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Subjective Probabilistic Expectations, Household Air Pollution, and Health: Evidence from cooking fuel use patterns in India

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Abstract

An increasing number of empirical studies have investigated the determinants of cooking fuel choice in developing countries, where health risk from household air pollution is one of the most important issues. We contribute to this stream of literature by examining individuals' subjective probabilistic expectations about health risks when using different types of fuel and their influence on cooking fuel usage patterns. We also explore how these patterns, in turn, affect health status. Using data collected from 557 rural Indian households, we find that subjective probabilistic expectations of becoming sick from dirty fuel usage have a negative influence on the fraction of days with dirty fuel usage in the household. The results also show that dirty fuel usage degrades the health of the individual. We then examine the effectiveness of information provision regarding the health risks of dirty/clean fuel usage. Our simulation demonstrates that although the provision of information results in statistically significant changes in the households' cooking fuel usage patterns and in the individuals' health status, the changes may be small in size.

Keywords: Subjective probabilistic expectations, Household air pollution, Cooking fuel usage pattern, Health, Developing country

JEL classification: I10, Q40, C83

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1. Introduction

Household air pollution (hereafter, HAP), caused mainly by the incomplete combustion of dirty cooking fuels¹ coupled with inefficient cooking practices, is a global health threat accounting for more than 1.45 million annual premature deaths worldwide (Alem et al., 2016). In particular, developing countries suffer from exposure to HAP, accounting for approximately 3.7% of the loss of disability-adjusted life years (WHO, 2007). The main victims seem to be women due to their primary responsibility for cooking activities in the household (Jeuland et al., 2015).

To lower exposure to HAP in developing countries and thereby prevent the related health hazards, it is important to design effective policies that help reduce the use of dirty cooking fuel as well as inefficient cooking practices. There is a growing body of literature exploring the effectiveness of the adoption of improved cook stoves (ICSs, hereafter) in mitigating HAP in developing countries. ICSs that optimize fuel efficiency and emission reduction are often provided by governmental or nongovernmental organizations in low-income economies as a potential tool to reduce HAP (Rehfuss et al., 2014). Empirical evidence suggests that fuel- and technology-related factors along with individual-specific covariates as well as the knowledge and perception of the users significantly influence the adoption of the ICS (Lewis and Pattanayak, 2012; Jeuland et al., 2014a). However, the effectiveness of the ICS in lowering HAP varies across regions and target households (Adrianzén, 2013).

Alternatively, it also becomes necessary to understand why a large part of the population in developing countries continues to use dirty cooking fuels, which has motivated researchers to explore the role of different factors in the choice of cooking fuel used in developing countries. For example, previous studies observe that other than economic and

¹Cooking fuels such as firewood, solid biomass fuels, kerosene and coal are categorized as dirty cooking fuels because of the high smoke emission during combustion (WHO, 2018). Similarly, fuels such as electricity and LPG are categorized as clean cooking fuels for causing low smoke emission.

demographic factors such as income (Heltberg, 2005) and education (Farsi et al., 2007), energy access significantly affects the cooking fuel choice of households in developing countries (Pachauri and Jiang, 2008). Jeuland et al. (2015) also note that the relative cost advantage and availability of dirty fuels may be drivers in the use of such fuels in developing countries. Gupta and Köhlin (2006) argue that individuals in developing countries tend to choose dirty cooking fuels due to dietary preferences because they believe that food tastes better when cooked with such fuels.

However, despite much evidence in the literature, there remains an unexplored aspect of the choice of household cooking fuel, specifically, the role of expectations about health risks from HAP. In the absence of precise estimates of and/or information about the health risks related to HAP, individuals may have different expectations about these health risks and therefore make different decisions regarding the use of dirty fuel, regardless of personal preferences. Furthermore, researchers typically have no information about individuals' expectations for HAP's health risks. As a result, it is difficult to infer whether preferences or expectations motivate the choice of cooking fuel because different combinations of expectations and preferences can lead to the same observed choice (Delavande, 2014; Manski, 2004). This identification problem limits the ability to devise effective behavioral interventions (Delavande and Kohler, 2015).

Although neglected in studies on the choice of household cooking fuel, the role of expectations in other choice situations has drawn increasing attention in economics. Examples of choices studied include purchases of water treatment products (Brown et al., 2017), multiple sexual partners (Delavande and Kohler, 2015), mental health and labor supply (Baranov et al., 2015), migration (McKenzie et al., 2013) and portfolio allocation (Kézdi and Willis, 2011). These studies confirm that expectations play a certain role in various choice situations.

This study attempts to bridge the existing gap in the literature on the choice of household cooking fuel. In particular, we investigate the impact of individuals' expectations of becoming sick with diseases typically observed from HAP exposure (specifically, dry cough, sore or runny eyes, and difficulty breathing) on their cooking fuel usage pattern and health status. By cooking the fuel usage pattern, we refer to the fraction of days in which dirty fuel is used over a 30-day period. We explore the direct impact of individuals' subjective probabilistic expectations (SPEs, hereafter) of falling sick with such diseases on their cooking fuel usage patterns. Concurrently, we investigate how the individual's cooking fuel usage pattern, in turn, affects his or her probability of suffering from common physical symptoms. This helps us determine the degree to which individuals' expectations about the health risks related to HAP can influence their health status indirectly by influencing their cooking fuel usage pattern.

We analyze a unique dataset on individuals' expectations elicited in probabilistic form from survey respondents in rural India. To elicit the individuals' SPEs about health risks related to HAP, we adopted an interactive elicitation method using visual aids developed by Delavande and Kohler (2009). Our results show that SPEs influence cooking fuel usage patterns, which in turn affect the health status of individuals. Given the significant role played by SPEs in cooking fuel usage patterns, we then explore the effectiveness of providing information on the health risks of dirty/clean fuel usage. Our simulation demonstrates that although the provision of information results in statistically significant changes in households' cooking fuel usage patterns and in individuals' health status, the changes may be small in size.

The remainder of the paper is organized as follows. Section 2 describes the survey methodology and variables considered for the study along with their summary statistics. It also elaborates the methodology used to elicit the SPEs. The next section presents our

empirical model and results. Section 4 discusses the policy simulation results with shedding light on the potential bias that may exist in the estimation, and Section 5 concludes by discussing the directions of future research.

2. Data

2.1 Survey design

To collect data from rural Indian households on expectations, health, and cooking-related behaviors, we conducted a survey in 17 villages under the Dhapdhapi-II village council in the state of West Bengal, India. West Bengal is the second most densely populated state in India, with a population density of 1029/sq. km (Census of India, 2011). Rural areas of West Bengal show a high use of dirty cooking fuels (91.8%) as the primary source of cooking fuel (Census of India, 2011). According to the most recent report of Census of India (2011), West Bengal holds the eleventh position among 29 states and 7 union territories in India in terms of dirty cooking fuel use in rural areas after Chattisgarh (97.75%), Jharkhand (97.05%), Madhya Pradesh (95.7%), Meghalaya (95.61%), Bihar (94.65%), Tripura (94.3%), Odisha (93.79%), Uttar Pradesh (92.88%), and Nagaland (92.72%). In contrast, the lowest dirty fuel use is observed in rural regions of Chandigarh (12.18%). This indicates that the use of dirty cooking fuels is quite prevalent in rural regions of West Bengal, thus motivating our research design.

Located approximately 40 kilometers from the state capital, Kolkata, the survey site had a population of approximately 14,000 and a population density of 0.7 thousand per square kilometer as of January 2016. Although the survey site does not have a large population size, its population density is high in comparison with the average in India (approximately 0.4 thousand/sq. km). Due to its proximity to Kolkata, the survey site has

access to modern amenities but retains the typical traits of a rural area in any developing country.

Out of the total households in those villages, 600 were randomly selected as a sample for our analysis. The enumerators visited the selected households from December 2016 to January 2017. Our respondents are the individuals primarily responsible for cooking in the household; consequently, all of the respondents were female. The survey was conducted via the door-to-door interview method, thus ensuring a high response rate (approximately 99%), and thus the sample size at the end of the first round was 596. From December 2017 to January 2018, the data collectors made second visit to those households surveyed in the first round and were able to elicit responses from 588 out of the 596 original respondents (representing an attrition rate of 1.34%). For our analysis, we exclude from the sample respondents who had no spouse or provided no information about their spouse. This reduces our sample size to 557. Table 1 presents descriptive statistics of the variables used in this study; these will be explained in the next subsection.

<Table 1 approximately here>

2.2 Descriptions of the variables and their summary statistics

Fuel usage pattern

Empirical evidence in developing countries, particularly in rural areas, indicates the simultaneous use of multiple cooking fuels, often referred to as fuel stacking (Cheng and Urpelainen, 2014). To account for this in this study, the fuel use pattern (represented by the proportion of days dirty fuel is used for cooking) is the variable of interest, instead of the primary cooking fuel type (choice between clean and dirty cooking fuel), as has been done in previous literature (for example, Kishore and Spears (2014)). This information has been

elicited by the following survey instrument: “*How many days in the 30 days prior to last month did you use the following kinds of fuels for cooking: electricity, LPG, kerosene, coal/charcoal, solid biomass fuels such as animal dung cake and agricultural crop residue, firewood, or any other variety?*”. We compute the fraction of days of dirty fuel usage using information on the number of days the respondents used coal/charcoal, solid biomass fuels and firewood². This variable was collected in the second round (2017–18) of the survey for reasons we will explain in the next section.

