Effects of indoor air pollution on household health: evidence from Turkey

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Abstract
Indoor air pollution caused by the use of biomass energy in heating and cooking adversely affects the health status of household members. In Turkey, with the rapid economic growth of the last decade, biomass has been among the most consumed types of household energy for heating and cooking due to inadequate infrastructure, dependence on foreign energy, and high energy prices. This study aims to add empirical evidence to the literature on health status and indoor air pollution in Turkey caused by households’ energy choices. This study analyzed these effects with random effects panel discrete ordered models using the Income Living Conditions Micro Longitudinal Data Set for the period 2014–2017. As a result of the analysis, we found that the factors of age, being female, having dependent children, and indoor air pollution have adverse effects on health status. However, education level and income level affect health status positively. The most important observation obtained from this study is that even high-income households are adversely affected by indoor air pollution due to the lack of access to clean energy resources.

Keywords Indoor air pollution · Health · Panel discrete ordered models · Turkey

Introduction
In developing countries, indoor air pollution is a public health hazard due to the use of solid biofuels such as manure, wood, crop residues, and coal for daily cooking and residential space heating. According to the World Health Organization, the use of these fuels by poor people, which number more than three billion, causes risk to households’ health by creating levels of air pollution greater than those allowed by international ambient air quality standards (WHO 2018). Indoor air pollution causes increased risk of several serious conditions such as chronic respiratory disease, lung cancer, low birth weight, pneumonia, stroke, asthma, and cataracts in adults and children (Bruce et al. 2002).

Energy choice theory is often based on the “energy stack” and the “energy ladder” models. The energy stack model assumes that households tend to choose mixed energy sources from among all alternatives and can switch energy types. On the other hand, the energy ladder model was designed as a hierarchical relationship between household income and socioeconomic status and the type of energy used for cooking and heating. The polluting effect, efficiency, and costs of fuel are generally identified by the “energy ladder” model. Fuels that are cheap, inefficient, and the heaviest polluting such as dry animal manure, fallen branches, and grasses are the bottom rung in the energy ladder. In the second rung, households use coal, kerosene, and charcoal. In the third rung, high-income households tend to use modern fuels such as electricity and LPG. Movement up the rungs of this ladder is based on the income growth of households (Barnes and Floor 1999). In developed countries, there has been a transition from biofuels to petroleum products (kerosene, LPG) and electricity. On the other hand, in developing countries, even when cleaner and more advanced fuels are available, households generally continue to use biomass (Smith 1987). Poverty is one of the main constraints in the adoption of cleaner fuels, and unfortunately, the slow growth rate in many countries indicates that biofuels...
will continue to be used by the poor. Hence, the possible
dangerous effects of indoor pollution on human health caused
by energy choices, which are closely related to household
income and socioeconomic characteristics, should be
considered.

In the literature, there have been various studies examining the
health risks of indoor air pollution caused by cooking fuels on
women and children, since they spend a significant amount of
time near cooking stoves (Cerqueiro et al. 1990; Armstrong and
Campbell 1991; Johnson and Aderele 1992; Collings et al. 1990;
Shah et al. 1994; Albalak et al. 1999; Commodore et al. 2013).
The first study analyzing the effect of indoor cooking smoke on
children’s respiratory diseases was conducted by Sofoluwe
(1968). Mishra et al. (2004) investigated the relationship between
the reliance on highly polluting biomass fuels such as wood,
manure, or straw preferred by households and the prevalence of
acute respiratory infections in children using the cross-
sectional logistic regression method. The results show that chil-
dren living in households using biomass fuels are more than
twice as likely to be exposed to acute respiratory diseases.
Agrawal and Yamamoto (2015) analyzed the effect of cooking
smoke produced by biomass and solid fuel combustion on asth-
ma reported among adult men and women in India using multi-
variante logistic regression on cross-sectional data. The results
show that adult women living in households using biomass and
solid fuels are more likely to have asthma. Again, Mishra (2003)
analyzed the effect of cooking smoke on asthma using logistic
regression for elderly adults. The study results suggest that ex-
posure to food smoke is strongly associated with asthma regardless
of other demographic factors such as age, education, and stan-
dard of living. Duflo et al. (2008), Bruce et al. (2000), De
Francisco et al. (1993), and Khalequzzaman et al. (2007) are
other studies investigating the effect of cooking smoke on health.

