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Effects of Indoor Air Pollution on Household Health: Evidence from Turkey

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Abstract

Indoor air pollution caused by use of biomass energy in heating and cooking affects the health status of household members adversely. In Turkey, despite with the rapid economic growth in the last decade, biomass has been among the most preferred type of energy by households for heating and cooking due to inadequate infrastructure, dependence on foreign energy, and high energy prices. This study aims to provide empirical evidence from Turkey to the literature on indoor air pollution caused by households' energy choice and health status. This study is analyzed these effects with the 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 age, being a woman, having dependent children, and indoor air pollution have adverse effects on the health status. However, education level, and income level affect the health status positively. The most important result obtained from this study is that even if households have high-income, the inability to access clean energy resources affects their health adversely.

Keywords: Indoor Air Pollution, Health, Panel Discrete Ordered Models, Turkey

1. Introduction

In developing countries, indoor air pollution has been a public health hazard because of using 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 this fuel by poor households, whose number is more than three billion, causes risk on households' health by creating more air pollution than levels allowed by international ambient air quality standards (WHO, 2018). Indoor air pollution causes to an increase in the risk of some important diseases such as chronic respiratory diseases and 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" model. The Energy stack model assumes that households tend to choose mix energy sources among all alternatives and households can switch to energy types. On the other hand, energy ladder model was designed as a hierarchical relationship between household' income and socio-economic status and energy type of households for cooking and heating. The polluting effect, efficiency, and costs of fuel are generally identified by the "energy ladder" model. Cheap, inefficient, and most polluting dry animal manure, dropped branches, and grasses are at the bottom of the stairs in the energy ladder. In the second stair, households use coal, kerosene, and charcoal. In the third stair, high-income households tend to use modern fuels such as electricity and LPG. Moving through the stairs of this ladder is based on the income growth of households (Barnes and Floor, 1999). There is a transition from biofuels to petroleum products (kerosene, LPG) and electricity in developed countries. On the other hand, in developing countries, even cleaner and more advanced fuels are available, households generally continue to use biomass (Smith, 1987). Poverty is one of the main constraints to 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 are various studies examined the disease risks of indoor air pollution caused by using the fuel in cooking for women and children, who are spending a significant amount of time near the cooking stove (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 relying 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 Yamamato (2015) analyzed the effect of cooking smoke produced by biomass and solid fuel combustion on asthma disease reported among adult men and women in India using multivariate logistic regression on cross-sectional data. The results show that adult women who live in a household using biomass and solid fuels more likely to have asthma. Again, Mishra (2003) analyzed the effect of cooking smoke on asthma using logistic regression for elderly adults. Study results provide that exposure to food smoke is strongly associated with asthma regardless of some demographic factors such as age, education, and standard of living. Duflo et al. 2008; Bruce et al. 2000; De Francisco 1993; Khalequzzaman et al. 2007 are also other studies investigating the effect of cooking smoke on health.

On the other hand, 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. Lakshimi 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 association 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, using the self-reported health data. They concluded that households living in houses heated with biomass have a high risk of respiratory disease. Besides, there are also various studies investigating the relationship between health status and indoor air pollution (Ezzati and Kammen 2001;2002; Demjen et al. 2000; Bruce et al. 2002; Smith et al. 2000).

Previous studies have also showed 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, some studies 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 cataracts and tuberculosis in adults (Ezzati and Kammen, 2001;2002; Mishra et al. 1999; Saha et al. 2005).

Although there are various studies investigating the effect of indoor pollution on health in less developed countries, there are relatively less studies on developing countries in the literature (Qui et al. 2019; Kim et al. 2011; Perez-Padilla et al. 2010). Despite the rapid economic growth in Turkey since the early 2000s, biomass fuels such as manure, straw, and wood have still preferred by poorest and most vulnerable households for cooking and heating due to some reasons such as inequalities in income distribution, high energy prices, lack of infrastructure.

On the other hand, generally, air pollution is considered only as outdoor air pollution. However, we spend most of our time indoors and indoors are significant microenvironments considering the impact of air pollution on health. Nowadays, the whole world continues to be affected by the rapid spread of the COVID-19 epidemic, which has been expanding globally since the beginning of 2020. Especially 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 have become an important issue again for researchers and politicians. Although indoor air pollution is generally caused by wet or damp walls, cigarette smoke, house dust, dwelling properties, energy fuel choice in the dwelling is the most critical factor that causes indoor pollution. Especially in developing countries, like Turkey, even though income, economic growth, or some socio-economic factors trigger the transition from dirty fuels to clean fuels, many households rely on biomass fuels for cooking and heating. Therefore, the main motivation of this is study is to provide important clues to policies targeting to reduce indoor air pollution and its effect on health by determining these effects of indoor pollution caused by energy choice in Turkey. With this motivation, in this study, we investigated the impacts of indoor air pollution caused by energy choice on the health status applying the random effects panel discrete ordered models on the Income and Living Conditions Research Micro Longitudinal Data Set (2014-2017). To our best of knowledge, this study is the first study analyzing the potential effects of indoor air pollution based on energy choice on physical health in Turkey. Thus, it is expected to fill gap in the relevant literature by providing empirical results of the effect of indoor air pollution on physical health in Turkey.