The fraction is found to be 0.68 on average (see Table 1), suggesting the prevalence of dirty fuel usage in rural areas of India. To better understand this variable, we also draw its distribution in Figure 1. Although a certain portion of households are observed at the endpoint of the fuel usage pattern variable, the use of both clean and dirty cooking fuel seems to be common among households. This property of the variable motivated us to model it by using the fractional response variable framework, as will be explained later.

<Figure 1 approximately here>

² Although WHO (2018) classifies kerosene to be dirty cooking fuel, we have implemented our survey before this classification was published. In our study conducted prior to 2018, we have consistently followed the nomenclature referred by Duflo et al. (2008), Heltberg (2005) Kishore and Spears (2014) among others, where kerosene is classified as clean cooking fuel. We have elicited the SPE of becoming sick from clean cooking fuels by mentioning about LPG/kerosene in 2016-17, i.e., prior to the publication of the WHO categorization. This has constrained us to revert to referring kerosene as dirty cooking fuel, as that may lead to data tampering, consequently violating research ethics. However, we have tried to emphasize that such constraint would lead to a negligible bias in this context, as evident from the following discussion.

In our effective sample, there is no observation that uses kerosene as the primary cooking fuel. Only 4% of the households use kerosene at least once in a 30-day period, thereby, having a non-zero value in the share of days of kerosene usage, keeping the remaining 96% observations as same. Even if we include kerosene to be a dirty cooking fuel, the variable ‘fraction of days of dirty fuel usage in a 30-day period’ is not changed much (mean changes from 0.678 to 0.686; standard deviation changes from 0.378 to 0.379). Furthermore, we have also found the association between the two versions of the variable ‘fraction of days of dirty fuel usage’ once including kerosene and once, excluding kerosene, for the households using the Pearson’s correlation coefficient which is obtained as 0.9934. We perform the large sample test of the hypothesis that the population correlation coefficient is 0.99 against the alternative that it is more than 0.99 using the z-transformation (Fisher, 1921). The value of the test statistic is obtained as 4.946 ($p < 0.001$) indicating an extremely significant and almost unity correlation coefficient between the two versions of the two variables. In other words, these two series may be considered to be almost same and this further indicates that even if there is any bias arising from not including kerosene in dirty cooking fuels, this bias is expected to be statistically insignificant.

Self-reported health status

Evidence of the association of HAP with various health risks, including cardiovascular, respiratory and vision-related diseases, is available in the literature (Smith and Pillarisetti, 2017). Therefore, ideally, we should have incorporated the health information of the individuals for the abovementioned symptoms using a professional medical team. However, the process of conducting clinical tests for each respondent in the sample would have been costly. As an alternative, we have followed Hanna et al. (2016) and incorporated information on physical symptoms using individuals' past recollection of the experience of suffering from such symptoms in the last 30 days. From the questionnaire of Hanna et al. (2016), we included ten cardio-vascular, respiratory and vision-related symptoms in our questionnaire during the pilot study in August 2016 among 70 households in the same locality. Of them, three symptoms, namely, dry cough, sore and runny eyes, and difficulty breathing, were found to be the most prominent features. Consequently, we selected them in the final questionnaire to conduct the detailed survey.

The self-reported health status of the respondents refers to whether the respondent has experienced at least one of three minor, yet common physical symptoms caused by HAP—dry cough, sore or runny eyes, and difficulty breathing—in the last 30 days. Indeed, these symptoms are found to be prevalent among the respondents; 76 percent of the respondents experienced at least one of the three symptoms (see Table 1). Along with the fuel usage pattern, this variable was collected in the second round (2017–18) of the survey.

Methodology to elicit SPEs and the elicited SPEs

Partly because the survey targets households in a rural area of India, it was not assumed that the respondents would have a good understanding of the meaning of the word “probability” or of probability concepts. Therefore, to facilitate elicitation of SPEs from the

respondents, we used an interactive method with visual aids, which is described in detail by Delavande (2014) and Delavande and Kohler (2015). This method makes it cognitively easier for the respondents to answer questions involving probability concepts than other methods (Brown et al., 2017).

In this elicitation method, we explicitly asked the respondent to link the number of candies placed in front of her to her perceived likelihood of the occurrence of an event. During the elicitation, the enumerators first provided the following instructions to the respondents: *“There are ten candies in front of you. Each candy denotes one chance for the occurrence of any event out of 10. To express how likely, you think that a specific event will occur, please choose and put aside some candies from the lot. If you are sure that the event will not occur, please do not put any candies aside. If you think the event is more likely to occur, please put more candies. If you think, the event is less likely to occur, please put fewer candies. If you are sure that the event will occur, please put all the candies.”*. The respondent’s perceived likelihood of an event is then obtained by dividing the number of candies by 10.

Following Godlonton and Thornton (2013), who examine individuals’ beliefs regarding the prevalence of HIV, we elicited responses about the SPEs of different health situations for a hypothetical individual. We presume that the respondent expects her likelihood of being sick in the next three months to be dependent only on her current health status and cooking fuel usage; in other words, the health status is assumed to follow a first-order Markov process conditional on cooking fuel usage.

In the survey, we asked for four SPEs about the transition probabilities of health status. The respondents were first asked about two SPEs conditional on dirty fuel usage, denoted as $SP(s_{t+1} = 1 | s_t = 1, d)$ and $SP(s_{t+1} = 1 | s_t = 0, d)$, where s represents an indicator for being sick and d symbolizes dirty fuel usage. The former (the latter) represents

the expected likelihood that the hypothetical individual will remain (become) sick in the next three months given that she is currently sick (not sick) and uses dirty fuels only. By “sick,” we refer only to the individuals having suffered from at least one of the three symptoms in the last 30 days—dry cough, sore or runny eyes, and difficulty breathing. Using $SP(s_{t+1} = 1|s_t = 1, d)$, we can compute the expected likelihood of transition from “sick” to “not sick,” i.e., $SP(s_{t+1} = 0|s_t = 1, d)$, as $1 - SP(s_{t+1} = 1|s_t = 1, d)$. Likewise, we can compute the expected likelihood of transition from “not sick” to “not sick,” i.e., $SP(s_{t+1} = 0|s_t = 0, d)$, as $1 - SP(s_{t+1} = 1|s_t = 0, d)$. We also asked the respondents about two SPEs conditional on clean fuel usage, $SP(s_{t+1} = 1|s_t = 1, c)$ and $SP(s_{t+1} = 1|s_t = 0, c)$, where c symbolizes clean fuel usage. The other two transition probabilities, $SP(s_{t+1} = 0|s_t = 1, c)$ and $SP(s_{t+1} = 0|s_t = 0, c)$, can be computed in a similar manner to their counterparts on dirty fuel usage. Table 2 is presented to facilitate understanding of these transition probabilities.

<Table 2 approximately here>

For elicitation, we asked each respondent to consider a hypothetical individual identical to her in all respects except her current health status and cooking fuel usage. The respondent is then asked, using a survey instrument, to state how likely she thinks it is that each of the following events will occur: *“Suppose that the individual is currently sick (not sick). How likely is it that she will remain (become) sick in the next 3 months if she uses: a) LPG/kerosene and b) coal/solid biomass fuels/firewood?”*. During elicitation, we carefully avoided mentioning the terms “clean” and “dirty,” as that would have acted as a signal to the respondents and thereby induced social desirability response bias. All SPE variables were collected in the first round of the survey, unlike the fuel usage pattern and the self-reported health status.

Characteristics of the elicited SPEs

<Figure 2 approximately here>

We plot the distributions of $SP(s_{t+1} = 1|s_t = 1, c)$ and of $SP(s_{t+1} = 1|s_t = 1, d)$ in panels I and II of Figure 2, respectively. These figures show that a majority of the respondents expressed a low (high) expected probability of transition from “sick” to “sick” in the next three months by using clean (dirty) fuels only. It is also revealed that approximately six percent of the respondents expressed surety about remaining sick from dirty fuel usage, while such a pattern was not observed for clean fuel usage. Based on these results, the respondents seem to recognize the possible health benefits from clean fuel usage. This is also evident in the difference between these two SPEs. As presented in Table 1, the mean of the difference is found to be -0.47: the respondents on average think that clean fuel usage is 47 percent more likely to ease the symptom of the disease, suggesting that a certain number of respondents recognize that sickness is linked to the type of cooking fuel they use.

Panel III displays the distribution of $SP(s_{t+1} = 1|s_t = 0, c)$. Comparing Panel III with Panel I, the distribution of $SP(s_{t+1} = 1|s_t = 0, c)$ differs in shape from that of $SP(s_{t+1} = 1|s_t = 1, c)$; the respondents seem to feel that health status in the next period depends on that in the current period. Panel III also shows that a majority of the respondents assigned a low likelihood to falling sick in the next three months when using clean fuels only.

In Panel IV, we present the distribution of $SP(s_{t+1} = 1|s_t = 0, d)$. Approximately 70 percent of the respondents assigned a moderately high probability (i.e., 0.4 to 0.6) to falling sick in the next period from dirty fuel usage, and a higher likelihood was expressed by approximately 20 percent of the respondents. These results seem to be consistent with the respondents tending to associate dirty fuel usage with the deterioration of health. This observation is also supported by the mean difference of -0.4 between $SP(s_{t+1} = 1|s_t = 0, c)$

and $SP(s_{t+1} = 1 | s_t = 0, d)$, as shown in Table 1; the respondents on average think that dirty fuel usage is 40 percent more likely to degrade their health than clean fuel usage.