Similarly, Boy et al. (2002) examined the relationship be-
tween exposure to indoor air pollution caused by heating en-
ergy choice during pregnancy and low birth weight in rural
Guatemala. Lakshmi et al. (2013) investigated the relationship
between indoor pollution and adverse pregnancy outcomes
such as miscarriage and postnatal infant mortality using the
Poisson regression. Both studies found a strong correlation
between stillbirths and low birth weight and indoor
pollution. Morris et al. (1990) analyzed the effects of fuels
used in heating on respiratory tract diseases using a multiple
logistic regression based on self-reported health data. They
concluded that households living in homes heated with bio-
mass have a high risk of respiratory disease. In addition, there
are also various studies investigating the relationship between
health status and indoor air pollution (Ezzati and Kammen
2001, 2002; Demjén et al. 2000; Bruce et al. 2002; Smith
et al. 2000).

Previous studies have also shown that there are strong as-
associations between indoor air pollution and acute lower respir-
atory tract infections in young children, chronic obstructive
pulmonary disease, and lung cancer in adult women (Fullerton
et al. 2008; Salvi and Barnes 2010; Dionisio et al. 2008; Ezzati
2005; Kim et al. 2011; Bruce et al. 2000, 2004). Moreover,
studies have determined the nexus between exposure to coal
and biomass smoke and lung cancer in men and women
(Subramanian and Govindan 2007; Shrestha and Shrestha
2005), asthma in school-age children (Smith et al. 2000;
Mishra 2003; Schei et al. 2002) Kovesi et al. 2006), and cat-
aracts and tuberculosis in adults (Ezzati and Kammen 2001,
2002; Mishra et al. 1999; Saha et al. 2005).

Although there are various studies investigating the health
effects of indoor pollution in less developed countries, there
are relatively few studies on developing countries in the liter-
ature (Qiu et al. 2019; Kim et al. 2011; Pérez-Padilla et al.
2010). Despite rapid economic growth in Turkey since the
early 2000s, biomass fuels such as manure, straw, and wood
are still preferred by the poorest and most vulnerable house-
holds for cooking and heating due to reasons such as inequal-
ities in income distribution, high energy prices, and lack of
infrastructure.

In general, the term air pollution is usually only considered in
the context of outdoor air pollution. However, the indoor micro-
environment has its own pollutants and pollution levels indoors
are generally higher than those outdoors (Hoskins 2003). In ad-
dition, cooking stoves and heaters are usually used for several
hours each day and at times when people are present indoors,
their exposure effectiveness is high; that is, the percentage of
their emissions that reaches people’s breathing zones is much
higher than for outdoor sources (Agrawal 2012). Over most of
the world cooking and heating add a considerable contribution to
the overall air pollution load in a dwelling (Smith 1993). Because
of this, indoor spaces are important micro-environments when
considering the impact of air pollution on health (Dutt et al. 1996;
Pearce 1996).

Presently, the whole world continues to be affected by the
rapid spread of the COVID-19 epidemic, which has spread
globally since the beginning of 2020. In particular, during
the COVID-19 pandemic, quarantine implications and lock-
downs have also increased the time spent indoors. Therefore,
determining the effects of indoor air pollution on human
health has again become an important issue for researchers
and politicians. Although indoor air pollution is generally
caused by wet or damp walls, cigarette smoke, house dust,
and the properties of the dwellings themselves, energy fuel
choice in dwellings is the most critical factor that causes
indoor pollution. Particularly in developing countries like
Turkey, even though income, economic growth, or socioeco-
omic factors trigger the transition from dirty fuels to clean
fuels, many households rely on biomass fuels for cooking and
heating. Therefore, the primary motivation for this study is to
provide important evidence for policies targeting a reduc-
tion in indoor air pollution and its effect on health. The study
investigated the impacts of indoor air pollution on health.
status caused by energy choice in Turkey by applying the random effects panel discrete ordered models on the Income and Living Conditions Research Micro Longitudinal Data Set (2014–2017). To the best of our knowledge, this study is the first to analyze the potential health effects of indoor air pollution based on energy choice in Turkey and is expected to fill a gap in the relevant literature by providing empirical results thereof.