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. Section 5 presents the discussion of the results.

2. Data and Methodology

2.1. 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. ILC contains 4-waves panel microdata including the overlapping records in the years of 2017-2016-2015-2014. The design of 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 household head were excluded from the data set. The data set is a four-year balanced panel, and the data set includes a total of 4881 households and 19524 observations.

In the analysis, the health status of the household head 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 the self-reported health status. In the survey, the household answered the question of "How is your health?". Since self-reported health status is an ordered categorical variable, we preferred the 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, in the analysis the energy choices of households are made under the assumption of the energy ladder hypothesis. According to this hypothesis, pollution decreases as the primitive fuels switch to modern fuels. For this reason, the energy type preferred by the households is considered as indoor air pollution in the study.

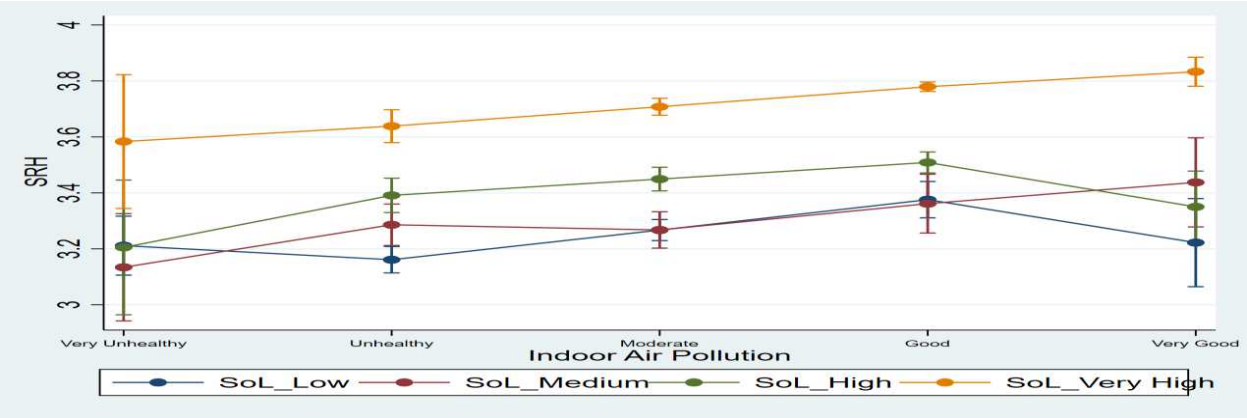
Besides indoor pollution, demographic and economic variables that are related to the health status of the individuals are also included in the model. Educational status, gender, age, marital status, and dependent child dummy variables were taken as demographic factors. Household economic status variables which are 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.

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
	Logincome	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

It is widely accepted that there is a strong relationship between individuals' health and housing conditions. Therefore, using the principal components analysis, we created the standard of the living index over physical properties of the house associated with health, such as a bathroom, toilet, kitchen, water system, hot water system, and economic assets such as telephone, internet, TV, and computer. After that, we divided the SoL index into four subgroups as low, medium, high, and very high, and after we clustered the households.

Graph 1: Estimated Means of SRH by Level of Indoor Air Pollution and SoL with %95 CIs



The energy ladder hypothesis assumes that households follow a certain energy path depending on household income levels or living standards. Graph1 clearly shows that as one goes up the steps of energy type used as a basis in the household, his health status is improving. Also, it presents a positive relationship between SoL and individuals' health

status. It also shows that there is a decrease in health status of the households using electricity as the primary energy source. Because even if households have sufficient income levels, electrical energy cannot be used efficiently for heating due to insufficient infrastructure. Moreover, the positive impact of electrical energy on health due to low emissions is significantly reduced because of insufficient heating.

2.2. Methodology

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

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

for $i = 1, \dots, n$ panels, where $t = 1, \dots, n_i$, y is the observed ordinal responses, $\boldsymbol{J}$ 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 are independent and identically distributed $N(0, \sigma_v^2)$. If $\Omega(.)$ is the logistic cumulative distribution function it is random effect ordered logit model. On the other hand, if $\Omega(.)$ is the standard normal cumulative distribution function, it is random effect ordered probit model.

