



## **Effect of Household Cooking Energy Poverty on Child Respiratory Health in Pakistan**

Abre-Rehmat Qurat-ul-Ann<sup>1</sup>, Sana Mahfooz<sup>2</sup>

<sup>1</sup> Lecturer, Department of Economics, University of Gujrat, Pakistan. Email: [abre.rehmat@uog.edu.pk](mailto:abre.rehmat@uog.edu.pk)

<sup>2</sup> Visiting Lecturer, Department of Economics, University of Gujrat, Pakistan.

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### **ABSTRACT**

Household cooking energy poverty can lead to serious health concerns for the household members generally and children under age five specifically. To attain sustainable development goal 3 of ensuring healthy lives and promoting well-being for all of all ages, Pakistan has to strive for development in the child health sector. The recent pandemic has amplified the significance of this issue many folds. This study aims to identify the effect of household cooking energy poverty on the respiratory health of children under the age of five using Pakistan demographic and health survey data, 2017-18. 26.4 percent of the sample households are cooking energy poor in Pakistan. Child health is at greater risk in Balochistan and Gilgit Baltistan due to a greater multidimensional incidence of cooking energy poverty. Rural areas with a higher incidence of energy poverty are also vulnerable in terms of child wellbeing. Negative binomial regression analysis estimates the effect of household cooking energy poverty on number of children with respiratory issues in Pakistan. Empirical results suggest that a one-unit increase in household cooking energy poverty in Pakistan leads to a significant increase in the expected log (count) of number of children with respiratory infection by 0.21. Household cooking energy poverty directly affects respiratory health of children under age five in Pakistan. The study recommends that through the development and adoption of the use of modern stoves and clean fuels, improvement in the indoor environment and health of children in Pakistan can be attained.



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**Corresponding Author's Email:** [abre.rehmat@uog.edu.pk](mailto:abre.rehmat@uog.edu.pk)

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## **1. Introduction**

Household energy poverty is the inability of a household to get the required level of energy services, generally defined as household access to clean cooking fuel and electricity (Bouzarovski, 2014). The lack of availability of clean energy sources for cooking and electricity is the main source of excessive use of polluting fuels in many developing economies, especially in Sub-Saharan Africa and South Asia (Rahut, ABDUL Mottaleb, & Ali, 2017). Every year, 7 million people die due to air pollutants, and out of those 4 million deaths in developing countries are due to indoor air pollution from practices of inefficient cooking with polluting fuels (WHO, 2018). Household air pollution causes many ailments in children under the age of five such as lung

cancer, stroke, chronic obstructive pulmonary disease (COPD), heart disease, and pneumonia (WHO, 2018). In developing economies, 3 billion people were using polluting fuels like firewood, crop waste, kerosene, charcoal, and dung in inefficient stoves and open fires (WHO, 2018).

Acute respiratory infection (ARI) has been among the top three leading causes of death and disability in both children and adults for decades. About 4 million people die annually due to ARI and it is the main source of mortality among children under age five. ARI in children can increase the risk of developing chronic respiratory disorders later in life (FIRS, 2017). Around 3.4 million people suffer from asthma and it is considered the long term disease in childhood, affecting 14 percent of children worldwide. Indoor air pollution can be generated through occupants' activities like cooking, smoking, and the use of electrical machines inside the house. Harmful pollutants for humans inside the houses include carbon monoxide, biological pollutants, particulate matter, and others (Tran, Park, & Lee, 2020).

ARI is a major cause of mortality and morbidity and leads to a significant burden on the health care system along with causing serious implications for economic and psychological burden at the household level in Pakistan (Mahmood, Khan, Abbasi, & Yahya, 2017). ARI had been a vital cause of health issues and deaths in developing economies. In South Asian region, 48 children out of 1000 die before the age of five. It is estimated that about 20 to 30 percent of children under age five die because of acute respiratory infections in Pakistan (Hussain, Ansari, Salman, Khan, & Asghar, 2016; R. Naz et al., 2019). Determining the impact of household cooking energy poverty at the national level is important for targeted and prioritized environmental and public health interventions. In developing economies, households are mostly dependent on biomass fuels for different needs like cooking, heating, and lighting as modern fuels are unavailable, and the cost of cleaner energy is exorbitant (Bruce, Perez-Padilla, & Albalak, 2000).

The majority of individuals spend time inside their houses, hence, the indoor environment plays a significant role in determining human health. Population exposure to various pollutants is higher indoors compared to outdoors. While inside the houses, people might face pollution from indoor sources and outdoor sources that can infiltrate the indoor household environment and pollute it (I. Colbeck, Nasir, & Ali, 2010). Therefore, access to clean energy sources plays an important role in determining a better indoor household environment. Few empirical studies estimated the impact of indoor air pollution on the respiratory infection (I. Colbeck et al., 2010; Haleem, Khan, & Athar, 2020; M. S. B. Khan & Lohano, 2018; S. Naz, Page, & Agho, 2017) at national level in Pakistan, to the best of our knowledge. Some examined the impact of type of cooking fuel used on respiratory health (M. S. B. Khan & Lohano, 2018) but did not discuss the indoor pollution factor. Respiratory diseases tend to increase child disabilities, morbidities, mortality rates, and health expenses of households. Therefore, to improve the living conditions of the households and to raise awareness about this issue; it is important to consider the effect of household cooking poverty on the respiratory health of children. Our empirical analysis fills this gap in literature as it identifies the effect of household cooking poverty on the number of children under age five with acute respiratory health issues in Pakistan. This study is helpful for Pakistan for attainment of its sustainable development target under SDG 3 of ending preventable deaths of newborns and children under five and guides policymakers to devise targeted policy measures and programs. The target is to bring under-5 mortality to at least as low as 25 per 1,000 live births by 2030 from its current level at 65.2 deaths per 1000 live births (UNICEF, 2020). Following are the objectives of the current study.

