Environmental Modeling & Assessment
https://doi.org/10.1007/s10666-023-09947-5

RESEARCH

Valuing Health Damage from Polluting Energies in Benin

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Received: 17 August 2022 / Accepted: 13 November 2023

Abstract
This research assesses the health consequences of indoor air pollution resulting from the use of polluting cooking energies in Benin, employing a nationally representative household dataset. Using the health production function approach, we calculated both direct costs (related to medical expenses) and indirect costs (linked to income loss) based on a structural model that accounts for averting behaviours and household heterogeneity. Our findings reveal that reliance on polluting cooking energies significantly increases the risk of illness, particularly respiratory infections and cardiovascular diseases. Notably, the economic costs associated with these dirty cooking energies outweigh the direct medical costs. These results underscore the urgency of promoting clean cooking alternatives in Benin. The estimated health damage can serve to raise awareness among households about the risks of using polluting cooking energies. Furthermore, the estimated costs can provide insights into households' willingness to invest in a transition from polluting to clean cooking energies, potentially informing targeted energy transition policies.

Keywords Polluting cooking energy · Health damage · Economic valuation

JEL code Q4 · Q51 · I18

1 Introduction

Sustainable Development Goal 7 (SDG 7) outlined in the United Nations' 2030 Agenda strives to ensure universal access to reliable, sustainable, and modern energy services that are affordable by the year 2030. SDG 7, through target 5, emphasizes the importance of developing energy infrastructure and innovative technologies to offer modern and sustainable energy services in all developing nations. However, as we are reaching the midpoint of the 2030 Agenda, a substantial portion of the global population, close to one-third, still lacks access to clean, dependable, and sustainable energy services that are essential for meeting basic requirements [1], with significant regional disparities. While some regions, like Latin America and Asia, have made significant progress and achieved near-universal access to electricity by 2019, sub-Saharan Africa lags behind with only 46% having access to electricity, and a substantial 83% of the population continues to rely on polluting cooking energy sources, particularly biomass fuels [2]. Benin, a country of focus in this study, predominantly depends on biomass energy sources, which are widely used in both urban and rural areas, constituting 60% of the total energy consumption. Although there have been advancements in the electricity sector, with an electricity access rate of 40% [3], more than 95% of households in Benin continue to rely on biomass-polluting fuels such as charcoal, firewood, and agricultural residues for their daily cooking needs [4]. An alarming concern is that the reliance on biomass cooking fuels remains consistent across different residential areas in Benin. This reliance was estimated at 97% in rural regions and 88% in urban areas. However, the consequences of this dependency are severe as air pollution, including both indoor and ambient air pollution, contributes to a substantial number of deaths in African nations. For example, Benin recorded 46,745 deaths in 2019 attributed to air pollution (IHME, 2020). Notably, the number of deaths has been on the rise over the past two decades, increasing by 10.2% from 2009 to 2019 [5].

A well-established consensus among scholars and policymakers emphasises the adverse implications of utilizing

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Published online: 05 December 2023

fossil and biomass fuels, which are known to emit hazardous pollutants with detrimental effects on human health. These pollutants encompass carbon monoxide, nitrogen dioxide, polycyclic aromatic hydrocarbons, benzene, formaldehyde, and various inhalable particles [6]. From a theoretical perspective, the indoor air pollution stemming from the use of fossil and biomass fuels for essential activities such as cooking, heating, and cooling is associated with a range of adverse health consequences, including the onset of acute respiratory infections and cardiovascular diseases [7]. In an empirical context, a growing body of literature highlights the detrimental health impacts of indoor air pollution arising from the combustion of fossil and biomass fuels, particularly in the developing regions of Asia and sub-Saharan Africa. In this vein, the study conducted by Masekela and Vanker [8] delved into the association between indoor air pollution, primarily emanating from the use of biomass cooking fuels, and the respiratory health of children in sub-Saharan Africa. Drawing upon a comprehensive review of 56 empirical studies spanning the years 2000 to 2020, their findings unequivocally indicated that reliance on polluting cooking fuels significantly increases the risk of acute respiratory tract infections and the carriage of pathogenic bacteria among children. Similarly, Li et al. [9] conducted a rigorous meta-analysis to examine the link between the use of biomass cooking fuels and the risk of hypertension. By meticulously scrutinizing and evaluating 3740 scientific articles published until November 2019, they selected 11 articles that served as the basis for a random effects model. The results of their analysis demonstrated a significant increase in the risk of hypertension associated with the use of biomass cooking fuels. Furthermore, Dietler et al. [10] undertook a comprehensive systematic literature review, encompassing the years 2013 to 2019, to explore the connection between indoor air pollution resulting from the use of biomass fuels for cooking, heating, and lighting, and the prevalence of cardiovascular diseases in sub-Saharan Africa. They found that reliance on biomass fuels had significant effects on the risk of premature cardiovascular diseases in sub-Saharan African countries. Krishnamoorthy et al. [11] also studied the effects of the use of polluting cooking energies on the cognitive function of elderly people in India. Using nationally representative longitudinal survey data, they revealed a marked decline in cognitive function among elderly individuals residing in households that utilized polluting cooking energies, as compared to those using clean energy sources.