Using the elicited SPEs conditional on dirty fuel usage, we calculate the equilibrium distribution of the Markov process, denoted as $SP(s = 1 | d)$ ³. This represents the expectation about the long-term fraction of periods during which the respondent would be sick provided that she uses dirty fuels only. It can therefore be interpreted as the perceived risk from dirty fuel usage on health. Likewise, we derive the equilibrium distribution of the Markov process conditional on clean fuel usage, i.e., $SP(s = 1 | c)$, which can be interpreted as the perceived health risk from clean cooking fuel usage.

<Figure 3 approximately here>

Panels I and II of Figure 3 present the distributions of $SP(s = 1 | c)$ and $SP(s = 1 | d)$, respectively. The two distributions differ greatly in shape. The mean of the latter (0.73) is much larger than that of the former (0.17), as presented in Table 1; the respondents, on average, expect that dirty fuel usage will result in considerably longer periods of sickness than clean fuel usage. Furthermore, $SP(s = 1 | c)$ has a right-skewed distribution, while $SP(s = 1 | d)$ has a left-skewed distribution; for a majority of the respondents, the perceived risk from dirty (clean) fuel usage on health is larger (smaller) than the mean value implies.

Control variables

In addition to the SPEs, individual and household specific factors may influence the respondents' cooking fuel usage pattern and health status. In our models, we therefore control

³ $SP(s = 1 | d) = \frac{SP(s_{t+1} = 1 | s_t = 0, d)}{1 + [SP(s_{t+1} = 1 | s_t = 0, d) - SP(s_{t+1} = 1 | s_t = 1, d)]}$. We can obtain the other equilibrium SPE, $SP(s = 1 | c)$ using this relationship, replacing the SPEs conditional on dirty fuel usage to the corresponding SPEs conditional on clean fuel usage.

for a set of factors including number of cooks (surrogate for household size), total monthly household expenditure, respondents' age and years of schooling, dummy for the occupation of the respondent (respondent is housewife), dummies for the occupation of the spouse (spouse works in the informal sector and in the agricultural sector), dummy for religion (respondent is Hindu), time needed to reach the nearest market on foot (in minutes), dummy for the location of the kitchen (kitchen is located within the dwelling space), dummy for ventilation (cooking area has ventilation facility), and dummies for the ownership of a television and for access to internet.

In rural areas, one can access cooking fuels without incurring any monetary cost. For example, individuals, particularly the women and children in households, spend long hours daily collecting fuels (IEA, 2017), such as firewood from forests, common lands, roadsides, and private fields; crop residues from farms; and dung gathered from domestic animals (Das and Srinivasan, 2012). Such access may influence the respondents' cooking fuel usage pattern. We therefore asked the respondents the following question: "*Do you have an opportunity to collect/get cooking fuels for free?*". Fifty-nine percent of the respondents were found to have access to free cooking fuels (see Table 1).

3. Estimation models and results

We address whether SPEs influence individuals' cooking fuel usage patterns, and in turn whether usage patterns affect individuals' health. If so, SPEs have a direct effect on cooking fuel usage patterns and an indirect effect on individuals' health. For this purpose, we take a two-step approach. In the first stage, we estimate the effect of SPEs on individuals' cooking fuel usage patterns. Second, we estimate the effect of cooking fuel usage patterns on individuals' health. This allows us to infer the extent to which SPEs influence individuals' health conditions indirectly through cooking fuel usage.

For this estimation, we need to address several econometric issues. First, the dependent variable in the first stage, that is, the individual's choice of fuel usage pattern, has a particular feature; specifically, it is restricted to values in the unit interval $[0,1]$. In addition, a non-negligible fraction of observations is located within the interval, as mentioned earlier. To fully account for this characteristic of the data, we use a fractional response variable framework (Papke and Wooldridge, 1996).

Second, the fuel usage pattern may be endogenous in the second stage regression of a binary health status variable. To address the nonlinearity of the model as well as the presence of the fractional endogenous regressor, we use the two-stage residual inclusion method (Terza et al., 2008).

Third, the simultaneous elicitation of responses related to cooking fuel usage patterns and SPEs may lead to the issue of reverse causality between them. To address bias due to reverse causality, we use lagged values of SPEs in modeling cooking fuel usage patterns. For this purpose, we conducted the survey in two rounds with a gap of one year, whereby SPE variables were elicited in the first round (2016–17) and responses related to cooking fuel usage behaviors were collected in the second round (2017–18), as mentioned earlier. In the next sub-sections, we describe the estimation model and results in detail.

3.1. Effect of SPEs on cooking fuel usage patterns

Estimation model

We assume that individual i chooses fuel usage pattern (w_i) based upon her SPEs of falling sick (denoted by the vector \mathbf{spe}_i), individual and household characteristics (\mathbf{z}_i), and opportunity to access free cooking fuels ($free_i$). In particular, we specify the conditional mean of w_i , given the observed characteristics, in the following manner:

$$E(w_i | \mathbf{spe}_i, \mathbf{z}_i, free_i) = \Phi(\beta_0 + \boldsymbol{\beta}_1 \mathbf{spe}_i + \boldsymbol{\beta}_2 \mathbf{z}_i + \beta_3 free_i), \quad (1)$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal random variable that ensures that predicted values are in the interval $[0,1]$, as required by the data. For later use, we re-express equation (1) in the following form:

$$w_i = \Phi(\beta_0 + \beta_1 \mathbf{spe}_i + \beta_2 \mathbf{z}_i + \beta_3 \mathbf{free}_i) + r_i, \quad (2)$$

where r_i is an idiosyncratic error term with $E(r_i | \mathbf{spe}_i, \mathbf{z}_i, \mathbf{free}_i) = 0$.

We estimate equation (1) (or, equivalently, equation (2)) by the Bernoulli quasi-maximum likelihood because the obtained estimator is robust to distributional assumptions. It can be shown that this estimator is consistent as long as the conditional mean function is correctly specified (Wooldridge, 2010). We compute robust standard errors, as recommended by Papke and Wooldridge (1996).

Estimation results

We estimate equation (1) by including the combinations of the four elicited SPEs as covariates. Specifically, we include the difference in the SPEs conditional on health status “sick” in period t (i.e., $SP(s_{t+1} = 1 | s_t = 1, c) - SP(s_{t+1} = 1 | s_t = 1, d)$) and the difference conditional on health status “not sick” in period t (i.e., $SP(s_{t+1} = 1 | s_t = 0, c) - SP(s_{t+1} = 1 | s_t = 0, d)$). The former (latter) difference refers to the expected reduction in the likelihood of being sick due to clean fuel usage, given that the current health status is “sick” (“not sick”).

<Table 3 approximately here>

Column 1 of Table 3 presents the estimation results. In line with the previous literature, the results show that individuals with higher income (proxied by household expenditure), higher levels of education, better access to information (via internet access), and an affiliation with the Hindu religion tend to reduce their dirty fuel usage. It is also found

that proximity to the market induces households to decrease dirty fuel usage, while access to free cooking fuels motivates them to increase dirty fuel usage. The difference in the elicited SPEs conditional on current health status “not sick” is positively associated with how often dirty fuel is used, but the level of significance is marginal ($p < 0.1$). This suggests that an increase in the expected reduction of health risks by clean fuel usage given that the current health status is “not sick” will lower the dirty fuel usage. However, the differences in the elicited SPE variables are not found to play an important role in cooking fuel usage patterns when separately including the difference of the SPEs conditional on “not sick” (Column 2) or conditional on “sick” (Column 3).

<Table 4 approximately here>

To the extent that individuals are concerned about the long-term fraction of time during which they would be sick, the equilibrium SPEs may play a role in cooking fuel usage patterns. To explore this possibility, we examine the equilibrium SPEs as covariates for equation (1). As presented in Column 1a of Table 4, the results show that although $SP(s = 1 | c)$ is not associated with cooking fuel usage patterns, $SP(s = 1 | d)$ is ($p < 0.05$). The average marginal effect of $SP(s = 1 | d)$ is found to be -0.188 (Column 1b), indicating that if an individual’s perceived health risk from dirty fuel usage increases by 10 percentage points, she will lower the fraction of days of dirty fuel usage by approximately 1.9 percentage points.

We also examine whether the difference between the equilibrium SPEs (i.e., $SP(s = 1 | c) - SP(s = 1 | d)$) and their ratio (i.e., $SP(s = 1 | c)/SP(s = 1 | d)$) matter to cooking fuel usage patterns. Both measures refer to the individuals’ perceived reduction in health risk from using clean cooking fuel instead of dirty fuel. As presented in Column 2a, the difference in the equilibrium SPEs is positively and significantly associated with the fraction of days of

dirty fuel usage ($p < 0.05$), suggesting that an increase in the expected reduction of health risks through clean fuel usage will lower dirty fuel usage. According to the average marginal effect (Column 2b), a reduction of 10 percentage points in the perceived health risk due to clean cooking fuel usage is associated with a 1.8 percentage point decrease in the fraction of days of dirty fuel usage. Similar results are obtained for the ratio of the equilibrium SPEs (Columns 3a and 3b), although the significance is marginal ($p < 0.1$). Overall, our results show that individuals' SPEs have some influence on their cooking fuel usage patterns, but the magnitude of the impact may be small.

<Table 5 approximately here>

To account for the distribution of the cooking fuel usage pattern, we used the fractional response variable framework. To examine the robustness of our results to estimation methods, we re-estimated equation (1) by fitting a linear regression. As Table 5 presents, the results are qualitatively and quantitatively similar to those based on the fractional response models. Our main results therefore do not seem to be driven by the fractional variable framework.

