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

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will continue to be used by the poor. Hence, the possible dangerous effects of indoor air 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 children 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 asthma reported among adult men and women in India using multivariate 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 exposure to food smoke is strongly associated with asthma regardless of other demographic factors such as age, education, and standard 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 between exposure to indoor air pollution caused by heating energy 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 biomass 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 associations between indoor air pollution and acute lower respiratory 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 catarracts 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 literature (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 households for cooking and heating due to reasons such as inequalities 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 addition, 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 lockdowns 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 socioeconomic 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 reduction 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 Research 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; Breysse 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.

$$\Pr(y_{it} > j | \mathbf{J}, x_{it}, v_i) = \Omega(x_{it}\beta + v_i - J_j) \quad (1)$$

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
	Marital status	If married =1 otherwise=0	0.80	0.40	0	1
	Age	Age is numerically measured.	50.54	15.11	18	95
	Dependent child	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	7.96	0.55	0	1
	Standard of living	(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

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

$$\begin{aligned}
 p_{itj} &\equiv \Pr(y_{it} = j | \mathbf{J}, x_{it}, v_i) = \Pr(j_{J-1} < X_{it}\beta + v_i + \varepsilon_{it} \leq j_j) \\
 &= \Pr(j_{J-1} - X_{it}\beta - v_i < \varepsilon_{it} \leq j_j - X_{it}\beta - v_i) \\
 &= \Omega(j_j - X_{it}\beta - v_i) - \Omega(j_{J-1} - X_{it}\beta - v_i)
 \end{aligned}
 \quad (2)$$

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_{it} 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:

$$SRH_{it}^* = X_{it}\beta + v_i + \varepsilon_{it} \quad (3)$$

$$SRH_{it} = \begin{cases} 1 & \text{if } SRH_{it}^* \leq j_1 \\ 2 & \text{if } j_1 < SRH_{it}^* \leq j_2 \\ \vdots & \\ J & \text{if } j_{j-1} < SRH_{it}^* \end{cases} \quad (4)$$

where SRH_{it}^* indicates the health status of the i th household head at time t . J is the number of possible outcomes, and j_i is a set of cut points. X_{it} 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. β is a predicting parameter vector of the explanatory variables. Depending on the distribution property of the error term ε_{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 ε_{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 ε_{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 β 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.¹

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 REOLOGIT model are given in Table 3.

¹ AIC and BIC values for restricted model are 35,857.17 and 35,809.85, respectively.

Table 2 Estimation results of REOPROBIT and REOLOGIT models

	Variables	REOPROBIT		REOLOGIT	
		Coefficient	Cluster robust Std. Err.	Coefficient	Cluster robust Std. Err.
Indoor air pollution	<i>Very unhealthy</i>	<i>Base category</i>			
	Unhealthy	0.2432**	0.0989	0.4281**	0.1813
	Moderate	0.2196**	0.0966	0.3877**	0.1773
	Good	0.2828***	0.0988	0.5163***	0.1813
	Very good	0.3170***	0.1133	0.5679***	0.2082
Demographics characteristics of head of household	Female	−0.3656***	0.0475	−0.6727***	0.0869
	Married	0.0004	0.0433	−0.0210	0.0788
	Age	−0.0460***	0.0014	−0.0842***	0.0025
	Dependent child: yes	−0.0814**	0.0331	−0.1355**	0.0604
	<i>No literacy</i>	<i>Base category</i>			
	Literate	0.2886***	0.0804	0.5317***	0.1465
	Primary school	0.5940***	0.0656	1.0647***	0.1204
	Secondary school	0.6565***	0.0803	1.1826***	0.1478
	High school	0.7923***	0.0776	1.4306***	0.1427
	Higher education	1.0630***	0.0805	1.9293***	0.1486
	Homeowner: yes	0.1257***	0.0322	0.2278***	0.0592
	Log income	0.0409	0.0274	0.0662	0.0500
Economic characteristics	<i>SoL_Low</i>	<i>Base category</i>			
	SoL_Medium	0.0956**	0.0474	0.1813**	0.0855
	SoL_High	0.1533***	0.0409	0.2728***	0.0740
	SoL_Very High	0.2729***	0.0408	0.4875***	0.0745
	/cut1	−4.7132***	0.2585	−8.8271***	0.4734
Cut points of outcomes	/cut2	−2.8533***	0.2534	−5.2832***	0.4631
	/cut3	−1.3550***	0.2514	−2.5791***	0.4596
	/cut4	1.4582***	0.2492	2.5570***	0.4554
	/sigma2_u	0.7174***	0.0306	2.4447***	0.1034
Model diagnostics	Number of Obs	19,524		19,524	
	Number of groups	4881		4881	
	Wald chi ² (18)	3130.24		3078.06	
	Wooldridge <i>F</i> (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 <i>R</i> ²	0.034		0.039	
	Mc Fadden <i>R</i> ²	0.034		0.039	
	Cox-Snell <i>R</i> ²	0.064		0.072	
	Cragg-Uhler <i>R</i> ²	0.075		0.084	

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

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 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	−0.0006**	−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

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 possibility 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 of households have serious impact on their health. In addition, we noted that although a household's socioeconomic variables affect health, these effects are relatively limited. On the other hand, indoor air pollution is an important variable that affects the health status of individuals. Moreover, the impact of indoor air pollution on health is higher than that of income level.

These findings are significant because indoor air pollution, which is caused by reliance on biomass energy in heating and cooking, has serious effects on the health status of individuals 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

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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