1. To determine the household cooking poverty for Pakistan.
2. To examine the incidence and intensity of multidimensional cooking poverty at the provincial and regional level in Pakistan.

3. To estimate the effect of household cooking poverty on the respiratory health of children under age five in Pakistan.

The rest of the paper is organized as follows. Section 2 discusses literature review, while, section 3 elaborates the research methodology. Section 4 discusses empirical results and section 5 concludes the discussion with appropriate policy recommendations.

## **2. Literature Review**

Cooking energy poverty affects the household environment in form of household air pollution which disturbs human health and capabilities. Household air pollution caused child mortality (Rana, Islam, Khan, Aliani, & Oulhote, 2021) and risks of infant and child mortality rate increased among children from households using unclean fuels compared to households which used cleaner fuels. Household air pollution caused increased infant mortality rate which could have been mitigated by using clean fuels along with the provision and use of efficient cooking stoves. Furthermore, energy poverty has a significant impact on poor health of children (Oliveras et al., 2021). Children in energy-poor households suffered from asthma problems three times more than those who are not living in energy poor households. Children under five in households with separate or outdoor kitchen had lower risk of respiratory infection compared to children from those houses which cooked their meals inside the house (Geremew, Gebremedhin, Mulugeta, & Yadeta, 2020).

Moreover, the use of unclean fuels and not having a separate room for cooking increase the risk of acute respiratory infection among children under the age five. Use of unclean fuels and living in a household without a separate kitchen raised the chance of acute respiratory infection by 36 percent among children under age five in India (Mondal & Paul, 2020). Increased particulate matter levels in the air increased respiratory infections among children, increased mortality rate, and caused premature deaths (Mahapatra, Walia, Avis, & Saggurti, 2020). Indoor pollution and cooking fuel choice are the leading causes of mortality among children in households (Basu, Byambasuren, Chau, & Khanna, 2020). Households with a healthy environment did not experience acute respiratory infections, whereas, in case of an unhealthy environment in the household, children would get infected easily. Energy poverty results in compromised health status, increased school dropout rates among children from energy-poor families and lower earning opportunities for household members (Phoumin & Kimura, 2019).

The causality between cooking energy poverty and the health of children has become an integral issue. A great amount of literature has reported that household air pollution and use of unclean fuels as primary sources of health issues among children (Balmes, 2019; Das, Pedit, Handa, & Jagger, 2018; Faizan & Thakur, 2019; Fatmi, Rahman, Kazi, Kadir, & Sathiakumar, 2010; Oluwole, Otaniyi, Ana, & Olopade, 2012; Ranathunga et al., 2019). In a developing economy like Nepal, use of solid fuels increased the chances of acute respiratory infection among children (Acharya, Mishra, & Berg-Beckhoff, 2015). Ethiopian households used biomass fuel most of the time which increased the prevalence of respiratory infection among children (Sanbata, Asfaw, & KUmie, 2014). In Nepal, smoke and insufficient ventilation in kitchen caused respiratory infection among young children where 50 percent of the children got infected more than 4 times and 46 percent got infection more than twice. 20 percent of the children were diagnosed with pneumonia due to indoor smoke inhalation (Thapa & Chaurasia, 2014).

Household air pollution caused many diseases like tuberculosis, lung cancer, chronic obstructive pulmonary disease (COPD), acute lower respiratory infection, and blindness among children and women because they spend most of their time in the kitchen (I. Colbeck et al., 2010). Khan and Lohano (2018) reported that children from households using polluting fuels are

one and half times more affected and have acute respiratory infection symptoms than the households which used modern fuels. Household air pollution and use of unclean fuels caused neo-natal, post-neonatal, and child mortality problems. Household air pollution caused a higher risk of deaths in post-neonatal children and children from age 1-4 in Nepal (S. Naz et al., 2017). Use of biomass fuels determined household air quality in both rural and urban areas of Pakistan. Those households which used biomass fuels in their kitchens had poor indoor air quality (Ian Colbeck, Nasir, Hasnain, & Sultan, 2007).

The literature showed that household air pollution plays a vital role in influencing the health of children under age five and females. Various studies also explain that prevalence of different diseases like COPD, tuberculosis and ARI increases due to household indoor air pollution. Most of the studies used different methodologies to analyze the relationship between indoor household pollution and health of children, women and girls. In Pakistan, there is a dearth of research on the effect of household cooking energy poverty on respiratory health of children. The indoor pollution indicator is not used for analysis and discussion on the inefficient cooking methods to identify health problems in the children is missing in literature. To fill this gap our study analyzes the effect of household cooking energy poverty on respiratory health of children under age five in Pakistan.