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

$$\begin{aligned} p_{itj} \equiv \Pr(y_{it} = j|\boldsymbol{J}, x_{it}, v_i) &= \Pr\left(j_{J-1} < X_{it}\beta + v_i + \varepsilon_{it} \le J_j\right) \\ &= \Pr\left(j_{J-1} - X_{it}\beta - v_i < \varepsilon_{it} \le J_j - X_{it}\beta - v_i\right) \\ &= \Omega\left(J_j - X_{it}\beta - v_i\right) - \Omega\left(j_{J-1} - X_{it}\beta - v_i\right) \end{aligned} \tag{2}$$

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.

$$SRH_{it}^* = X_{it}\beta + v_i + \varepsilon_{it} \tag{3}$$

$$SRH_{it} = \begin{cases} 1 \;\; if & SRH_{it}^* \le j_1 \\ 2 \;\; if & j_1 < SRH_{it}^* \le j_2 \\ & \vdots \\ J \;\; if & j_{j-1} < SRH_{it}^* \end{cases} \tag{4}$$

SRH_{it}^* indicates the health status of the ith household head at time t, is a latent variable and random effect discrete ordered model is given above. 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 energy type of household (dry dung, firewood, charcoal, natural gas, and electricity) and socioeconomic variables (such as age, gender, education, income and SoL) for the household. β is predicting parameter vector of the explanatory variables. ε_{it} time-varying unobservable heterogeneity. Depending on the distribution property of the error term ε_{it}, random effect discrete ordered model is divided into two as random effect ordered logit and random effect ordered probit model. If the errors term ε_{it} distributed as standard normal with mean zero and variance one, it is called a random effect probit model. However, if the errors term ε_{it} is distributed as logistic with mean zero and variance $\pi^2/3$, it is called 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.

2.3. 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 existence many clusters and the disturbances are uncorrelated across the clusters. The panel variable must be nested within the cluster variable because of the within-panel correlation, which is generally induced by the random-effects transform 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 0.10 level. Although there are many evidence that the assumptions of the ordered models are frequently violated (Long & 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 & 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, random effects ordered logit model fit 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 Equation 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.

Table 2: Estimation Results of REOPROBIT and REOLOGIT Models

		REOPROBIT		**REOLOGIT**	
	Variables	**Coefficient**	**Cluster Robust Std. Err.**	**Coefficient**	**Cluster Robust Std. Err.**
Indoor Air Pollution	*Very Unhealthy*	*Base category*			
	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
	No literacy	*Base category*			
	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
Economic Characteristics	Homeowner: Yes	0.1257***	0.0322	0.2278***	0.0592
	logincome	0.0409	0.0274	0.0662	0.0500

[1] AIC and BIC values for restricted model are 35857.17, 35809.85 respectively.

	SoL_Low	*Base category*			
	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
Cut points of Outcomes	/cut1	-4.7132***	0.2585	-8.8271***	0.4734
	/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		19524		19524
	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		-17842.454		-17756.499
	AIC		35730.91		35559.00
	BIC		35912.13		35740.22
	Pseudo R^2		0.034		0.039
	Mc Fadden R^2		0.034		0.039
	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.

Since both model estimation coefficients are not practical for interpretation directly, marginal effects are estimated to understand better the analysis results. Marginal effects are estimated when other estimators 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.

Table 3: Marginal effects at the sample mean.

Variable	**SRH=1**	**SRH=2**	**SRH=3**	**SRH=4**	**SRH=5**
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.

Table 3 shows the effect of the factor affecting the health status compared to the reference group based on each health level when the other variables are constant at their average levels. As level of indoor pollution is getting better 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 with good and very good health levels, as the level of indoor pollution is getting better, the probability of being at these health levels increases significantly. Households with well health levels increase their chances of having this health level by 6%, 5.5%, 7%, and 7.8%, respectively, depending on the indoor air pollution.

Moreover, age, having dependent children, and being a woman increase the probability of being at fair and lower health status but decreases the possibility of having a good and very good health status level. These results are consistent with existing literature and the realities of the country. Because women are responsible for cooking and they spend a long time at home due to the gender role women have in Turkey. Furthermore, income level, education level, and homeownership decrease the probability of being at a fair and below health status and increase the possibility of being at a good and very good health status level.

Conclusion

Approximately half of the world's population prefers biomass fuels and coal such as wood, animal manure, and 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 been decreased significantly over the years (Bruce et al. 2002). It causes to increase 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 the random effects panel discrete ordered models on the Micro Longitudinal Data Set in Turkey. Differently to previous studies we consider unobserved heterogeneity between the households. We found that age, gender, and having dependent children in the household affect household health negatively. However, income, education, and homeownership affect positively. Education is an important variable that positively affects a person's health status. We also measured the standard of living of households and showed the effect on indoor air pollution. We noted that although the socioeconomic variables of the household 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 are significant because indoor air pollution, which is caused by relying on biomass energy in heating and cooking, has serious effects on the health status of individuals living in the household. Therefore, determining this effect empirically will provide some clues to decision-makers in energy and environmental policies. As a result of the study, we report that even if households have high-income levels, their inability to access clean energy resources has serious negative effects on health. Especially in developing countries such as Turkey, only economic development and increases in the national income are not good enough to increase public health. In such countries, access to clean and safe energy sources should be increased, as well. For this reason, policymakers should pay attention to infrastructure services to increase households' access to clean and reliable energy sources.

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Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Availability of data and materials

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Competing interests

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Authors' contributions

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.

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