3.2. Effect of cooking fuel usage pattern on health

Estimation model

We assume that the underlying health status of individual i (s_i^*) is unobservable and depends on the fuel usage pattern (w_i), individual and household specific characteristics, and individuals' SPEs ($\mathbf{x}_i = [\mathbf{z}_i \mathbf{spe}_i]$):

$$s_i^* = \gamma_0 + \gamma_1 w_i + \boldsymbol{\gamma}_2 \mathbf{x}_i + \gamma_3 r_i + u_i, \quad (3)$$

where u_i is an idiosyncratic error term that is uncorrelated with w_i and \mathbf{x}_i . In our estimation,

the opportunity to access free cooking fuels ($free_i$) plays a role as an instrument.

For our instrument to be valid, it must be sufficiently correlated with the endogenous regressor (i.e., instrument relevance), while it must not be correlated with the error term in equation (3) or must not directly influence the dependent variable (i.e., instrument exogeneity). The instrument seems to be relevant in that it is strongly correlated with the fuel use pattern (captured by the fraction of days of dirty fuel use), as presented in Tables 3 and 4. On the other hand, the exogeneity of the instrument cannot be tested formally because the model is just identified. We therefore discuss the plausibility of the exogeneity assumption.

First, it is not unreasonable to assume that the opportunity to access free cooking fuels does not directly influence the health status of the individual. If the opportunity to access free cooking fuels is associated with the health status of the individuals, the fuel use pattern should be a mediator, representing the only way through which free cooking fuel is indirectly associated with health status.

The most likely threat to the exogeneity assumption is unobserved individual-specific factors. A usual suspect is the degree of health unconsciousness that is contained in the error term of equation (3) and reflects that health-conscious individuals tend to have better health than their health-unconscious counterparts. This factor may invalidate the exogeneity assumption of our instrument by inducing correlation between the error term and our instrument. The correlation may occur because health-unconscious individuals prefer to use firewood more than their health-conscious counterparts; the former may be more likely than the latter to choose to live where they can collect free firewood.

The threat, however, may not be so plausible when considering that the sample has been collected in India. Indian society is essentially patriarchal in nature (Perianayagam and Goli, 2012), which is clearly reflected in the structure of marriage. Ethnographic studies suggest that women have a low or no say over marriage decisions (including the choice of

spouse or in-laws) in India (Allendorf, 2013). The patrilocal residence system prevalent in India furthermore offers married women limited or no chance to choose the location of the household (Khalil and Mookerjee, 2018; Dalmia and Lawrence, 2005). Since the respondents in our sample are essentially married women, they are unlikely to have a choice about the location of their households, regardless of whether they are health-(un)conscious. As a result, the opportunity to access cooking fuel for free is unlikely to be correlated with the degree of health-(un)consciousness.

Despite the argument, we admit that the exogeneity of our instrument may remain questionable. We will therefore discuss whether our main results are maintained when the exogeneity assumption is not satisfied by considering the likely direction of the bias in the estimator of the coefficient on the fuel use pattern.

Estimation results

<Table 6 approximately here>

Columns 1a and 1b in Table 6 present the estimated coefficients and corresponding average marginal effects, respectively, where the first stage model is specified as in Column 1a of Table 4. We find that the coefficient on the first stage residual is not significant at the ten percent level; in other words, there is little evidence that the fuel usage pattern is endogenous in equation (4). We also observe that the fuel usage pattern is positively and significantly associated with the likelihood of being sick with at least one of the physical symptoms ($p < 0.01$). Based on the average marginal effect, the likelihood increases by approximately six percentage points with an increase in dirty fuel usage of ten percentage points. These results seem to remain largely unchanged even when the first stage model is specified as in either Columns 2a or Column 3a of Table 4. Overall, the results for equation

(4), along with those for equation (1), support the finding that the SPEs indirectly affect health status by influencing cooking fuel usage patterns.

4. Discussion

4.1. Simulation of policies

Because SPEs were most likely made based on very limited information or even no information except past experience, respondents could update their SPEs upon obtaining information regarding dirty/clean fuel usage. This provides a rationale for information provision policies, given our evidence that SPEs matter to cooking fuel usage patterns. Several studies have shown that information provision may reduce health and environmental risks in developing countries (Somanathan, 2010). For example, the disclosure of information on water contamination has induced households to switch their drinking water source (Barnwal et al., 2017) or adopt related preventive measures (Brown et al., 2017). Likewise, Dendup and Arimura (2019) established that access to information can influence clean cooking fuel usage in their study of rural Bhutanese households. However, contradictory evidence is also available in the literature. For instance, Delavande and Kohler (2015) concluded that information provision about the transmission risk of HIV disease has limited impact on risky sexual behavior in rural Malawi. Correspondingly, the provision of information about health seems to be ineffective in the adoption of preventive measures for malarial diseases in Kenya (Dupas, 2009).

In this section, we consider and evaluate different information provision alternatives by simulating the extent to which they influence the fuel usage patterns and consequently the health of individuals. We assume that in response to information provision about the health risks associated with different cooking fuel categories, all individuals update their SPEs to a preset benchmark level. It would be ideal to examine how individuals respond when

information is provided on the “true” risk of dirty/clean fuel usage, as it could serve as a benchmark. Unfortunately, such information is not available to us. We therefore consider cases in which individuals are informed of the proportion of sick individuals among those who predominantly use clean (dirty) fuels as the benchmark level. In our sample, 47 (397) respondents out of 130 (458) who primarily used clean (dirty) fuels were found to be sick; 0.36 (0.87) is therefore set as the benchmark probability of becoming sick from clean (dirty) fuel usage.

We explore three alternative outcomes: first, when only information about health risk from clean cooking fuel is provided; second, when only information about health risks associated with dirty cooking fuel is provided; and finally, when both types of information are provided simultaneously. For the policy simulation analysis, we use the estimated models specified in Column 1a of Table 4 and Table A1. The model in Table A1 is a restricted version of that reported in Table 6, where the first stage residuals are excluded from a set of regressors. Table 7 presents summary statistics for the predicted fuel usage patterns and the proportions of sick individuals under the policy alternatives. The table also provides the average changes in predicted probabilities and proportions of individuals whose predicted dirty fuel usage increased or decreased from the baseline scenario.

<Table 7 approximately here>

In response to information provision about the health risks from clean cooking fuels, 547 (41) individuals who had an $SP(s = 1|c)$ below (above) than 0.36 update to the benchmark level. If the objective of information provision is to reduce (increase) dirty (clean) fuel usage among households, the policy maker is likely to have an undesirable outcome. Most of the individuals (approximately 93%) become pessimistic about clean cooking fuels

and increase their usage of dirty fuel compared to the no-policy situation; specifically, the average fraction of days of dirty fuel usage increases from 67.8% to 70.9%. This increase in dirty fuel usage also adversely affects the health of the individuals. On average, the predicted proportion of sick individuals increases to 83.5% from the baseline (82.3%).

When only information about health risks associated with dirty cooking fuels is provided, 510 (78) individuals who had an $SP(s = 1|d)$ below (above) than 0.87 updated to that level. Under this policy alternative, the majority of the individuals become aware of the health risks associated with dirty fuel usage. On average, the fraction of days of dirty fuel usage reduces to 65.3% from the baseline situation (67.8%). This reduction possibly occurs because approximately 87% of the individuals reduce their dirty fuel usage compared with the baseline situation, as they turn pessimistic about dirty cooking fuels. As a result of this reduction in dirty fuel usage, the associated health conditions among the individuals improve. The average predicted proportion of sick individuals reduces to 80.5% compared to the no-policy situation (82.3%). Although the average change in predicted probabilities of becoming sick is quite small (1.8%) in our sample, this result suggests that providing information about the health risks related to dirty cooking fuel may lead to a reduction in dirty fuel usage among the households and consequently improve the related health status.

Because the impact of information works in the opposite direction for clean fuel versus dirty fuel usage, the effect of the policy becomes nullified when information on the health risks associated with both clean and dirty cooking fuels is provided simultaneously. We observe that the mean fraction of days of dirty fuel usage remains almost unchanged at 68% of days under this policy alternative. Accordingly, simultaneous information provision also does not affect the proportion of sick individuals; the mean predicted proportion of sick individuals remains almost unchanged at 82%. However, in comparison with the situation in which only information about the health risks from clean cooking fuels is provided,

approximately 40% of the individuals decrease their dirty fuel usage under this policy alternative.

Summarizing the impacts of different policy scenarios on cooking fuel usage patterns and health risks, we can conclude that information provision on the risks of dirty cooking fuel may lead to a reduction of dirty fuel usage and consequently improve health status, but the magnitude of the change is limited in our analysis. On the other hand, information provision about clean cooking fuels may have an undesired effect on the fuel usage pattern and consequently on health.

The impact of health information on the choice of clean cooking technologies seems ambiguous. Dendup and Arimura (2019) have provided evidence that access to information may influence the clean cooking fuel choice in developing countries. Analogous evidence of the effectiveness of information provision on the adoption of clean cooking technology is also available in the literature (Hazra et al., 2014). In contrast, there is a growing literature that discusses the limited impact of information provision on the use of clean cooking technology. For example, Jeuland et al. (2014b) established the limited impact of information provision on ICS adoption in their study in rural India. Similar evidence is also available in other developing countries (Lambe et al., 2019; Thurber et al., 2013). Our policy simulation results indicate that health information about dirty cooking fuels may have a limited impact in magnitude on the choice of clean fuel and health improvement, which is consistent with these findings.