The remainder of the paper is organized as follows: Section 2 provides the data sets used for the empirical analysis, Section 3 details the empirical strategy, Section 4 presents the econometric results, and Section 5 presents the discussion of the results.

**Data and methodology**

**Data**

In this study, the Income and Living Conditions Micro Longitudinal Data Set (ILC) was used in determining the nexus between household health status and indoor air pollution in Turkey. The ILC contains 4-waves panel microdata including overlapping records in the years of 2017-2016-2015-2014. The design of the ILC is a two-stage stratified cluster sampling. Household is described as the final sampling unit in the survey. It is possible to produce country-wide estimates from the annual panel research results. In the study, observations without available data for the basic variables, and observations for household members except the heads of households were excluded from the data set. The data set is a 4-year balanced panel, and it includes a total of 4881 households and 19,524 observations.

In the analysis, the health status of the head of the household was used as the dependent variable. Health status was measured as a 5-Likert scale (from 1=very bad to 5=very good) based on self-reported health status. In the survey, the household answered the question “How is your health?” Since self-reported health status is an ordered categorical variable, we preferred random effects panel discrete ordered models in the study. Indoor air pollution refers to chemical, biological, and physical contamination of indoor air. It may result in adverse health effects (OECD 2021). However, indoor air pollution is not directly measurable and the ILC data set includes only the primary energy source used by households. Therefore, the energy choices of households have been analyzed under the assumption of the energy ladder hypothesis. According to this hypothesis, pollution decreases as primitive fuels are exchanged for modern fuels. For this reason, the energy type preferred by households is regarded as indoor air pollution in the study.

Besides indoor pollution, frequently used demographic and economic variables that are related to the individuals’ health status in the literature are also included in the model. Educational status, gender, age, marital status, and dependent child dummy variables were taken as demographic factors. The household economic status variables of homeownership, log income, and SoL index were also added to the model as exogenous variables. Table 1 provides definitions and summary statistics of the variables used in the study.

It is widely accepted that there is a strong relationship between individuals’ health and housing conditions. Exposure to indoor air pollution is tightly linked with household access to, and choice of, energy source (Ezzati 2005). Therefore, using the principal components analysis, we created the standard of living index using physical properties of homes associated with health, such as bathrooms, toilets, kitchens, water systems, hot water systems, and economic assets such as telephones, internet services, TVs, and computers. Subsequently, we divided the Sol index into four subgroups of low, medium, high, and very high, and later the households were clustered.

Although there are external environmental factors such as air temperature, humidity, air quality, precipitation, and land surface wetness can all influence the indoor environment (Institute of Medicine 2011:18). These factors are generally taken into account through region or urban/rural variables in the literature (Albalak et al. 2001; Breyssse et al. 2010; Dionisio et al. 2008; Gao et al. 2009). However, we could not consider external environmental factors in this study neither directly nor indirectly due to lack of data availability.

The energy ladder hypothesis assumes that households follow a certain energy path depending on household income levels or living standards. Graph 1 clearly shows that as one ascends the steps of energy type used as a basis in the household, health status improves. Also, it presents a positive relationship between SoL and individuals’ health status. It also shows that there is a decrease in the health status of households using electricity as their primary energy source. This is due to the fact that even when households have sufficient income levels, electrical energy cannot be used efficiently for heating due to inadequate infrastructure. Moreover, the positive impact of electrical energy on health due to low emissions is significantly reduced because of insufficient heating.

**Methodology**

The health status of the head of household was used as a dependent variable in the study. Because this variable is ordered and categorical, we preferred ordered discrete choice models considering the unobserved individual heterogeneity. Random effect discrete ordered models fit via maximum likelihood the random effects model.

\[
Pr(y_{it} > j|J, x_{it}, v_i) = \Omega(x_{it}\beta + v_i - J_j)
\]  

(1)
for $i = 1, \ldots, n$ panels, where $t = 1, \ldots, n_i$, $y$ is the observed ordinal responses, $J$ is a set of cut points $j_1, j_2, \ldots, j_{J-1}$, where $J$ is the number of possible outcomes, and $v_i$ is independent and identically distributed $N(0, \sigma_v^2)$. If $\Omega(.)$ is the logistic cumulative distribution function, it is a random effect ordered logit model. On the other hand, if $\Omega(.)$ is the standard normal cumulative distribution function, it is a random effect ordered probit model.