### **3. Data and Methodology**

This study used Pakistan Demographic and health survey (PDHS) 2017-18 data, conducted in collaboration with the ministry of health services, regulations and coordination (GOP, 2019). This survey provides basic estimates for demographic and health indicators and offers comprehensive view about population, maternal and child health issues in Pakistan. This survey data is representative of population of Pakistan including Azad Jammu Kashmir and tribal areas (FATA) which were previously not included in the 2012-13 PDHS survey. For this survey, approximately 16,240 households were identified from which 15,671 households were selected for gathering information and out of 15,671, only 14,540 households responded. The dataset also includes information on 12,708 children under the age of 5 which has been employed for this study. PDHS statistics also provide information on indicators related to sustainable development goals; i.e. goal 3 (to ensure healthy lives) and goal 7 (access to reliable and affordable energy to all). This research includes data on 7,174 households and children under age five who have respiratory infection. Moreover, frequency of people who smoke inside the house, and number of rooms for sleeping are also extracted from PDHS 2017-18 (GOP, 2019).

Child respiratory health variable is measured as number of children with respiratory infections. PDHS asks mothers if the child has been ill with fever, has an ailment with a cough and difficulty in breathing in the last two weeks (GOP, 2019). Children who suffered from illness, with cough and had problem of breathing are assigned value of '1', whereas, '0' otherwise. The total number of children who suffered from any illness, cough and breathing issues in a household were computed from data. If one child had a respiratory infection in one household, the count is one, and if there is more than one infected child in a house, study counted them 2, 3 or more, accordingly.

If there is no infected child, variable takes the value '0'. The independent variable includes household cooking energy poverty index (which shows a set of cooking energy poverty deprivations) along with variables on household characteristics (rooms for sleeping), household member characteristic (Smoking status) and economic status of the households. The effect of location in a certain province i.e. Punjab, Sindh, Balochistan, KP and Gilgit Baltistan and residence in rural or urban areas on child health is measured to see the regional and provincial effect on number of children suffering from respiratory infection (See table 1).

### 3.1 Household Cooking Energy Poverty

Household cooking energy poverty was measured by using the energy poverty index approach (which shows a set of cooking energy poverty deprivations). Household cooking energy poverty index (HCEPI) measure is based on the literature on multidimensional poverty measures (Alkire & Fang, 2018; Alkire & Foster, 2009; Alkire & Jahan, 2018; Alkire & Santos, 2011). A household is considered deprived if the combination of deprivations is more than some pre-defined threshold level. The household cooking energy index is the result of the product of percentage of households who are cooking energy poor (Headcount ratio) and the average percentage of dimensions in which households are poor (intensity of deprivation).

Cooking dimension shows the accessibility of clean cooking fuel resources at household level in Pakistan. Fuels identified as cooking fuels in PDHS data are, kerosene oil, dung cake, crops, charcoal, firewood, natural gas, liquefied petroleum gas (LPG), electricity, shrubs and others. Those households using electricity, natural gas, and liquefied petroleum gas are not considered energy-poor and are assigned '0' value. Whereas, those households which use firewood, shrubs, dung, kerosene oil, and other sources for cooking are considered cooking energy-poor and are assigned '1' value in this dimension. The second indicator of indoor pollution shows households having a separate room for cooking. If the households do not have a separate room or kitchen or they cook inside the house, they are considered cooking energy-poor and assigned the value '1', while, those households which have a separate room or building for cooking are not considered cooking energy-poor with zero '0' value assigned in this dimension. Dimension 'lighting' represents access to electricity at the household level. The households with electricity access are considered non-energy poor while those without electricity access are considered energy poor. Household cooking energy poverty scores were generated through equal weights method. Household characteristics (number of rooms), and household member characteristics (Smoking status) were also used as independent variables. Normative weighting strategies like equal weights method can be used for the measurement of household cooking energy poverty index, when we have minimal knowledge about the significance of the indicators (Alkire & Fang, 2018; Alkire & Jahan, 2018). If the decision-maker has no information about true weights of the indicators, then true weight could be attained through a uniform distribution (Roszkowska, 2013). For sensitivity analysis rank sum weighting method is used where the dimensions were ranked based on the evidence of their significance in literature (see table 2).

HCEPI measures household cooking energy poverty in 'd' dimensions across 'n' number of households.  $Y = [y_{ij}]$  is equal to achievement matrix  $n \times d$  where i represents household and j represents dimensions. So,  $[y_{ij}]$  represents the achievements of 'i' household across 'j' dimensions. Each row vector  $Y_i = (y_{i1}, y_{i2}, \dots, y_{id})$  shows the i<sup>th</sup> household achievements in 'd' dimensions of cooking energy poverty and  $Y_j = (y_{1j}, y_{2j}, y_{3j}, \dots, y_{nj})$  column vector represents the distribution of achievements in the dimension 'j' across households 'i' (Alkire & Santos, 2011; Nussbaumer, Bazilian, Modi, & Yumkella, 2011; Qurat-ul-Ann & Mirza, 2021). For assigning the weight to dimension 'j' there is weighting vector 'w' consisting of  $w_j$  elements represent weights where sum of the dimension weights equals one,  $\sum_{j=1}^d W_j = 1$ .  $Z_j$  shows the deprivation cut-off in dimension/ indicator 'j' that identify how much households are deprived in one dimension (Alkire & Santos, 2011; Nussbaumer et al., 2011; Qurat-ul-Ann & Mirza, 2021).