Our proposed policy is related to the current policies adopted by the government of India to reduce HAP and promote clean cooking fuel adoption. In 2016, the government of India launched the Pradhan Mantri Ujjwala Yojana (PMUY) scheme that aims to provide free LPG connections to households, thus contributing to reducing HAP (Ministry of Petroleum and Natural Gas, 2016). Despite this initiative, the majority of households continue to use

dirty cooking fuels as either their primary or secondary sources of cooking fuel (Gould and Urpelainen, 2018). For example, as a result of the PMUY scheme, the percentage of rural LPG connections increased from 22% in 2015 to 68% in 2018 in rural West Bengal (CEEW, 2019), but only 24.5% of these households use LPG as the primary cooking fuel (NSSO, 2019). Since household interventions may be more socially acceptable and easier to implement than other forms of interventions (Chowdhury et al, 2019), our policy simulation result may indicate that information provision policy about dirty cooking fuels is expected to act as a stimulator for government policy, thus increasing its efficiency, particularly in rural areas.

4.2. Potential bias in our estimates

In the previous section, we have made an argument based on ethnographic evidence to justify the validity of our instrument, i.e., opportunity to access cooking fuel for free. The exogeneity of the instrument may still remain questioned, however, because the argument cannot be fully substantiated. For this reason, in this section, we assume that the instrument is not valid and speculate regarding the likely direction of the bias in the coefficient estimator for dirty fuel use.

The direction of the bias depends on the correlation between the instrument and the endogenous regressor as well as the correlation between the instrument and the error term. As we have already found that the sign of the former correlation is positive (Tables 3, 4, and 5), the sign of the latter is the question under discussion. As mentioned in the previous section, health unconsciousness is an omitted factor that can induce correlation between the instrument and the error term in equation (3). The sign of the correlation is likely to be positive because health-unconscious women are more likely to suffer from disease symptoms and more likely to prefer to use firewood and, hence, more likely to prefer to collect free

firewood than their health-conscious counterparts.

The two correlations combined, the direction of the bias in the coefficient estimate on dirty fuel use is expected to be positive. In other words, it is likely that we have overestimated the effect of dirty cooking fuel use on the likelihood of suffering from disease symptoms. This overestimation in turn suggests that the estimated impacts of information provision (presented in Table 7) on the likelihood that women suffer from disease symptoms are also larger in magnitude than they actually are, given that the estimated coefficients of equation (3) are used for simulation. Overall, the implication of the policy simulation seems unaffected by whether the exogeneity assumption of our instrument is satisfied or not; that is, information provision may only have a limited, if statistically significant, impact on the likelihood of a woman suffering from disease symptoms.

5. Conclusion

In this study, we analyze a unique dataset from rural Indian households to examine individuals' SPEs of becoming sick with the diseases typically observed from HAP exposure and their impact on cooking fuel usage patterns. Simultaneously, we also investigate how individuals' cooking fuel usage patterns, in turn, affect their health status. Our results support the hypothesis that individuals' expectations have some influence on cooking fuel usage patterns, although the magnitude of the impact seems to be rather small. The results also show that the increased usage of dirty cooking fuels is likely to increase individuals' likelihood of suffering from physical symptoms related to HAP. Based on the estimated coefficients, the policy simulation analysis suggests that providing information on the health risks of dirty cooking fuels will reduce dirty fuel usage among the individuals and consequently enhance the associated health status. However, the magnitude of the change is limited in our analysis.

At least two limitations of our analyses should be mentioned. First, we do not have detailed knowledge on how individuals update beliefs. In our policy simulation, we presumed that individuals update their beliefs immediately and accurately when they receive information. However, this may not be the case. Our simulation is based upon this assumption, and therefore, our results would represent the upper (or lower) bound of the effects of information provision. A study on the mechanism of belief updating is required. Second, examination of the content of information provision is not sufficient. We used, for simplicity, information on the proportion of sick individuals disaggregated by the primary fuel used, which can be different from the objective probability. More detailed analyses on “true” risk are required, including evaluation of heterogeneity regarding individual characteristics.

Although we have confined our attention to the health status of the respondents, this may be an oversimplification. To analyze the health impact of HAP holistically, we need to investigate the health status of the other household members, particularly that of children. Focusing only on the respondents’ expectations may be another oversimplification because cooking fuel usage is a household decision that may involve a trade-off between the perceptions of the respondent and her family members regarding cooking fuels. One future research avenue is the extension of our analysis by incorporating intra-household expectations. Finally, to comprehensively assess the role of SPEs on health, we plan to focus on the long-term health effects of HAP, which may demand the involvement of professional medical teams during the elicitation of responses.

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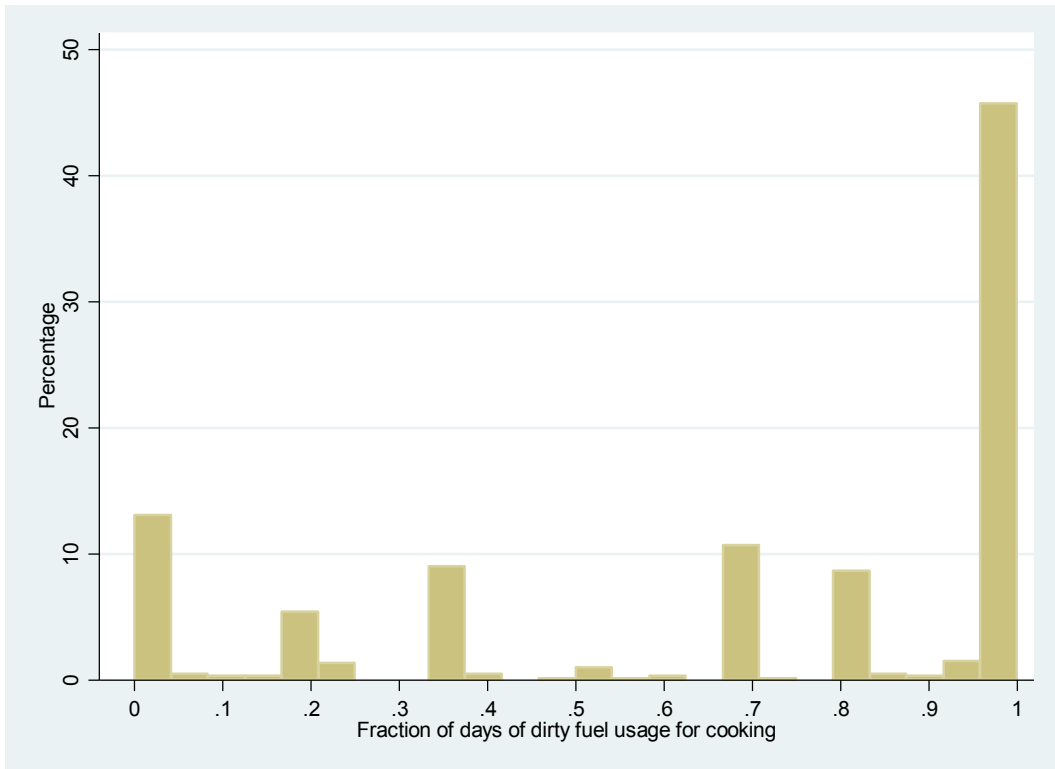