From the above, we can derive the probability of observing outcome $j$ for response $y_{it}$ as

$$ p_{itj} = \Pr(y_{it} = j | J, x_{it}, v_i) = \Pr(j_{j-1} < X_{it}^T\beta + v_i + \varepsilon_{it} \leq j_j) $$

$$ = \Pr(j_{j-1} - X_{it}^T\beta - v_i < \varepsilon_{it} \leq j_j - X_{it}^T\beta - v_i) $$

$$ = \Omega(j_j - X_{it}^T\beta - v_i) - \Omega(j_{j-1} - X_{it}^T\beta - v_i) $$

(2)

### Table 1: Description of variables

| Variable                                      | Definition                                      | Mean  | S.D.  | Min  | Max  |
|------------------------------------------------|------------------------------------------------|-------|-------|------|------|
| Dependent variable                            | Self-reported health                            |       |       |      |      |
| (1) Very bad                                   |                                               | 0.01  | 0.10  | 0    | 1    |
| (2) Bad                                        |                                               | 0.11  | 0.32  | 0    | 1    |
| (3) Fair                                       |                                               | 0.26  | 0.44  | 0    | 1    |
| (4) Good                                       |                                               | 0.55  | 0.50  | 0    | 1    |
| (5) Very good                                  |                                               | 0.05  | 0.23  | 0    | 1    |
| Indoor air pollution (caused by type of main energy sources of households) | Level of indoor air pollution |       |       |      |      |
| Very unhealthy                                 |                                               | 0.02  | 0.15  | 0    | 1    |
| Unhealthy                                      |                                               | 0.16  | 0.37  | 0    | 1    |
| Moderate                                       |                                               | 0.33  | 0.47  | 0    | 1    |
| Good                                           |                                               | 0.41  | 0.49  | 0    | 1    |
| Very good                                      |                                               | 0.05  | 0.22  | 0    | 1    |
| Demographics characteristics of head of household | Gender                                       |       |       |      |      |
| If female=1 otherwise=0                        |                                               | 0.18  | 0.39  | 0    | 1    |
| If married =1 otherwise=0                      |                                               | 0.80  | 0.40  | 0    | 1    |
| Age is numerically measured.                   |                                               | 50.54 | 15.11 | 18   | 95   |
| Demographics characteristics of head of household | Marital status                                |       |       |      |      |
| If married =1 otherwise=0                      |                                               | 0.80  | 0.40  | 0    | 1    |
| Age is numerically measured.                   |                                               | 50.54 | 15.11 | 18   | 95   |
| Demographics characteristics of head of household | Age                                           |       |       |      |      |
| If there is a dependent child= 1               |                                               | 0.57  | 0.50  | 0    | 1    |
| Education                                      |                                               |       |       |      |      |
| No literacy                                    |                                               | 0.07  | 0.26  | 0    | 1    |
| Literate                                       |                                               | 0.06  | 0.23  | 0    | 1    |
| Primary school                                 |                                               | 0.41  | 0.49  | 0    | 1    |
| Secondary school                               |                                               | 0.12  | 0.32  | 0    | 1    |
| High school                                    |                                               | 0.18  | 0.38  | 0    | 1    |
| Higher education                               |                                               | 0.17  | 0.37  | 0    | 1    |
| Economic characteristics                       | Home ownership                                 |       |       |      |      |
| Homeownership=1 otherwise=0                    |                                               | 0.66  | 0.47  | 0    | 1    |
| Log income                                     | Log of household income                        |       |       | 0    | 1    |
| (1) Low                                        |                                               | 0.24  | 0.43  | 0    | 1    |
| (2) Medium                                     |                                               | 0.08  | 0.27  | 0    | 1    |
| (3) High                                       |                                               | 0.20  | 0.40  | 0    | 1    |
| (4) Very high                                  |                                               | 0.46  | 0.49  | 0    | 1    |

Graph 1: Estimated means of SRH by level of indoor air pollution and SoL with 95% CIs
where $j_0$ is taken as $-\infty$, and $j_J$ is taken as $+\infty$. Here, $X_i$ does not contain a constant term, because its effect is absorbed into the cut points.