Let deprivation matrix  $g = [g_{ij}]$ , which consists of  $g_{ij}$  element defined as  $g_{ij} = w_{ij}$ , when  $y_{ij} < z_{ij}$  and  $g_{ij} = 0$ , when  $y_{ij} \geq z_{ij}$ . The elements in a matrix of achievements are all strictly non-numeric. So, threshold level is described as a set of requirements that must be met. Element ' $g_{ij}$ ' of the matrix is equal to weight of the variables ' $w_{ij}$ ' when household 'i' is deprived in indicator 'j'. Following all of this, construct a column which is based on deprivation counts vector

$c_i$ , where 'i<sup>th</sup>' entry  $c_i = \sum_{j=1}^d g_{ij}$  is the aggregate of weighted deprivations suffered by 'i' household (Alkire & Santos, 2011; Nussbaumer et al., 2011; Qurat-ul-Ann & Mirza, 2021). For the identification of the household as cooking energy poor, the study set a threshold score of  $k=0.30$  i.e. 30 percent threshold level is applied on column vector ' $c_i$ '. A household is considered deprived if its weighted deprivation count ' $c_i$ ' is greater than ' $k$ '. Here  $c_i(k)$  equals to zero when  $c_i \leq k$ , and equals to  $c_i$  when  $c_i$  is greater than  $k$  (Alkire & Santos, 2011; Nussbaumer et al., 2011; Qurat-ul-Ann & Mirza, 2021). HCEPI is the product of 'H' headcount ratio (the percentage of households that are cooking energy poor), and 'A' (the average intensity of deprivation of the cooking energy poor) (see equation 3 and 4).

$$H=q/n \tag{1}$$

**Table 1**  
**Variable Description**

| Variable                                       | Definition  |
|--|---|
| Outcome Variable                               | Whether the child have symptoms of respiratory infection or COPD in a household   |
| Independent Variable                           | Set of energy poverty deprivations  |
| Household Cooking energy poverty index (HCEPI) | Whether Smoking or not where 1, if yes or 0 otherwise   |
| Smoking status of Household member (SHM)       | Number of rooms used for sleeping where 1 if households have 1 or 0 rooms and otherwise 0 if households two or more than two rooms for sleeping |
| Number of rooms (HR)                           | Rural   |
| Region (R)                                     | Punjab  |
| P  | Sindh   |
| S  | Balochishtan  |
| B  | Gilgit Baltistan  |
| GB   | Wealth index which is classified as poorest, poorer, middle, richer and richest   |
| Wealth Index (WI)                              |   |

Note: See (GOP, 2019)

$$A = \sum_{i=1}^n c_i(k)/q \tag{2}$$

$$HCEPI = H \times A \tag{3}$$

$$HCEPI = \frac{q}{n} \times \sum_{i=1}^n c_i(k)/q = \sum_{i=1}^n c_i(k)/n \tag{4}$$

'H' represents incidence of multidimensional cooking energy poverty, 'q', depicts cooking energy poor households and 'n' refers to total number of households (equation 1). 'A' in equation (2) refers to the intensity of household cooking energy poverty, where  $c_i(k)$  represents the censored vector of deprivation counts. It is different from ' $c$ ' as it counts zero for those households which are non-poor in household cooking energy poverty (Alkire & Santos, 2011; Nussbaumer et al., 2011; Qurat-ul-Ann & Mirza, 2021).

Table 2 depicts household cooking energy poverty for the sample households in Pakistan. Overall estimates show that 46.7 percent of households are cooking energy poor in at least one dimension. The intensity measure shows 56.5 percent households as deprived in 30 percent of the total dimensions. The adjusted multidimensional headcount ratio represent that 26.4 percent of the households are multi-dimensionally cooking energy poor. Sensitivity analysis tells us that these results are sensitive to the change in the weighting scheme.