Figure 1. Distribution of fraction of days of dirty fuel usage for cooking

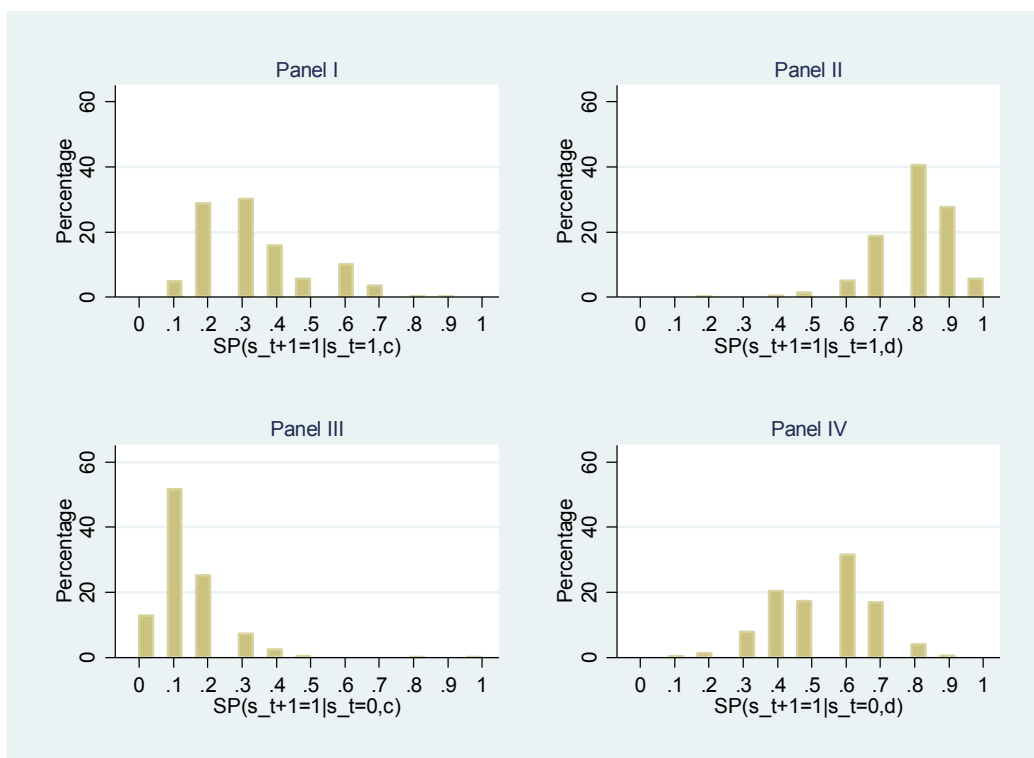


Figure 2. Distribution of the elicited SPEs

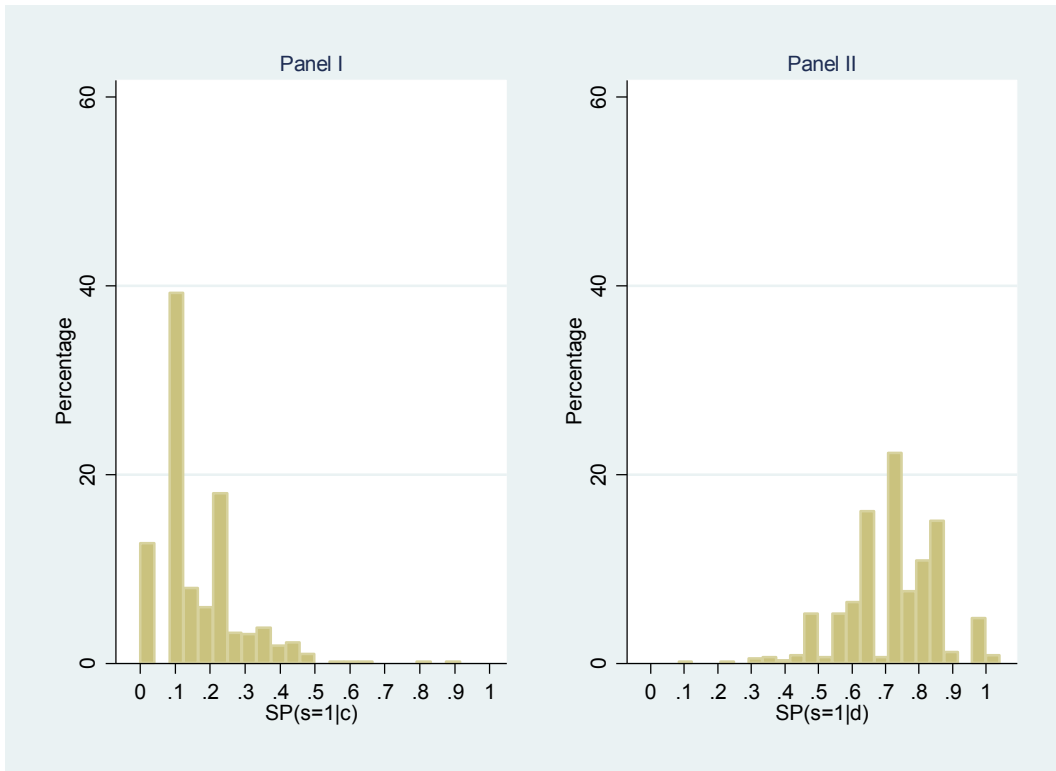


Figure 3. Distribution of the equilibrium SPEs

Table 1. Descriptive statistics (N = 557)

| Variable | Mean | SD | Min | Max |
|--------------------------------------------------------------------------------|-------|-------|------|------|
| <i>Sick in last 30 days with at least one physical symptom</i> (binary) | 0.76 | 0.43 | 0 | 1 |
| <i>Fraction of days of dirty fuel usage in 30 days prior to previous month</i> | 0.68 | 0.38 | 0 | 1 |
| <i>Subjective probabilistic expectations (SPE) variables</i> | | | | |
| $SP(s_{t+1} = 1 s_t = 0, c) - SP(s_{t+1} = 1 s_t = 0, d)$ | -0.40 | 0.15 | -0.8 | 0.5 |
| $SP(s_{t+1} = 1 s_t = 1, c) - SP(s_{t+1} = 1 s_t = 1, d)$ | -0.47 | 0.16 | -0.8 | 0.7 |
| $SP(s = 1 c)$ | 0.17 | 0.12 | 0 | 0.91 |
| $SP(s = 1 d)$ | 0.73 | 0.14 | 0.11 | 1 |
| $SP(s = 1 c) - SP(s = 1 d)$ | -0.56 | 0.17 | -1 | 0.52 |
| $SP(s = 1 c) / SP(s = 1 d)$ | 0.25 | 0.24 | 0 | 4 |
| <i>Control Variables</i> | | | | |
| Number of cooks | 1.13 | 0.41 | 1 | 4 |
| Age | 37.78 | 10.79 | 17 | 76 |
| Years of schooling | 4.83 | 4.13 | 0 | 17 |
| Hindu (binary) | 0.68 | 0.47 | 0 | 1 |
| Housewife (binary) | 0.97 | 0.17 | 0 | 1 |
| Spouse works in informal sector (binary) | 0.43 | 0.50 | 0 | 1 |
| Spouse works in agricultural sector (binary) | 0.30 | 0.46 | 0 | 1 |
| Kitchen located inside dwelling unit (binary) | 0.16 | 0.36 | 0 | 1 |
| Access to ventilation in cooking area (binary) | 0.97 | 0.16 | 0 | 1 |
| Time to market (minutes) | 17.52 | 13.60 | 1 | 120 |
| Expenditure (in INR 1,000) | 7.51 | 3.74 | 2.3 | 55 |
| Access to internet (binary) | 0.24 | 0.43 | 0 | 1 |
| Owns television (binary) | 0.86 | 0.35 | 0 | 1 |
| Opportunity to collect cooking fuels for free (binary) | 0.59 | 0.49 | 0 | 1 |

Note: In subjective probabilistic expectation (SPE) variables, $SP(\cdot | \cdot)$, s denotes the state of being sick with at least one of the physical symptoms (dry cough, sore or runny eyes, and difficulty breathing) and c (d) represents clean (dirty) fuel usage.

Table 2. SPEs about transition probabilities of health status conditional on dirty cooking fuel usage

| Health status in period t | Health status in period $t+1$ | |
|-----------------------------|-----------------------------------|-----------------------------------|
| | <i>sick</i> | <i>not sick</i> |
| <i>sick</i> | $SP(s_{t+1} = 1 \mid s_t = 1, d)$ | $SP(s_{t+1} = 0 \mid s_t = 1, d)$ |
| <i>not sick</i> | $SP(s_{t+1} = 1 \mid s_t = 0, d)$ | $SP(s_{t+1} = 0 \mid s_t = 0, d)$ |

Note: This table is provided to facilitate understanding our notations for the SPE variables. Replace d (dirty fuel usage) with c (clean fuel usage) for the SPEs about transition probabilities of health status conditional on clean cooking fuel usage.

Table 3 First stage results with the elicited SPEs (average marginal effects)

| | (1) | (2) | (3) |
|-----------------------------------------------------------|-----------|-----------|-----------|
| $SP(s_{t+1} = 1 s_t = 0, c) - SP(s_{t+1} = 1 s_t = 0, d)$ | 0.161* | 0.137 | |
| | (0.095) | (0.092) | |
| $SP(s_{t+1} = 1 s_t = 1, c) - SP(s_{t+1} = 1 s_t = 1, d)$ | -0.071 | | -0.021 |
| | (0.084) | | (0.081) |
| Number of cooks | 0.079** | 0.078** | 0.083** |
| | (0.032) | (0.032) | (0.032) |
| Age | -0.002* | -0.002* | -0.002* |
| | (0.001) | (0.001) | (0.001) |
| Years of schooling | -0.014*** | -0.014*** | -0.014*** |
| | (0.003) | (0.003) | (0.003) |
| Hindu | -0.154*** | -0.153*** | -0.157*** |
| | (0.029) | (0.029) | (0.029) |
| Housewife | -0.09 | 0.087 | -0.098 |
| | (0.064) | (0.064) | (0.066) |
| Spouse works in informal sector | 0.012 | 0.013 | 0.007 |
| | (0.03) | (0.03) | (0.03) |
| Spouse works in agricultural sector | 0.082** | 0.082** | 0.078** |
| | (0.035) | (0.035) | (0.035) |
| Kitchen located inside dwelling unit | 0.018 | 0.021 | 0.022 |
| | (0.038) | (0.038) | (0.038) |
| Access to ventilation | 0.086 | 0.088 | 0.081 |
| | (0.082) | (0.055) | (0.082) |
| Time to market | 0.003*** | 0.003*** | 0.003*** |
| | (0.001) | (0.001) | (0.001) |
| Expenditure | -0.017*** | -0.018*** | -0.018*** |
| | (0.004) | (0.005) | (0.005) |
| Access to internet | -0.13*** | -0.129*** | -0.13*** |
| | (0.028) | (0.028) | (0.028) |
| Owens television | -0.08 | -0.083*** | -0.082*** |
| | (0.042) | (0.042) | (0.041) |
| Opportunity to access free cooking fuel | 0.192*** | 0.193*** | 0.189*** |
| | (0.024) | (0.024) | (0.024) |
| <i>Pseudo log-likelihood</i> | -274.059 | -274.244 | -274.897 |
| <i>Pseudo R²</i> | 0.216 | 0.216 | 0.214 |
| χ^2 | 282.67 | 284.09 | 284.59 |

Note: This table provides estimation results for equation (1), where the dependent variable is the fraction of days of dirty fuel usage. Average marginal effects of the variables are presented. The sample size is 557. ***, ** and * indicate statistical significance at the one, five and ten percent levels, respectively. Standard errors in parentheses are computed by the delta method with robust standard errors for the parameters.