Despite the mounting evidence pertaining to the adverse health consequences of relying on polluting cooking energies, studies dedicated to the monetary valuation of these health damages in sub-Saharan African countries, particularly Benin, have been notably scarce. To the best of our knowledge, the limited number of studies that have undertaken a cost analysis of the use of polluting cooking energies have largely been confined to Asian countries [12–15]. Furthermore, these studies often omitted to account for households' behavioural factors, particularly the adoption of averting measures. Notably, a recent study by Fisher et al. [16] assessed the economic costs linked to ambient and indoor air pollution in three countries, namely Ethiopia, Ghana, and Rwanda. This study, while estimating the economic output loss attributed to air pollution in terms of labour income, exhibited certain limitations. Primarily, it focused on estimating economic output losses in terms of labour income due to air pollution. Additionally, it relied on country-level data for its cost analysis, thereby neglecting the behavioural factors and heterogeneity at the household level. The novelty of our study is 3-fold: Firstly, in contrast to Fisher et al. [16], our study takes into account not only economic output losses in terms of labour income but also the direct expenses linked to medical expenditures. Secondly, we consider behavioural aspects such as households' adoption of averting measures when estimating the damage associated with indoor air pollution. Thirdly, we leverage microdata drawn from a nationally representative dataset, encompassing individual-level and household-level information, in contrast to relying on country-level data. This approach is geared towards capturing the inherent heterogeneity within households.

The main objective of our study is to estimate the health damage attributed to the use of polluting cooking energies in Benin. To achieve this, we address two fundamental research questions. First, we explore the direct costs in terms of medical expenses incurred due to the use of polluting cooking fuels. Second, we assess the significance of economic costs in this context. Our empirical approach is founded on a structural framework that takes into account the adoption of averting measures by households to mitigate their exposure to indoor air pollution.

The rest of the paper is organized as follows. Section 2 presents the literature review, and section 3 is devoted to the methodology and data. The results and discussion are presented in section 4, while section 5 concludes and presents policy implications.

2 Literature Review

2.1 Health Implications of Indoor Air Pollution

According to Laffont [17], the issue of environmental quality falls within the framework of public goods management and has been at the heart of the theory of externalities. While this author demonstrated the effect of environmental quality on well-being, others focused on the channels through which pollution affects individuals' well-being. Thus, Grossman [18] used human capital theory to demonstrate the effect of pollution on human health. Based on an economic rather than a medical approach, he was interested in the monetary valuation of the damage caused by morbidity and mortality due to air pollution.