**Table 2**  
**Household Cooking Energy Poverty in Pakistan**

|   | <b>Incidence<br/>(H)</b> | <b>Intensity<br/>(A)</b> | <b>Adjusted Multidimensional<br/>Incidence(M<sub>0</sub>)</b> |
|---|--------------------------|--------------------------|---|
| Estimates of HCEPI<br>(Equal weights method)                                    | 0.467<br>(0.004) **      | 0.565<br>(0.002) **      | 0.264<br>(0.003) **   |
| Estimates of HCEPI<br>(Rank sum weight method)                                  | 0.971<br>(0.001) **      | 0.512<br>(0.002) **      | 0.497<br>(0.002) **   |
| N=14,540  |                          |                          |   |
| <i>Equal weights method: Cooking (0.5) and Lighting (0.5)</i>                   |                          |                          |   |
| <i>Rank sum weight method: Cooking- Rank 1(0.666), Lighting- Rank 2 (0.333)</i> |                          |                          |   |
| <i>Note: Source Authors' own calculations</i>                                   |                          |                          |   |

Balochistan and Gilgit Baltistan provinces experienced the highest cooking energy poverty of 30.5 percent and 36.3 percent, respectively (See table 3). These estimates are based on equal weighting method. Sensitivity analysis of cooking energy poverty index using rank-sum method estimates represents that Balochistan and Gilgit Baltistan faced the highest cooking energy poverty i.e. 50.9 percent and 56.4 percent, respectively. Moreover, Punjab faced 47.3 percent, KP experienced 49.9 percent and Sindh 48.1 percent while 33.7 percent of the sample population was cooking energy-poor.

**Table 3**  
**Household Cooking Energy Poverty by Province**

| <b>Energy poverty cut-off</b>                   |                  | <b>0.3</b> |        |       |             |       |
|---|------------------|------------|--------|-------|-------------|-------|
|   |                  | KP         | Punjab | Sindh | Balochistan | GB    |
| <b>Equal</b>                                    | Incidence (H)    | 0.457      | 0.412  | 0.390 | 0.506       | 0.727 |
| <b>Weight</b>                                   | Intensity (A)    | 0.551      | 0.549  | 0.603 | 0.603       | 0.499 |
| <b>method</b>                                   | M <sub>0</sub>   | 0.252      | 0.226  | 0.252 | 0.305       | 0.363 |
| <b>Rank Sum</b>                                 | Incidence (H)    | 0.995      | 0.972  | 0.966 | 0.942       | 0.966 |
| <b>Method</b>                                   | Intensity (A)    | 0.502      | 0.487  | 0.498 | 0.540       | 0.584 |
|   | M <sub>0</sub>   | 0.499      | 0.473  | 0.481 | 0.509       | 0.564 |
|   | Population share | 0.144      | 0.237  | 0.185 | 0.105       | 0.067 |
| <i>Note: Source: Authors' own calculations.</i> |                  |            |        |       |             |       |

**Table 4**  
**Regional Household Cooking Energy Poverty in Pakistan**

| <b>Energy Poverty cut-off</b>            |                | <b>0.3</b> |       |
|--|----------------|------------|-------|
|  |                | Rural      | Urban |
| <b>Equal Weight method</b>               | Incidence (H)  | 0.772      | 0.212 |
|  | Intensity (A)  | 0.575      | 0.533 |
|  | M <sub>0</sub> | 0.415      | 0.113 |
| <b>Rank Sum Method</b>                   | Incidence (H)  | 0.989      | 0.952 |
|  | Intensity (A)  | 0.609      | 0.412 |
|  | M <sub>0</sub> | 0.603      | 0.392 |
| <i>Source: Authors' own calculations</i> |                |            |       |

Rural regions faced higher cooking energy poverty, with 41.5 percent of the households as multi-dimensionally cooking energy poor (See table 4). As compared to rural areas urban areas experienced lower cooking energy poverty with 11 percent (at k=0.30) of sample households as multi-dimensionally cooking energy poor. The division of cooking energy poverty index estimates represents that rural region faced higher cooking energy poverty 60.3 percent of sample households are multi-dimensionally cooking energy poor in rural areas and 39 percent of sample households cooking energy poor in urban areas at a threshold level of 0.30.

### 3.2 Effect of Household Cooking Energy Poverty on Child Respiratory Health

The number of children who have a respiratory infection, is a count outcome within the given population. Classical regression modeling can give biased, inconsistent, and inefficient parameters due to non-negative integers and skewed distribution as the mean value is low. To compare the goodness of fit between two models such as Poisson regression model, negative binomial regression model, we used Akaike information criterion to check the suitable test for the model (Ismail & Zamani, 2013).

Hence, for the count regression analysis, we used negative binomial regression model. Negative binomial regression model is the extending version of Poisson regression model by positing that the conditional mean  $\mu_i$  is not only determined by  $X_i$  but also by a latent heterogeneity variable  $e_i$ , independent of  $X_i$ . Suppose expected  $\exp(e_i)$  is distributed with  $(\frac{1}{\alpha}, \frac{1}{\alpha})$  gamma, we get the negative binomial model with density function shown in equation (5) (Xia et al., 2012).

$$P(Y_i=y_i) = \frac{\Gamma(y_i + \frac{1}{\alpha})}{\Gamma(y_i + 1)\Gamma(\frac{1}{\alpha})} \left(\frac{1}{\alpha}\right)^{\frac{1}{\alpha}} \left(\frac{\mu_i}{\frac{1}{\alpha} + \mu_i}\right)^{y_i} \quad (5)$$

If the over-dispersion is due to the excess of zeros, then negative binomial inflated model will be applied because in case of excess zeros the probabilities of zeros are underestimated (Dwivedi, Dwivedi, Deo, Shukla, & Kopras, 2010). The empirical model for count data is given in equation (6).

$$\widehat{CH}_i = \lambda_i = \exp(\beta_0 + \beta_1 HCEPI_i + \beta_3 SHM_i + \beta_4 HR + \beta_6 WI + \beta_7 P + \beta_8 S + \beta_9 B + \beta_{10} GB + \beta_{10} R) \quad (6)$$

Where  $\exp(\beta_0 + \beta_1 HCEPI_i + \beta_3 SHM_i + \beta_4 HR + \beta_6 WI + \beta_7 P + \beta_8 S + \beta_9 B + \beta_{10} GB + \beta_{10} R)$  shows the expected number of children with respiratory infection.