We may also express this model in terms of a latent linear response, where observed ordinal responses $y_{it}$ are generated from the latent continuous responses, such that:

$$SRH_{it} = X_i \beta + v_i + \varepsilon_{it}$$

$$SRH_{it} = \begin{cases} 1 & \text{if } SRH_{it}^* \leq j_1 \\ 2 & \text{if } j_1 < SRH_{it}^* \leq j_2 \\ \vdots & \\ J & \text{if } j_{J-1} < SRH_{it}^* \end{cases}$$

where $SRH_{it}^*$ indicates the health status of the $i$th household at time $t$, $J$ is the number of possible outcomes, and $j_j$ is a set of cut points. $X_i$ is a matrix of explanatory variables, representing indoor pollution caused by household energy type (dried dung, firewood, charcoal, natural gas, and electricity) and socioeconomic variables (such as age, gender, education, income, and SoL) for the household. $\beta$ is a predicting parameter vector of the explanatory variables. Depending on the distribution property of the error term $\varepsilon_{it}$, the random effect discrete ordered model is separated into either random effect ordered logit or random effect ordered probit models. If the error term $\varepsilon_{it}$ is distributed as standard normal with mean zero and variance one, it is called a random effect probit model. However, if the error term $\varepsilon_{it}$ is distributed as logistic with mean zero and variance $\pi^2/3$, it is called a random effect ordered logit model. Except for the assumption of the distribution of error terms, there is no significant difference between the two models. For this reason, in the study, the model results are estimated by both methods and the findings are interpreted based on the goodness of fit model results.

**Empirical results**

In analyses, if there is a serial correlation in the error term or the panel data do not have an identical distribution, clustering over the panel variable allows us to obtain consistent estimators (Wooldridge 2002; Baltagi 2001). For this reason, we applied the Wooldridge autocorrelation test for serial correlation. The null hypothesis, which claims there is no serial correlation, was rejected. Therefore, we obtained robust clustered standard errors by Huber/White/sandwich variance-covariance matrix estimators (Wooldridge 2020).

Clustering on the panel variable produces a consistent VCE estimator when the disturbances are not identically distributed over the panels or existence serial correlation in the error term. The cluster robust VCE estimator requires the existence of many clusters and for the disturbances to be uncorrelated across them. The panel variable must be nested within the cluster variable because of the within-panel correlation, which is generally induced by the random effects transformation when heteroskedasticity or within-panel serial correlation in the idiosyncratic errors exists.

Equation 2 shows that parameters $\beta$ do not have a subscript $j$. It implies that the estimated coefficients in discrete ordered models are assumed to be the same regardless of the category of the output variable. This assumption is called the parallel line assumption or the proportional-odds assumption. In our model, log income ($P$-value 0.55), the homeowner ($P$-value 0.23), and marital status ($P$-value 0.11) violate the parallel line assumption at the 0.10 level. Although there is much evidence that the assumptions of the ordered models are frequently violated (Long and Freese 2014), we applied the parallel lines restriction for these three variables. The AIC and BIC statistics can be used to evaluate the trade-off between the better fit of the restricted model and the loss of parsimony from having a $J-1$ coefficient for each independent variable instead of just one (Long and Freese 2014). The smaller values of both the AIC and BIC statistics were obtained for the unrestricted model in which the parallel regression assumption is relaxed compared with the restricted model.\footnote{AIC and BIC values for restricted model are 35,857.17 and 35,809.85, respectively.}

Table 2 contains both random effects ordered logit and random effects ordered probit model results. The estimation results of both models are parallel to each other. However, a random effect ordered logit model fits the data set better when the AIC, BIC, and Log pseudo-likelihood values are compared. Moreover, Mc Fadden, Cox-Snell, and Cragg-Uhler pseudo $R^2$ values are calculated for the model goodness of fit. All pseudo $R^2$ values show that the random effect logit model has higher goodness of fit than the random effect probit model. The panel-level variance component of the random effect (sigma2_u) is both large and significant. This result supports that our empirical model captures unobserved heterogeneity between the households. Cut points represent the values of $j_j$ in Eq. 2 and are not expected to be statistically equal. If the ordered cut points are identical to each other, the relevant cut point must be eliminated. The null hypothesis is tested by the Wald test and the null hypothesis is strongly rejected. It implies that cut points are not statistically equal.

