991)	(1.000)		
(D) 2SRI with interaction terms	0.993	0.995	0.983	1.000	
	(0.990)	(0.995)	(0.981)	(1.000)	
(E) HAS-probit	0.991	0.989	0.987	0.988	1.000
	(0.994)	(0.991)	(0.990)	(0.989)	(1.000)

Notes: This table reports Pearson correlation coefficients among the individual-specific coefficients of SRBFs calculated by using the (estimated) objective risks obtained from the five models. The Spearman rank correlation coefficients are in parentheses. The number of observations is 588.

Table 5. Individual-specific SRBF by groups of characteristic variables

	(1)	(2)	(3)
Variable: $\Delta s_i / \Delta r_i$		Mean (SD) [Sample size]	
Panel A: Continuous variables	Low	Middle	High
Age of the respondent	0.691 (0.256) [196]	0.678 (0.261) [196]	0.665 (0.278) [196]
Years of education of the respondent	0.655 (0.275) [196]	0.681 (0.238) [196]	0.699 (0.278) [196]
Monthly household income (thousand INR)	0.669 (0.247) [196]	0.664 (0.264) [196]	0.702 (0.283) [196]
Household size	0.679 (0.254) [196]	0.676 (0.271) [196]	0.679 (0.270) [196]
Cumulative years of clean fuel usage until the first round (CY)	0.671 (0.265) [196]	0.667 (0.251) [196]	0.697 (0.278) [196]
Panel B: Binary variables	0		1
Hindu religion	0.608 (0.241) [180]		0.709*** (0.269) [408]
Respondent is a housewife	0.615 (0.257) [28]		0.681 (0.265) [560]
Number of cooks in the household is more than one	0. 679 (0. 265) [526]		0. 673 (0. 265) [62]
Kitchen is located outside the dwelling space	0.674 (0.267) [495]		0.701 (0.254) [93]
Household owns a personal computer	0.679 (0.264) [550]		0.662 (0.283) [38]

Notes: This table reports the means of the coefficients of an individual-specific SRBF by groups of characteristic variables. In panel A, the means are reported by three groups of characteristic variables: low (lower third), middle (middle third) and high (upper third). In panel B, the means are reported by events for binary characteristic variables by events. The SRBFs are calculated using a model of (A) probit. Standard deviations are reported in parentheses. The sample sizes for each group are reported in brackets. We randomly ranked and classified the samples that took the same value. The means of the SRBF coefficients are statistically significantly different in a dummy variable for "Hindu religion" (p-value of 0.000). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Estimation of the subjective risk belief function with characteristics (OLS)