## 4. Empirical Results on the Effect of Household Cooking Energy Poverty and Health

As our dependent variable (no. of children with respiratory infection) is count variable, therefore, we applied negative binomial regression model under Poisson regression model. Zero inflated and zero inflated negative binomial regression models were also used for sensitivity assessment of our analysis.

Number of children under age five having acute respiratory symptoms are presented in table 5. The variance (0.708) of the dependent variable is greater than the mean (0.570) indicating that number of children with respiratory infection are far from its mean. Figure 1 also shows that our number of children with respiratory infection variable is over-dispersed with mean 0.570 and variance 0.708 (Fenta, Fenta, & Ayenew, 2020; Pandey & Kaur, 2015; Shaaban, Peleteiro, & Martins, 2021). It implies that poisson model is not suitable for our data.

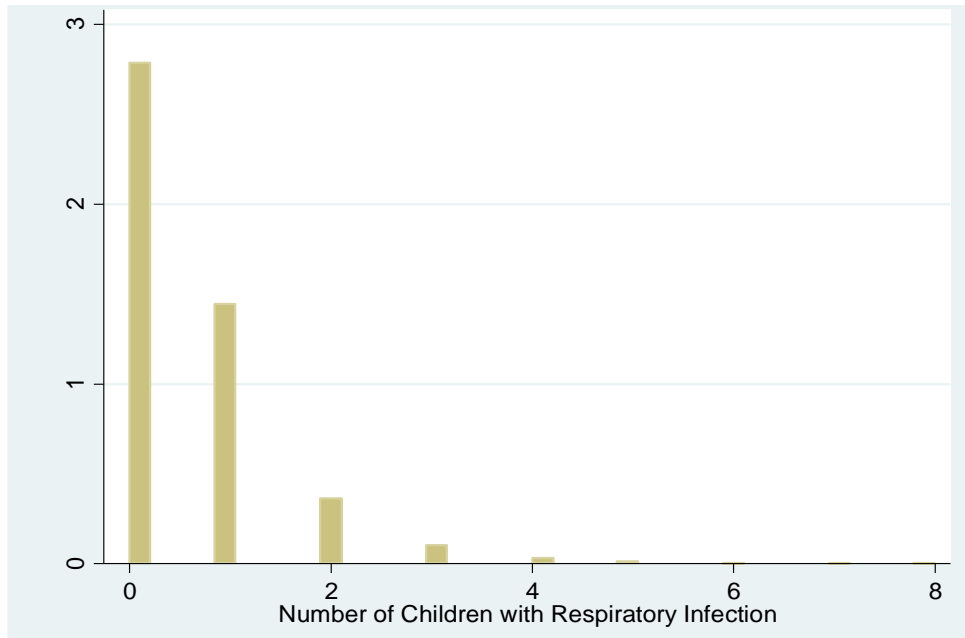
Table 6 shows the likelihood test ratio of alpha ( $\chi^2$ ) probability value,  $p \leq \chi^2 = 0.000$ , which suggests that there is over dispersion in the outcome variable and hence, likelihood test is significant. Vuong test indicates that z-test is significant in case zero inflated Poisson and Poisson regression  $p > z = 0.0014$  and it is insignificant  $p > z = 0.5018$ , in case of zero-inflated binomial regression model and standard binomial regression respectively. It indicates that Poisson regression is not an appropriate model for our data as alpha is significant which shows negative binomial regression is preferred over poisson regression and insignificant Vuong test shows negative binomial regression model is preferred over zero-inflated negative binomial regression model (Hardin & Hilbe, 2014; Shaaban et al., 2021; Xu, Zhu, & Han, 2017).



**Table 5**  
**Number Of Children Having Respiratory Infection**

| Number of Children with Respiratory infection | Frequency | Percent |
|---|-----------|---------|
| 0   | 4,211     | 58.70   |
| 1   | 2,184     | 30.44   |
| 2   | 549       | 7.65    |
| 3   | 155       | 2.16    |
| 4   | 46        | 0.64    |
| 5   | 19        | 0.26    |
| 6   | 6         | 0.08    |
| 7   | 3         | 0.04    |
| 8   | 1         | 0.01    |
| <b>Mean</b>                                   | 0.570     |         |
| <b>Variance</b>                               | 0.708     |         |
| <b>Number of Households with children</b>     | 7,174     |         |

Source: Authors' calculations. Data Source: (GOP, 2019)