A rich literature has been identified on the economic methods of valuing such damages, followed by several empirical verifications. In this line, pioneering studies valued the costs of morbidity and mortality due to air pollution in developed countries using various methodological approaches [19–21]. More recently, studies have focused on developing countries, particularly emerging countries where air pollution is highly concentrated [15, 22, 23]. For example, Pandey et al. [15] used the cost-of-illness method to estimate the damage to morbidity and mortality from pollution related to biomass cooking fuels in India. Their results showed that 3.5% of deaths were attributed to solid fuel pollution in households, which accounted for 37% of air pollution deaths. In addition, they estimated the annual per capita cost at 26.5 USD. Zhang et al. [23] used the cost-of-illness approach to estimate the health costs and benefits of the transition from coal to electricity for household heating in the Beijing-Tianjin-Hebei region of China. The authors estimated at 124.8 million USD. Han et al. [12] analysed the impacts of electricity consumption on households' welfare in Cambodia. Based on nationally representative household survey data, the authors showed that the transition from biomass energy to electricity consumption significantly improved household welfare through economic benefits (greater income, greater food and nonfood consumption, better school performance for children, and better health) and environmental benefits (reduction in charcoal and firewood consumption). Irfan, Muhammad, and Hassan [13, 14] analysed the costs and benefits of households' strategies to mitigate indoor air pollution in Pakistan. Based on many energy alternatives and cooking technologies, such as liquefied petroleum gas, natural gas, biogas, electric stoves, and improved cook stoves, they estimated the net benefits of such strategies in terms of morbidity and mortality over 10 years. The authors concluded that liquefied petroleum gas had the highest benefits, equivalent to an annual amount of 30 USD. This amount includes benefits from fuel savings, medical expenses shrinking, productivity gains, and time savings. In Africa, Fisher et al. [16] used data from the WHO Global Health Observatory and Global Burden of Disease in 2019 to cost health damage due to air pollution in three African countries, Ethiopia, Ghana, and Rwanda. Their strategy consisted of evaluating the labour income lost associated with morbidity and mortality of ambient and indoor air pollution. First, they found that the output lost due to air pollution-related mortality was greater than that related to morbidity. Second, they indicated that the economic output lost due to household indoor air pollution-related health (morbidity and mortality) was greater than that due to ambient air pollution for all three countries. Viagannou [24] assessed the damage of morbidity due to air pollution in Benin using data collected from a sample of 600 resident households in Benin's economic capital (Cotonou). The author used a contingent valuation approach to estimate an average willligness to pay (WTP) of 2.9 USD per month per adult for improving air quality in Cotonou by half. To the best of our knowledge, Viagannou's [24] work is among the rare empirical studies that used an economic approach to analyse the relationship between pollution and well-being in Benin.

In sum, it appears from this literature that the literature on the cost and benefit analysis of household indoor air pollution in Africa is still scant. Our study follows that of Fisher et al. [16], who estimated the economic output lost due to ambient and indoor air pollution in three African countries. More specifically, we address some drawbacks of their study. First, their work estimated the economic output lost related to air pollution in terms of labour income. Second, they used country-level data for their costing analysis. The novelty of our study is 3-fold: (i) contrary to Fisher et al. [16], our study combines both economic outputs lost in terms of labour income and direct expenses related to medical expenditures; (ii) we take into consideration behavioural factors such as the adoption of averting measures by households when estimating indoor air pollution-related damage; and (iii) we use household-level data rather than country-level data to better capture household heterogeneity.

2.2 Economic Evaluation Approaches

Environmental economics offers a rich literature on the economic valuation of the welfare loss caused by a degradation in the quality of an environmental good. In measuring individual well-being through health, the monetizing methods of loss of welfare can be categorized into two groups, namely, direct valuation methods based on stated preferences and so-called indirect physical methods based on the production function approach. Direct methods seek to estimate the individual's WTP for an improvement in the quality of the environmental good (air or water quality, for example) or the willingness to receive for a deterioration in the quality of the environmental good [25]. The most direct valuation methods used in environmental and health economics are the contingent valuation methods (stated preference approach) and the travel cost method (revealed preference approach). One of the main advantages of direct methods is the simplicity of implementation, while they are subject to several biases, such as hypothetical bias and strategic bias. In addition, direct methods are biased in the allocation and valuation of individuals' time. For example, if solid fuel collection is done during leisure time, using the wage rate to value the time taken for collection would produce biased results; in particular, they will overestimate the value of the good. This is of particular concern in developing countries such as Benin, where women who are typically engaged in solid fuel collection often perform these activities after their farming activities. Physical or indirect methods of assessing the health damage of pollution are based on the direct effects of pollution on the morbidity and mortality of individuals. These methods include the cost-of-illness method, the dose–response function method and the health production function. All of these methods are based on human capital theory and consumer choice theory [18, 19]. The production function method extends the Grossman [18] model by introducing the quality of the environment into the health production function. In this model, the consumer is considered a producer of goods (good health) for consumption and investment. Thus, in such a model, good "good health" is considered both a consumption good and a capital good for the consumer. To cope with a deterioration in the quality of the environment, the consumer can adjust his or her consumption of health goods to maintain the same level of utility under the same budget constraint. Consequently, it is possible to derive the consumer's marginal WTP for the improvement in environmental quality. The difference between the Gerking and Stanlay [19] models is that the former assumes that the quality of the environment does not directly affect individual health but rather the rate of depreciation of the health stock. In contrast, Gerking and Stanlay [19] directly introduced environmental quality as a determinant of the health production function. Long before the work of Gerking and Stanlay [19], other authors used the dose–response function method to assess the damage to morbidity from air pollution [20, 25]. The difference between the health production function model and the dose–response function model is that the former considers the health good as endogenous in the health production function, whereas the dose–response function model assumes that the health production function is determined by purely exogenous factors such as expenditures on health goods and individuals' socioeconomic and demographic characteristics. The main drawback of the indirect methods is that the value of health damage is also influenced by the standard of living of the regions (rural and urban) through different wage rates. However, this bias can be corrected by taking the average wage rate in the sample to remove differences in wage rates between regions.