Since both model estimation coefficients are not practical for interpretation directly, marginal effects are estimated to better understand the analysis results. Marginal effects are estimated when other estimators are assumed constant at a certain level (usually for mean or median values), and they represent the relationship between their predicted probabilities. In other words, marginal effects measure how the probability of the output changes when the value of the estimator changes by one unit. Marginal effects of the RELOGIT model are given in Table 3.
Table 3 shows the effect of the factor affecting health status compared to the reference group based on each health level when the other variables are constant at their average levels. As the level of indoor air pollution improves in households with very bad, poor, and moderate health levels, the probability of being at their current health level decreases. On the other hand, in households at the good and very good health levels, as the level of indoor pollution improves, the probability of being at these health levels increases significantly. Households with good health levels increase their chances of achieving the unhealthy, moderate, good, and very good indoor air pollution levels by 6%, 5.5%, 7%, and 7.8%, respectively.

Table 2  Estimation results of REOPROBIT and REOLOGIT models

| Variables | REOPROBIT | REOLOGIT |
|-----------|-----------|-----------|
| Indoor air pollution | | |
| Very unhealthy | Base category | | |
| Unhealthy | 0.2432** | 0.4281** |
| Moderate | 0.2196** | 0.3877*** |
| Good | 0.2828*** | 0.5163*** |
| Very good | 0.3170*** | 0.5679*** |
| Demographics characteristics | | |
| of head of household | | |
| Female | −0.3656*** | −0.6727*** |
| Married | 0.0004 | −0.0210 |
| Age | −0.0460*** | −0.0842*** |
| Dependent child: yes | −0.0814*** | −0.1355*** |
| No literacy | | |
| Literate | 0.2886*** | 0.5317*** |
| Primary school | 0.5940*** | 1.0647*** |
| Secondary school | 0.6565*** | 1.1826*** |
| High school | 0.7923*** | 1.4306*** |
| Higher education | 1.0630*** | 1.9293*** |
| Economic characteristics | | |
| Homeowner: yes | 0.1257*** | 0.2278*** |
| Log income | 0.0409 | 0.0662 |
| SoL_Low | Base category | | |
| SoL_Medium | 0.0956** | 0.1813** |
| SoL_High | 0.1533*** | 0.2728*** |
| SoL_Very High | 0.2729*** | 0.4875*** |
| Cut points of outcomes | | |
| /cut1 | −4.7132*** | −8.8271*** |
| /cut2 | −2.8533*** | −5.2832*** |
| /cut3 | −1.3550*** | −2.5791*** |
| /cut4 | 1.4582*** | 2.5570*** |
| /sigma2_u | 0.7174*** | 2.4447*** |
| Model diagnostics | | |
| Number of Obs | 19,524 | 19,524 |
| Number of groups | 4881 | 4881 |
| Wald chi² (18) | 3130.24 | 3078.06 |
| Wooldridge F(1,4880) | 36.394*** | 36.394*** |
| Goodness of fits | | |
| Log pseudolikelihood | −17,842.454 | −17,756.499 |
| AIC | 35,730.91 | 35,559.00 |
| BIC | 35,912.13 | 35,740.22 |
| Pseudo $R^2$ | 0.034 | 0.034 |
| Mc Fadden $R^2$ | 0.034 | 0.034 |
| Cox-Snell $R^2$ | 0.064 | 0.072 |
| Cragg-Uhler $R^2$ | 0.075 | 0.084 |

***$P < 0.01$, **$P < 0.05$, *$P < 0.10$
Moreover, the factors of age, having dependent children, and being a woman increase the probability of being at fair and lower health status and decrease the probability of having good or very good health status levels. These results are consistent with existing literature and the realities of the country, since women are responsible for cooking and spend long periods at home due to their gender role in Turkey. Furthermore, income level, education level, and homeownership decrease the probability of having fair or below health status and increase the possibility of having good or very good health status levels.