**Figure 1: Bar Plot Of Distribution Of Children Having ARI**

**Table 6**  
**Model Selection By Likelihood Ratio Test and Vuong Test**

| Likelihood-ratio test of alpha | Vuong Test             |                          |
|--------------------------------|------------------------|--------------------------|
|                                | ZIP vs PRM             | NBRM vs ZINB             |
| 0.327                          | 3.00                   | -0.00                    |
| (0.000)                        | (0.0014)               | (0.5018)                 |
|                                | ZIP preferred over PRM | NBRM preferred over ZINB |

$H_0: \alpha = 0; H_1: \alpha \neq 0, H_1: \alpha > 0$

We checked the goodness of fit between count models with the help of Akaike information criterion (AIC) and Bayesian information criterion (BIC) (Ismail & Zamani, 2013; Shaaban et al., 2021; Verma, Swain, Singh, & Khetan, 2020; Xu et al., 2017). AIC and BIC value of negative

binomial distribution is the smallest among all other models (see table 7). Therefore, negative binomial regression model is considered a better fit regression model to analyze our outcome variable compared to other count regression models.

**Table 7**  
**Model Selection Criteria For The Count Regression Models**

| Model                                  | df | AIC      | BIC      |
|--|----|----------|----------|
| Poisson                                | 13 | 14588.06 | 14677.48 |
| NB (Negative Binomial)                 | 14 | 14481.6  | 14577.9  |
| ZIP (Zero Inflated Poisson)            | 16 | 14545.19 | 14655.24 |
| ZINB (Zero Inflated Negative Binomial) | 17 | 14487.6  | 14604.53 |

Negative binomial regression result shows the effect of household cooking energy poverty on number of children with acute respiratory infection count distribution. Household cooking energy poverty and smoking status of household members significantly affect acute respiratory infection among children at 5% level (see table 8). One-point increase in household cooking energy poverty leads to significant increase in the expected  $\log(\text{count})$  of number of children with respiratory infection by 0.209 units, holding all other variables constant, at 5% level of significance. Incidence rate ratio (IRR) shows that with every unit increase in household cooking energy poverty, the rate of acute respiratory infection among children under age five is expected to increase by a factor of 1.232, holding all other variables constant. This result showed that household cooking energy poverty directly cause of acute respiratory infection among children under age five. The results are consistent with the literature (Acharya et al., 2015; Anteneh & Hassen, 2020; M. S. B. Khan & Lohano, 2018). (M. S. B. Khan & Lohano, 2018) indicated that children living in households using unclean fuels are more prone to have respiratory infection. Those children suffer 1.5 times more from respiratory infection who live in cooking energy poor households compared to those in a non-energy poor household. (Acharya et al., 2015) found that acute respiratory infection is directly associated with indoor pollution. Increase in the use of polluted fuels result in increase in the number of children with respiratory infection; i.e. 1.79 times higher in cooking energy poor households than non-energy poor households. (Anteneh & Hassen, 2020) indicated that use of polluted fuels significantly affect the acute respiratory infection among children.

**Table 8**  
**Negative Binomial Regression Results**

| Variables                                  | $\beta$ | Z     | P     | IRR   |
|--|---------|-------|-------|-------|
| Household cooking energy poverty           | 0.209*  | 2.01  | 0.044 | 1.232 |
| Household members smoking inside the house | 0.098*  | 2.66  | 0.008 | 1.103 |
| Household room numbers for sleeping        | -0.311  | -8.29 | 0.000 | 0.733 |
| <b>Wealth Index</b>                        |         |       |       |       |
| Poorest                                    | -0.083  | -1.27 | 0.205 | 0.920 |
| Poorer                                     | 0.048   | 0.94  | 0.346 | 1.049 |
| Middle                                     | 0.144*  | 2.62  | 0.009 | 1.154 |
| Richer                                     | 0.113   | 1.83  | 0.067 | 1.119 |
| <b>Place of Residence</b>                  |         |       |       |       |
| Rural                                      | 0.0359  | 0.88  | 0.381 | 1.036 |
| <b>Provincial</b>                          |         |       |       |       |
| Punjab                                     | -0.214* | -4.75 | 0.000 | 0.807 |
| Sindh                                      | -0.128* | -2.40 | 0.016 | 0.880 |
| Balochistan                                | -0.087  | -1.45 | 0.147 | 0.916 |
| Gilgit Baltistan                           | -0.294* | -3.90 | 0.000 | 0.745 |

Source: Authors' own calculations.

Note: Under wealth index 'Richest' is the reference group. Among province dummies, KP is the reference group. Against 'rural' dummy, urban is taken as reference group.

In more crowded households (less number of rooms), there is an increased risk of acute respiratory infection. Table 9 shows that one additional room in the households for sleeping leads to a significant decrease in the expected log(count) of number of children with respiratory infection by 0.311 units, holding all other variables constant, at 5% level of significance. Incidence rate ratio (IRR) shows every unit increase in number of rooms in the household for sleeping, the rate of respiratory infection among children under age five is expected to decrease by a factor of 0.733, holding all other variables constant. Findings are consistent with the literature (Baker, McDonald, Zhang, & Howden-Chapman, 2013; Cardoso, Cousens, de Góes Siqueira, Alves, & D'Angelo, 2004) and contrary to the analysis of (M. S. B. Khan & Lohano, 2018). Number of rooms in a house for sleeping is not a significant predictor of respiratory infection among children (R. E. A. Khan, Bari, & Raza, 2018). However, household crowding is significantly associated with the respiratory infection among children. The greater the crowding, greater will be the risk of respiratory infection (Baker et al., 2013; Cardoso et al., 2004).