Table 4. First stage results with the equilibrium SPEs

| | (1a) | (1b) | (2a) | (2b) | (3a) | (3b) |
|-----------------------------------------|-----------|-----------|-----------|-----------|-----------|-----------|
| | Coef. | AME | Coef. | AME | Coef. | AME |
| $SP(s = 1 c)$ | 0.585 | 0.161 | | | | |
| | [0.424] | (0.117) | | | | |
| $SP(s = 1 d)$ | -0.682** | -0.188** | | | | |
| | [0.345] | (0.095) | | | | |
| $SP(s = 1 c) - SP(s = 1 d)$ | | | 0.641** | 0.177** | | |
| | | | [0.285] | (0.079) | | |
| $SP(s = 1 c)/SP(s = 1 d)$ | | | | | 0.396* | 0.109* |
| | | | | | [0.223] | (0.062) |
| Number of cooks | 0.287** | 0.079** | 0.286** | 0.079** | 0.288** | 0.079** |
| | [0.116] | (0.032) | [0.116] | (0.032) | [0.117] | (0.032) |
| Age | -0.008* | -0.002* | -0.008* | -0.002* | -0.008* | -0.002* |
| | [0.005] | (0.001) | [0.05] | (0.001) | [0.005] | (0.001) |
| Years of schooling | -0.052*** | -0.014*** | -0.052*** | -0.014*** | -0.051*** | -0.014*** |
| | [0.012] | (0.003) | [0.012] | (0.003) | [0.012] | (0.003) |
| Hindu | -0.531*** | -0.146*** | -0.532*** | -0.147*** | -0.558*** | -0.154*** |
| | [0.110] | (0.029) | [0.11] | (0.029) | [0.109] | (0.029) |
| Housewife | -0.304 | -0.084 | -0.305 | -0.084 | -0.336 | -0.092 |
| | [0.229] | (0.063) | [0.228] | (0.063) | [0.229] | (0.063) |
| Spouse works in informal sector | 0.071 | 0.019 | 0.071 | 0.02 | 0.045 | 0.012 |
| | [0.111] | (0.031) | [0.111] | (0.031) | [0.11] | (0.03) |
| Spouse works in agricultural sector | 0.299** | 0.083** | 0.298** | 0.082** | 0.285** | 0.079** |
| | [0.126] | (0.035) | [0.126] | (0.035) | [0.126] | (0.035) |
| Kitchen located inside dwelling unit | 0.077 | 0.021 | 0.078 | 0.021 | 0.087 | 0.024 |
| | [0.141] | (0.038) | [0.121] | (0.038) | [0.14] | (0.038) |
| Access to ventilation | 0.329 | 0.096 | 0.33 | 0.096 | 0.303 | 0.087 |
| | [0.274] | (0.083) | [0.274] | (0.083) | [0.272] | (0.082) |
| Time to market | 0.01*** | 0.003*** | 0.01** | 0.003*** | 0.01** | 0.003** |
| | [0.004] | (0.001) | [0.004] | (0.001) | [0.004] | (0.001) |
| Expenditure | -0.063*** | -0.018*** | -0.064*** | -0.018*** | 0.065*** | -0.018*** |
| | [0.017] | (0.005) | [0.017] | (0.005) | [0.017] | (0.004) |
| Access to internet | -0.458*** | -0.126*** | -0.458*** | -0.127*** | -0.461*** | -0.127*** |
| | [0.103] | (0.028) | [0.103] | (0.028) | [0.103] | (0.028) |
| Owns television | -0.298* | -0.082* | -0.296* | -0.082* | -0.288* | -0.079* |
| | [0.152] | (0.042) | [0.152] | (0.042) | [0.149] | (0.041) |
| Opportunity to access free cooking fuel | 0.714*** | 0.197*** | 0.714*** | 0.197*** | 0.704*** | 0.194*** |
| | [0.092] | (0.024) | [0.092] | (0.024) | [0.091] | (0.024) |
| <i>Log-likelihood</i> | -273.459 | | -273.469 | | -273.979 | |
| <i>Pseudo R²</i> | 0.218 | | 0.218 | | 0.216 | |
| χ^2 | 295.6 | | 295.04 | | 292.16 | |

Note: The dependent variable is the fraction of days of dirty fuel usage. AME denotes average marginal effects. The sample size is 557. ***, ** and * indicate statistical significance at the one, five and ten percent levels, respectively. Robust standard errors are in brackets. Standard errors in parentheses are computed by the delta method with robust standard errors for the parameters. The constant terms are not reported for the sake of space.

Table 5. Robustness check of first stage estimation (linear regression)

| | (1) | (2) | (3) |
|-----------------------------------------|----------------------|----------------------|----------------------|
| $SP(s = 1 c)$ | 0.147 (0.116) | | |
| $SP(s = 1 d)$ | -0.197** (0.096) | | |
| $SP(s = 1 c) - SP(s = 1 d)$ | | 0.176** (0.079) | |
| $SP(s = 1 c)/SP(s = 1 d)$ | | | 0.093** (0.043) |
| Number of cooks | 0.058** (0.029) | 0.058** (0.029) | 0.059** (0.03) |
| Age | -0.002* (0.001) | -0.002* (0.001) | -0.002* (0.001) |
| Years of schooling | -0.016*** (0.004) | -0.016*** (0.004) | -0.016*** (0.004) |
| Hindu | -0.152*** (0.029) | -0.152*** (0.029) | -0.16*** (0.029) |
| Housewife | -0.088 (0.067) | -0.088 (0.067) | -0.097 (0.067) |
| Spouse works in informal sector | 0.022 (0.036) | 0.023 (0.036) | 0.015 (0.036) |
| Spouse works in agricultural sector | 0.08** (0.038) | 0.079** (0.038) | 0.076** (0.038) |
| Kitchen located inside | 0.029 (0.04) | 0.03 (0.039) | 0.033 (0.04) |
| Access to ventilation | 0.108 (0.083) | 0.108 (0.083) | 0.1 (0.083) |
| Time to market | 0.003*** (0.001) | 0.003*** (0.001) | 0.003*** (0.001) |
| Expenditure | -0.013*** (0.005) | -0.013*** (0.005) | -0.013*** (0.005) |
| Access to internet | -0.157*** (0.035) | -0.158*** (0.035) | -0.159*** (0.036) |
| Ownership of television | -0.073** (0.032) | -0.073** (0.032) | -0.07** (0.031) |
| Opportunity to access free cooking fuel | 0.211*** (0.029) | 0.211*** (0.029) | 0.209*** (0.029) |
| R^2 | 0.373 | 0.372 | 0.369 |
| $Adjusted R^2$ | 0.354 | 0.355 | 0.352 |
| $F(1,557)$ | 29.4 | 31.32 | 31.07 |

Note: The dependent variable is the fraction of days of dirty fuel usage. Average marginal effects of the variables are presented. The sample size is 557. ***, ** and * indicate statistical significance at the one, five and ten percent levels, respectively. Robust standard errors are in parentheses. The constant terms are not reported for the sake of space.