2.3 Taking Into Consideration Averting Behaviours

Economic theory indicates that when conditions change, rational economic agents will modify their behaviours to reflect the new state. Hence, adaptive behaviors should be taken into account in valuing the health damage from polluting cooking energies. For example, if households adopt measures to reduce their exposure to pollution from polluting cooking energies, such as the adoption of improved cookstoves, cooking in the open air, or separating kitchens from living quarters, the occurrence of illnesses related to the use of polluting cooking energies may be lower than would be expected in the absence of such avoidance measures. Therefore, ignoring such behaviors may lead to biased results. Given this parameter, we use the production function method as opposed to the cost-of-illness method, which does not allow for the inclusion of averting measures [21]. In addition, the health production function method reduces the bias of the difference in average wage rates in different regions of the country.

2.4 The Mechanism of the Health Effects of Polluting Energies

Figure 1 shows the channels through which the use of polluting energy affects the well-being of the population (Fig. 2 appears at the end of Sub-section 2.4). The dependence of households on polluting energy sources releases microparticles of pollutants that are propagated in the indoor air of the household as well as the outdoor air. The concentration of these pollutants has a direct effect on human health and increases the risk of respiratory, chronic, infectious, cardiovascular and cancer illnesses. These different illnesses increase morbidity and mortality. To cope with these two phenomena, households adopt defensive strategies involving treatment and prevention expenditures. They also incur indirect costs in terms of lost productivity due to time spent on illness. All these costs borne by households are likely to induce a loss of well-being.

2.5 Modelling Polluting Cooking Energy-Related Health Damage

This section presented the methodology, notably the theoretical and empirical models, the estimation methods, and data and model flow.

2.6 Economic Model

The assessment model for health damage caused by pollution resulting from the use of polluting cooking energies is built upon the foundation of the household health production function. This concept, initially introduced by Grossman [18], and further extended by Harrington and Portney [26], has been instrumental in deriving the implicit price of morbidity through an individual's health production process. Moreover, the extensions by Cropper [27] have facilitated the incorporation of environmental quality as a factor within the health production function. Harrington and Portney's [26] adaptations of this model have accounted for individual health-protective behaviours and preventive measures. Consequently, this later version of the health production function aligns well with the objectives of our study. Drawing