Household members who smoke inside directly affect the child acute respiratory health in their dwellings at 5 percent level of significance. Increased number of smokers in the house causes increased acute respiratory infection prevalence in children under age five. Results suggested that one-unit increase in household members smoking inside the house leads to increase in the expected log(count) of number of children with respiratory infection by 0.098 units, holding all other variables constant, at 5% level of significance. Incidence rate ratio (IRR) shows for every unit increase in members smoking inside the household, the number of children suffering from respiratory infection is expected to increase by a factor of 1.10, holding all other variables constant. Our results are consistent with (Mishra, Smith, & Retherford, 2005), which found that indoor tobacco smoking causes increase in the respiratory infections and indicated that there is positive and significant relationship between household members' indoor tobacco smoking with respiratory infection.

Economic status of households is captured by wealth index which shows that expected number of children with respiratory infection are higher in poorer, middle, richer compared to the richest households in Pakistan. Poorest households' quintile shows that there is less expected number of children with respiratory infection than the richest households and gives insignificant result which is consistent with the result of (R. E. A. Khan et al., 2018). Provincial analysis shows that in Punjab, Sindh and Gilgit Baltistan the expected number of children with respiratory infection are less than compared to KP province holding other variables constant. Sample population in Balochistan shows less expected number of children with respiratory infection compared to KP province but the coefficient value is insignificant at 5 percent level of significance. Rural areas have more expected number of children with respiratory infection as compared to urban areas of Pakistan.

## **5. Conclusion and Policy Implications**

Acute respiratory infections are major source of mortality and disability among children under age five in Pakistan. This study helps to explore and investigate the impact of household cooking energy poverty on respiratory health of children under the age of five in Pakistan using PDHS 2017-18 data. Household cooking energy poverty is assessed from the perspective of availability of clean fuels, indoor pollution and access to electricity. Factors like number of rooms in the household for sleeping and household members smoking inside the households also play an important role in determining the respiratory health of children under age five.

Results suggest that increase in the household cooking poverty directly affects the child acute respiratory health in Pakistan. Number of children suffering from respiratory infection increases as household cooking energy poverty increases. Use of solid, unclean fuels inside the

house and having no separate kitchen for cooking are greater risk factors of acute respiratory infection among children under age five in Pakistan. Our empirical findings revealed that smoking by household members inside the household directly affect the health of children. Increased number of smokers in the house causes increase in acute respiratory infection in children under age five. Our findings also indicate that increase in number of rooms for sleeping causes decrease in respiratory infection among children under age five. Less rooms for sleeping, or more crowd in less space lead to rapid spreading of infection from one person to another. Provincial analysis shows that out of all provinces, KP province has the highest number of children with respiratory infection, while rural areas in Pakistan has more prevalence of children with respiratory infection due to household cooking energy poverty compared to urban areas.

The study recommends that government of Pakistan should ensure access to and provide modern cooking energy fuels like LPG, natural gas at affordable rates for households. Government should subsidize efficient cooking stoves and provide clean fuels to the households at cheaper cost. Public awareness regarding health effects of household air pollution should be integrated and through the development and adoption of modern stoves, chances to improve indoor environment and, hence, health of children in Pakistan can be improved. There is need to increase public awareness through programs and policies by policy makers, government organizations and non-governmental organizations regarding household cooking energy poverty and its harmful impacts on the health of household members. Access to modern, alternative clean cooking fuels and creating safe spaces inside the household for the well-being of young females and children can only lead to the attainment of sustainable development goal 3 by Pakistan till 2030.

Children from low-income households are more likely to get exposed to and have a higher risk of respiratory infections than children from higher-income households, hence, government policy for providing a clean energy strategy should be prioritized for low-income households with children under age five. Cooking energy-poor households are more likely to have out-of-pocket expenses related to sickness, particularly respiratory infections among children and women than non-poor households, the government policy regarding offering minimal medical health insurance for cooking energy-poor households should be taken into account.

In order to eliminate health problems that are associated with cooking poverty, investment in cooking energy efficiency measures should be prioritized, with the goal of reducing public health care spending. Households as a major group of energy users should be kept on top priority while developing health and welfare policies as, without such efforts, a sustainable development path cannot be achieved. The safety and healthy growth of the future generation of Pakistan along with nourishment inside the household are not possible otherwise.

### **Authors Contribution**

Abre-Rehmat Qurat-ul-Ann: Idea, Conceptualization, Methodology, Analysis, Discussion, drafting  
Sana Mahfooz: Conceptualization, Data Collection, Data Analysis, Results & Discussion, drafting

### **Conflict of Interests/Disclosures**

The authors declared no potential conflicts of interest w.r.t the research, authorship and/or publication of this article.

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