Table 6. Second stage results with the equilibrium SPEs

| | (1a) | (1b) | (2a) | (2b) | (3a) | (3b) |
|--------------------------------------|----------|----------|----------|----------|----------|----------|
| | Coef. | AME | Coef. | AME | Coef. | AME |
| Fraction of days of dirty fuel usage | 4.111*** | 0.614*** | 4.115*** | 0.616*** | 4.172*** | 0.623*** |
| | [0.754] | (0.105) | [0.747] | (0.104) | [0.751] | (0.104) |
| $SP(s = 1 c)$ | -0.335 | -0.05 | | | | |
| | [0.638] | (0.095) | | | | |
| $SP(s = 1 d)$ | 0.060 | 0.009 | | | | |
| | [0.693] | (0.104) | | | | |
| $SP(s = 1 c) - SP(s = 1 d)$ | | | -0.18 | -0.027 | | |
| | | | [0.439] | (0.065) | | |
| $SP(s = 1 c)/SP(s = 1 d)$ | | | | | -0.151 | -0.022 |
| | | | | | [0.337] | (0.05) |
| Number of cooks | 0.032 | 0.005 | 0.027 | 0.004 | 0.023 | 0.003 |
| | [0.237] | [0.035] | [0.232] | (0.035) | [0.231] | (0.034) |
| Age | 0.018* | 0.003* | 0.019* | 0.003* | 0.019* | 0.002* |
| | [0.01] | [0.001] | [0.009] | (0.001) | [0.009] | (0.001) |
| Years of schooling | 0.022 | 0.003 | 0.022 | 0.003 | 0.023 | 0.003 |
| | [0.029] | [0.004] | [0.028] | (0.004) | [0.028] | (0.004) |
| Hindu | 0.163 | 0.024 | 0.166 | 0.025 | 0.178 | 0.027 |
| | [0.269] | (0.04) | [0.27] | (0.041) | [0.267] | (0.04) |
| Housewife | 0.872** | 0.13** | 0.867** | 0.129** | 0.879** | 0.131** |
| | [0.401] | (0.059) | [0.4] | (0.059) | [0.395] | (0.058) |
| Spouse works in informal sector | 0.234 | 0.035 | 0.232 | 0.035 | 0.236 | 0.035 |
| | [0.228] | (0.033) | [0.225] | (0.033) | [0.223] | (0.033) |
| Spouse works in agricultural sector | -0.355 | -0.053 | -0.358 | -0.053 | -0.362 | -0.054 |
| | [0.268] | (0.04) | [0.264] | (0.039) | [0.265] | (0.039) |
| Kitchen located inside dwelling unit | 0.159 | 0.023 | 0.166 | 0.024 | 0.161 | 0.024 |
| | [0.235] | (0.034) | [0.237] | (0.034) | [0.237] | (0.034) |
| Access to ventilation | 0.709 | 0.119 | 0.7 | 0.117 | 0.704 | 0.118 |
| | [0.592] | (0.112) | [0.578] | (0.109) | [0.581] | (0.11) |
| Time to market | 0.003 | 0.000 | 0.003 | 0.000 | 0.002 | 0.000 |
| | [0.009] | (0.001) | [0.009] | (0.001) | [0.008] | (0.001) |
| Expenditure | 0.003 | 0.000 | 0.002 | 0.000 | 0.003 | 0.000 |
| | [0.025] | (0.004) | [0.025] | (0.003) | [0.025] | (0.004) |
| Access to internet | 0.208 | 0.031 | 0.206 | 0.031 | 0.215 | 0.032 |
| | [0.258] | (0.038) | [0.255] | (0.038) | [0.253] | (0.037) |
| Owns television | 0.270 | 0.04 | 0.271 | 0.041 | 0.276 | 0.041 |
| | [0.393] | (0.059) | [0.391] | (0.059) | [0.389] | (0.059) |
| First stage residuals | -0.773 | -0.116 | -0.774 | -0.116 | -0.835 | -0.125 |
| | [0.769] | (0.115) | [0.762] | (0.114) | [0.76] | (0.114) |
| <i>Log-likelihood</i> | -150.739 | | -150.739 | | -150.686 | |
| <i>Pseudo R²</i> | 0.510 | | 0.509 | | 0.510 | |
| χ^2 | 128.77 | | 128.77 | | 132.47 | |

Note: This table provides estimation results for equation (3), where the dependent variable is the self-reported health status of the individuals (= 1 if the respondent has experienced at least one of the three physical symptoms). AME denotes average marginal effects. The sample size is 557. ***, ** and * indicate statistical significance at the one, five and ten percent levels, respectively. Standard errors in parentheses are computed by the delta method with bootstrap standard errors for the parameters (number of replications 500). The constant terms are not reported for the sake of space.

Table 7. Policy simulation results

| | Baseline | Information about the health risks of clean fuels | Information about the health risks of dirty fuels | Information about the health risks of both fuels |
|---------------------------------------------------------------------------------|---------------|---------------------------------------------------|---------------------------------------------------|--------------------------------------------------|
| <i>Panel I: On fraction of days of dirty fuel usage</i> | | | | |
| Predicted probability | | | | |
| 25% | 0.504 (0.021) | 0.553 (0.018) | 0.481 (0.024) | 0.534 (0.019) |
| 50% | 0.739 (0.015) | 0.775 (0.01) | 0.706 (0.013) | 0.751 (0.014) |
| 75% | 0.879 (0.011) | 0.893 (0.009) | 0.857 (0.009) | 0.875 (0.009) |
| Mean | 0.678 (0.01) | 0.709 (0.009) | 0.653 (0.01) | 0.686 (0.01) |
| % with reduced dirty fuel usage | | 7.01% | 87.07% | 39.86% |
| % with increased dirty fuel usage | | 92.99% | 12.93% | 60.14% |
| Average change in predicted probability conditional on reduced dirty fuel usage | | 0.031 (0.001) | -0.025 (0.001) | 0.008 (0.001) |
| conditional on increased dirty fuel usage | | -0.013 (0.003) | -0.030 (0.001) | -0.021 (0.001) |
| | | 0.034 (0.001) | 0.013 (0.002) | 0.026 (0.001) |
| <i>Panel-II: On probability of being sick</i> | | | | |
| Predicted probability | | | | |
| 25% | 0.745 (0.019) | 0.779 (0.017) | 0.719 (0.019) | 0.749 (0.016) |
| 50% | 0.911 (0.008) | 0.923 (0.006) | 0.897 (0.007) | 0.908 (0.006) |
| 75% | 0.963 (0.003) | 0.964 (0.003) | 0.957 (0.003) | 0.959 (0.003) |
| Mean | 0.823 (0.008) | 0.835 (0.008) | 0.805 (0.009) | 0.818 (0.009) |
| Average change in predicted probability | | 0.013 (0.001) | -0.018 (0.001) | -0.005 (0.001) |

Note: The results in this table are based on the estimated coefficients in Column 1a of Table 4 and Table A1. Bootstrap standard errors are in parentheses (number of replications 500). The values are approximated up to the third decimal place.

Appendix

Table A1. Second stage results with the equilibrium SPE (excluding residuals)

| | (1a) | (1b) | (2a) | (2b) | (3a) | (3b) |
|--------------------------------------|----------|----------|----------|----------|----------|----------|
| | Coef. | AME | Coef. | AME | Coef. | AME |
| Fraction of days of dirty fuel usage | 3.423*** | 0.515*** | 3.426*** | 0.516*** | 3.424*** | 0.515*** |
| | [.338] | (0.029) | [0.334] | (0.029) | [0.333] | (0.029) |
| $SP(s = 1 c)$ | -0.303 | -0.046 | | | | |
| | [0.635] | (0.095) | | | | |
| $SP(s = 1 d)$ | 0.015 | 0.002 | | | | |
| | [0.687] | (0.103) | | | | |
| $SP(s = 1 c) - SP(s = 1 d)$ | | | -0.141 | -0.021 | | |
| | | | [0.433] | (0.065) | | |
| $SP(s = 1 c)/SP(s = 1 d)$ | | | | | -0.123 | -0.019 |
| | | | | | [0.331] | (0.049) |
| Number of cooks | 0.078 | 0.012 | 0.073 | 0.011 | 0.074 | 0.011 |
| | [0.23] | (0.035) | [0.226] | (0.034) | [0.226] | (0.034) |
| Age | 0.017* | 0.003* | 0.018* | 0.003* | 0.017* | 0.003* |
| | [0.01] | (0.001) | [0.01] | (0.001) | [0.01] | (0.001) |
| Years of schooling | 0.008 | 0.001 | 0.009 | 0.001 | 0.009 | 0.001 |
| | [0.025] | (0.004) | [0.025] | (0.004) | [0.025] | (-0.004) |
| Hindu | 0.071 | 0.011 | 0.073 | 0.011 | 0.075 | 0.011 |
| | [0.242] | (0.037) | [0.243] | (0.037) | [0.238] | (0.036) |
| Housewife | 0.833** | 0.125** | 0.828** | 0.125** | 0.833** | 0.125** |
| | [0.392] | (0.058) | [0.392] | (0.058) | [0.385] | (0.057) |
| Spouse works in informal sector | 0.245 | 0.037 | 0.244 | 0.037 | 0.25 | 0.038 |
| | [0.224] | (0.033) | [0.222] | (0.033) | [0.22] | (0.033) |
| Spouse works in agricultural sector | -0.264 | -0.04 | -0.266 | -0.04 | -0.261 | -0.039 |
| | [0.264] | (0.04) | [0.26] | (0.039) | [0.262] | (0.04) |
| Kitchen located inside dwelling unit | 0.158 | 0.023 | 0.165 | 0.024 | 0.161 | 0.024 |
| | [0.235] | (0.034) | [0.236] | (0.034) | [0.235] | (0.034) |
| Access to ventilation | 0.779 | 0.133 | 0.77 | 0.131 | 0.779 | 0.133 |
| | [0.577] | (0.113) | [0.563] | (0.109) | [0.566] | (0.11) |
| Time to market | 0.005 | 0.001 | 0.005 | 0.001 | 0.005 | 0.001 |
| | [0.009] | (0.001) | [0.009] | (0.001) | [0.009] | (0.001) |
| Expenditure | -0.007 | -0.001 | -0.007 | -0.001 | -0.007 | -0.001 |
| | [0.022] | (0.003) | [0.022] | (0.003) | [0.022] | (0.003) |
| Access to internet | 0.09 | 0.014 | 0.087 | 0.013 | 0.088 | 0.013 |
| | [0.213] | (0.032) | [0.211] | (0.032) | [0.211] | (0.032) |
| Owns television | 0.216 | 0.032 | 0.218 | 0.033 | 0.218 | 0.033 |
| | [0.394] | (0.06) | [0.393] | (0.059) | [0.391] | (0.059) |
| <i>Log-likelihood</i> | -151.321 | | -151.37 | | -151.36 | |
| <i>Pseudo R²</i> | 0.508 | | 0.508 | | 0.508 | |
| $\chi^2(df)$ | 131.01 | | 134.7 | | 134.63 | |

Note: This table provides estimation results for equation (3), where the dependent variable is the self-reported health status of the individuals (= 1 if the respondent has experienced at least one of the three physical symptoms). The models in this table are restricted versions of those in Table 6 in that the first stage residuals are excluded from a set of regressors. AME denotes average marginal effects. The sample size is 557. ***, ** and * indicate statistical significance at the one, five and ten percent levels, respectively. Standard errors in parentheses are computed by the delta method with bootstrap standard errors for the parameters (number of replications: 500)