Dependent variable: s_i	(1)	(2)	(3)	(4)	(5)	(6)
Model of the health risk	(A) Probit	(A) Probit	(A) Probit	(A) Probit	(A) Probit	(A) Probit
Sample	Full	Full	Full	Full	Hindu	Muslim
Estimated risk (r_i)	0.673***	0.647***	0.674***	0.554***	0.705***	0.606***
	(0.011)	(0.046)	(0.011)	(0.077)	(0.013)	(0.018)
Age of the respondent	-0.000	0.000	-0.001	-0.000	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hindu religion	-0.011	-0.066***	-0.014	-0.069***		
	(0.012)	(0.017)	(0.012)	(0.017)		
Years of education of the respondent	-0.001	-0.001	-0.001	-0.001	-0.001	-0.004
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)
$r_i \times$ Age		-0.001		-0.001		
		(0.001)		(0.001)		
$r_i \times$ Hindu religion		0.099***		0.100***		
		(0.023)		(0.024)		
$r_i \times$ Years of education		-0.000		-0.001		
		(0.003)		(0.003)		
Monthly household income			0.000	-0.001	0.002	-0.007*
			(0.002)	(0.003)	(0.002)	(0.004)
Household size			-0.005	-0.007	-0.004	-0.009
			(0.004)	(0.005)	(0.004)	(0.007)
Respondent is a housewife			-0.037	-0.073**	-0.052*	0.022
			(0.026)	(0.032)	(0.029)	(0.042)
Number of cooks in the household			-0.008	0.002	-0.014	0.011
			(0.015)	(0.022)	(0.019)	(0.027)
Kitchen is located outside the dwelling space			-0.037***	-0.052**	-0.046**	-0.012
			(0.014)	(0.021)	(0.018)	(0.024)
Cumulative years of clean fuel usage			-0.001	-0.003	-0.002	-0.000
			(0.001)	(0.002)	(0.002)	(0.001)
Household owns a personal computer			0.006	0.024	0.013	0.028
			(0.022)	(0.033)	(0.029)	(0.032)
$r_i \times$ Monthly household income				0.003		
				(0.003)		
$r_i \times$ Household size				0.003		
				(0.006)		
$r_i \times$ Respondent is a housewife				0.074		
				(0.051)		
$r_i \times$ Number of cooks in the household				-0.017		
				(0.032)		
$r_i \times$ Kitchen is located outside the dwelling space				0.026		
				(0.028)		
$r_i \times$ Cumulative years of clean fuel usage				0.003		
				(0.003)		
$r_i \times$ Household owns a personal computer				-0.036		
				(0.052)		
Constant	0.122***	0.136***	0.201***	0.263***	0.185***	0.217***
	(0.026)	(0.035)	(0.039)	(0.055)	(0.046)	(0.063)
Observations	1176	1176	1176	1176	816	360
R squared	0.723	0.727	0.727	0.732	0.742	0.705

Notes: This table reports the results of the estimation of the subjective risk belief function. The numbers in parentheses are standard errors clustered at the respondent level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix

Table A1. Risk of dirty fuel for physical symptoms (average marginal effects)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	$Symp_i$	$Symp_i$	$Dirty_i$	$Symp_i$	$Symp_i$	$Symp_i$
Probit models:	Standard	Standard	Fractional	2SRI	2SRI	HAS
$Dirty_i$	0.502***	0.519***		0.462**	0.608**	0.473***
	(0.022)	(0.029)		(0.208)	(0.269)	(0.024)
Age of the respondent	0.001	0.001	0.000	0.001	0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hindu religion	0.008	0.009	-0.150***	0.002	0.022	0.012
	(0.036)	(0.034)	(0.037)	(0.046)	(0.050)	(0.033)
Years of education of the	0.001	0.001	-0.013***	0.000	0.003	0.001
respondent	(0.003)	(0.003)	(0.003)	(0.005)	(0.006)	(0.003)
Monthly household income	0.003	0.009*	-0.024***	0.003	0.011	0.001
(thousand INR)	(0.003)	(0.005)	(0.004)	(0.007)	(0.011)	(0.003)
Household size	0.003	0.002	0.031***	0.005	-0.000	0.007
	(0.009)	(0.009)	(0.007)	(0.014)	(0.016)	(0.008)
Respondent is a housewife	0.124***	0.150***	-0.030	0.122**	0.154**	0.123***
	(0.041)	(0.056)	(0.079)	(0.048)	(0.064)	(0.044)
Number of cooks in the	-0.013	-0.014	-0.013	-0.015	-0.011	-0.020
household	(0.037)	(0.040)	(0.055)	(0.041)	(0.045)	(0.039)
Kitchen is located outside	0.009	0.015	-0.022	0.009	0.016	0.043
the dwelling space	(0.036)	(0.036)	(0.037)	(0.040)	(0.040)	(0.037)
CY5	0.089*	0.081**	-0.334***	0.073	0.107	0.096***
	(0.050)	(0.040)	(0.051)	(0.108)	(0.089)	(0.037)
CY15	-0.062	-0.042	-0.292**	-0.074	-0.011	0.059
	(0.082)	(0.095)	(0.116)	(0.102)	(0.130)	(0.059)
Household owns a personal	-0.116*	-0.120	-0.127**	-0.119*	-0.109	-0.144***
computer	(0.061)	(0.084)	(0.052)	(0.072)	(0.101)	(0.056)
$Time\ to\ road_i$			0.004***			
			(0.001)			
First-stage residual ($\hat{u}_i$)				0.041	-0.089	
				(0.210)	(0.256)	
$Dirty_i$ × Age	No	Yes	No	No	Yes	No
$Dirty_i$ × Monthly income	No	Yes	No	No	Yes	No
Misclassificationα_0	No	No	No	No	No	Yes
Misclassificationα_1	No	No	No	No	No	Yes
Observations	588	588	588	588	588	588
Log likelihood	-163.400	-161.338	-300.8	-163.370	-161.233	-159.198
AIC	352.800	350.675	627.625	354.740	354.467	348.396
BIC	409.697	411.949	684.523	416.014	424.494	414.046