**Conclusion**

Approximately half of the world’s population prefers coal or biomass fuels such as wood, animal manure, or crop residues for their energy needs (WHO 2018). There is evidence that the transition from biomass to cleaner fuels in heating and cooking, especially in low-income groups, has decreased significantly over the years (Bruce et al. 2002). This in turn has caused increased indoor air pollution and health problems.

Although the health impacts of air pollution have been examined by many studies in Turkey, the number of studies on the health effects of indoor air pollution has been limited. In this paper, we determined the effects of indoor air pollution caused by households’ energy choice on household health, applying random effects panel discrete ordered models on the Micro Longitudinal Data Set in Turkey. In contrast to previous studies, we considered unobserved heterogeneity between the households. We found that age, gender, and having dependent children in the household negatively affect household health. However, income, education, and homeownership are positively affected. Education is an important variable that positively affects a person’s health status. We also created the standard of living index using various indoor settings and economic variables. While the major determinants of the health-related indoor settings are toilets, kitchens, water systems, and hot water systems, the minor determinants are internet services, TVs, and computers. With the help of standard of living index, we found that higher standard of living in a household. Therefore, determining this effect empirically will provide guidance for decision-makers in energy and environmental policies. As a result of the study, we can report that even if households have high-income levels, their inability to access clean energy resources has serious negative effects on health. Particularly in developing countries such as Turkey, economic development and increases in the national

### Table 3 Marginal effects at the sample mean

| Variable          | SRH=1 Very bad | SRH=2 Bad | SRH=3 Fair | SRH=4 Good | SRH=5 Very good |
|-------------------|----------------|-----------|------------|------------|-----------------|
| Unhealthy         | −0.0016**     | −0.0282** | −0.0426**  | 0.0610**   | 0.0113***       |
| Moderate          | −0.0015*      | −0.0257** | −0.0383**  | 0.0554**   | 0.0101***       |
| Good              | −0.0018**     | −0.0321** | −0.0499*** | 0.0702***  | 0.0136***       |
| Very good         | −0.0020**     | −0.0354***| −0.0563*** | 0.0780***  | 0.0156***       |
| Female            | 0.0024***     | 0.0418*** | 0.0642***  | −0.0909*** | −0.0175***      |
| Age               | 0.0002***     | 0.0047*** | 0.0085***  | −0.0108*** | −0.0026***      |
| Dependent child   | 0.0004***     | 0.0082**  | 0.0150**   | −0.0190**  | −0.0046**       |
| Literate          | −0.0041***    | −0.0461***| −0.0371*** | 0.0800***  | 0.0073***       |
| Primary school    | −0.0066***    | −0.0845***| −0.0881*** | 0.1594***  | 0.0198***       |
| Secondary school  | −0.0069***    | −0.0911***| −0.0995*** | 0.1743***  | 0.0232***       |
| High school       | −0.0075***    | −0.1039***| −0.1249*** | 0.2048***  | 0.0315***       |
| Higher education  | −0.0082***    | −0.1242***| −0.1760*** | 0.2552***  | 0.0532***       |
| Homeowner         | −0.0007***    | −0.0131***| −0.0230*** | 0.0299***  | 0.0068***       |
| SoL_Medium        | −0.0016**     | −0.0110** | −0.0169**  | 0.0239**   | 0.0045*         |
| SoL_High          | −0.0009***    | −0.0171***| −0.0273*** | 0.0378***  | 0.0075***       |
| SoL_Very high     | −0.0015**     | −0.0287***| −0.0496*** | 0.0650***  | 0.0147***       |

***P < 0.01, **P < 0.05, *P < 0.10

Note: Only the statistically significant effects are listed. Marginal effects of the REOPROBIT are available upon request
income are not adequate for increasing public health. In these countries, access to clean and safe energy sources should also be increased. For this reason, policymakers should focus on infrastructure services to increase households’ access to clean and reliable energy sources.

Author contribution All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Özlem İpek and Egemen İpek. The first draft of the manuscript was written by Özlem İpek and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript and agree to be accountable for all aspects of the work.

Availability of data and materials The data supporting the findings of this study are available from the Turkish Statistical Institute. Restrictions apply to the availability of these data, which were used under license for this study.

Declarations

Ethics approval and consent to participate Not applicable

Consent for publication Not applicable

Competing interests The authors declare no competing interests.

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