Notes: This table reports the average marginal effects. The numbers in parentheses are delta-method standard errors clustered at the *part* level in Columns 1–5 and delta-method standard errors in Column 6. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A2. The instructions used in the elicitation of subjective beliefs

<table>
<tr><th colspan="6">Subjective Probability-Related Information</th></tr>
<tr><td colspan="6">I will now ask you a few questions regarding the likelihood of the occurrence of the following events. There is no right or wrong answer. I just want to know what you think. There are 10 candies in front of you. One candy denotes one chance of the occurrence of any event out of 10. To express how likely you think it is that a specific event will occur, please choose and put aside some candies from the lot. If you put ZERO candies on the plate, this means that you are SURE that the event will NOT happen. As you ADD candies, this means you think that the LIKELIHOOD that the event will happen INCREASES. If you put one or two candies, it means that you think the event is unlikely to happen but is still possible. If you pick five candies, this means that it is just as likely to happen as it is likely not to happen. If you pick eight candies, this means that the event is more likely to happen than not to happen. If you put TEN candies on the plate, this means that you are SURE the event WILL HAPPEN.</td></tr>
<tr><td colspan="6">To the enumerator: If the SCORE calculated from Q3a is > 0, go to 10. If the SCORE is 0, skip 10 and go to 11</td></tr>
<tr><td>10</td><td colspan="4">How likely do you think it is that exposure to smoke from burning cooking fuel caused your disease symptoms?</td><td></td></tr>
<tr><td colspan="6">To the enumerator: Please explain the health status definitions in section VA of <u>Note to the Enumerators.</u></td></tr>
<tr><td>11</td><td colspan="5">Consider a hypothetical individual who is identical to you. Imagine that there are options regarding the primary fuel for cooking. In each health status situation, please answer how likely you think it is that she will become/remain sick in the next 30 days if she used [fuels] in all the previous 30 days?</td></tr>
<tr><td colspan="6">To the enumerator: Please ask only regarding the likelihood of falling <u>sick</u>. Please calculate 10 minus [candies for the likelihood of falling sick] and confirm the likelihood of staying healthy.</td></tr>
<tr><td colspan="2">Description of health status</td><td colspan="2">Case I: She is <u>healthy</u></td><td colspan="2">Case II: She is <u>sick</u></td></tr>
<tr><td colspan="2">Fuel used for cooking on all 30 days in the last month</td><td>LPG/kerosene/ electricity</td><td>Firewood/ cow dung cakes/coal</td><td>LPG/kerosene/ electricity</td><td>Firewood/cow dung cakes/coal</td></tr>
<tr><td>a</td><td>Sick</td><td></td><td></td><td></td><td></td></tr>
<tr><td>b = 10–a</td><td>Healthy</td><td></td><td></td><td></td><td></td></tr>
</table>

Notes: This is an English version of the subjective risk section in the second-round survey. See the Online Appendix for the full version of the questionnaire.