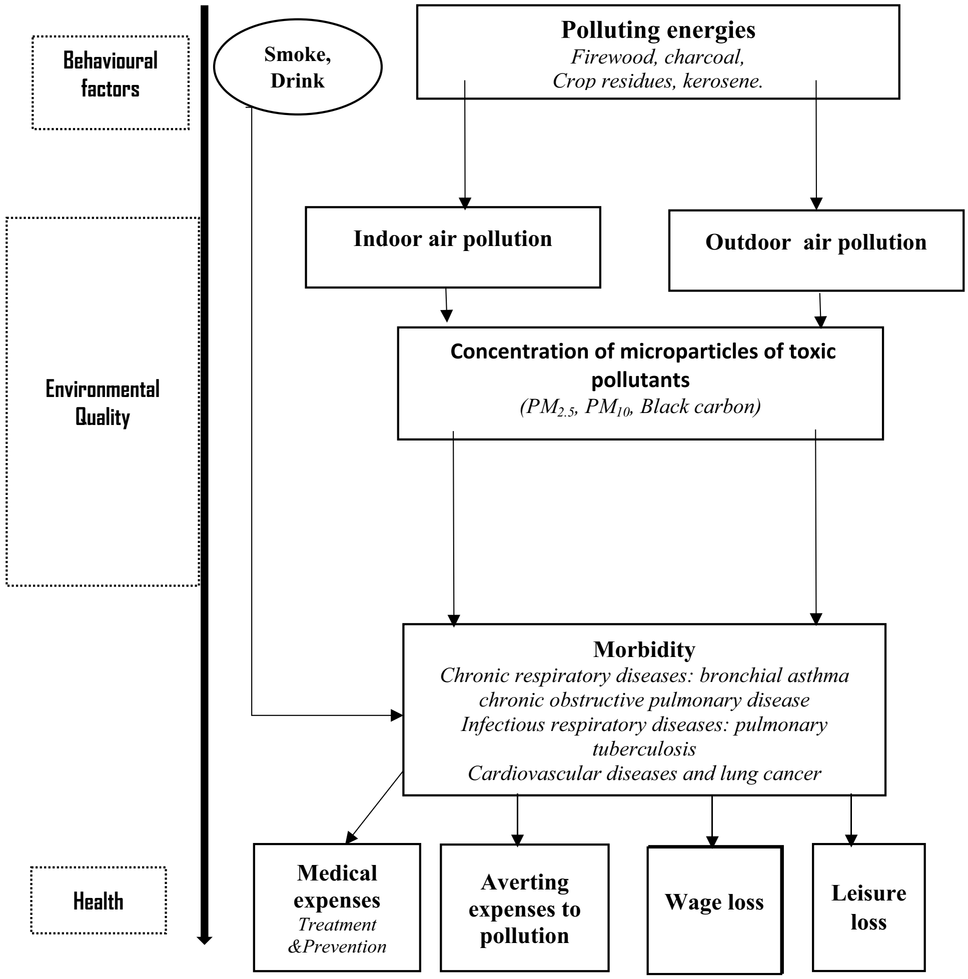


Fig. 1 Cooking energy-health. The use of dirty cooking fuels emits fine particles of harmful pollutants that have adverse effects on human health

upon principles of consumer utility theory, and building upon prior research [19, 26], we define the household utility function as follows:

$$U = U(X, T; B), \tag{1}$$

where (X) represents consumption goods, excluding energy goods, (T) represents the household available time per period (month) that could be allocated to work (T^w), leisure (T^l), illness (T^i), and preventive measures (T^p), and B holds for other behavioural factors, such as smoking cigarettes. The price of consumption goods is taken as a numeraire. The household utility function can be rewritten as:

$$U = U\left(\mathrm{X}, T^l, T^i; B\right). \tag{2}$$

The first and second partial derivatives of Equation 2 (see Appendix 1) evidence that the household derives benefits from the consumption good, leisure, and other behavioural factors at a decreasing rate (Equations 20 to 22 in Appendix 1).

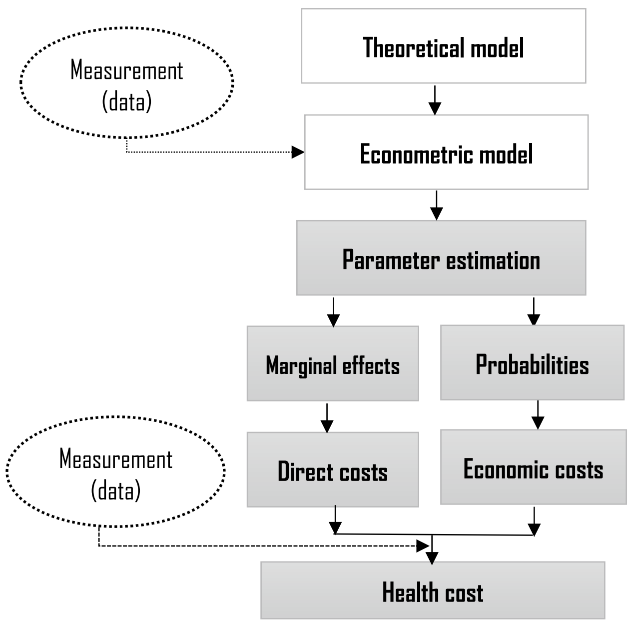
Let us now assume that time spent on illness *(T^i)* (lung cancer, chronic respiratory diseases, cardiovascular diseases) increases with the exposure of household members to smoke and heat released from the use of polluting energies *(E)*, other individual behavioural factors *(B)*, and the preventive measures adopted by the household to reduce exposure to smoke and heat *(T^p)*. According to Alberini et al. [28], preventive measures could be estimated in terms of time spent on preventive measures *(T^p)*. The time spent on illness (T^i) is specified as:

$$T^i = T^i(E, T^p; B), \tag{3}$$

where $\partial T^i/\partial T^p < 0$, meaning that preventive measures reduce the time spent on illness. Let w denote the wage rate, R_0 the nonlabour income, and P the cost of a unit of time spent on preventive measures. Household income (R) is therefore defined as:

$$R = R_0 + R(T^w), \tag{4}$$

where $\mathrm{R}(T^w) = w(T - T^i - T^p - T^l)$. It can be seen that the units of time available to paid work within a household is equivalent to the total units of time available (T) each period minus the time allocated to leisure (T^l), preventive measures (T^p), and time spent on illness (T^i). Furthermore, the household budget constraint is defined as:



Source: authors

Fig. 2 Analysis flow. Theoretical model is transformed into an econometric model, which, using data, allow us to derive probability of illness and to monetise the cost of illness.

$$R_0 + w\left(T - T^i - T^p - T^l\right) \geq X + P.T^p. \tag{5}$$

Finally, the household maximization problem is:

$$MaxU = U\left[X, T^l, T^i(\mathrm{E}, T^p; B)\right], \tag{6}$$

Subject to:

$$R_0 + w\left(T - T^l - T^i(\mathrm{E}, T^p; B) - T^p\right) \geq X + P.T^p, \tag{7}$$

$$T - T^l - T^i(\mathrm{E}, T^p; B) - T^p \geq 0, \tag{8}$$

$$T^l \geq 0; T^i(\mathrm{E}, T^p; B) \geq 0; T^p \geq 0. \tag{9}$$

To solve the household maximization problem, we made the following assumptions: (i) there is no social security or private insurance to keep part of the income when individuals are ill; (ii) the time spent on leisure and health investment is assumed substitutes instead of complements; and (iii) health hazards are conceptually stochastic, without uncertainty in the decision problem. The following proposition offer a characterization of the trade-off between the consumption of market good (a numeraire) and the time invested in preventive measures within the households.

Proposition *The net marginal cost of the preventive measures is:* $p + w + wT^{i\prime}_{T^p}$ *(proof in Appendix 2).*

This proposition implies that, in the presence of health expenses associated with the use of polluting cooking energies, the adoption of preventive measures is advantageous when their benefit exceeds the sum of the price of the prevention technology per unit time, the wage rate (the opportunity cost of the time invested in prevention) net the benefit associated to the reduction of the time in illness due to the prevention measures.

The optimal solutions of time spent on preventive measures (Equation 10) and time spent on illness (Equation 11) are:

$$T^{p*} = T^{p*}[w, P, \mathrm{R}, \mathrm{E}], \tag{10}$$

$$T^i = T^i(T^{p*}, E). \tag{11}$$

The functional form of Equations (10) and (11) can be estimated econometrically using observed household-level data. For example, *(T^p)* can be measured by a latent variable y that takes the value *1* if the household adopts preventive measures to reduce or avoid exposure to smoke and heat from polluting energy use and *0* otherwise. As the time spent on preventive measures can be evaluated in terms of expenditures, we measure these expenditures through the costs incurred by households when cooking in a separate building or outdoors to reduce the exposure to smoke from the use of polluting cooking energies such as firewood, charcoal, and agricultural residues. We finally measure the preventive measures through a latent variable taking the value 1 if the household cooks in a separate building or outdoors. Similarly, (T^i) can be measured by a latent variable z that denotes the occurrence of illness in the household due to exposure to smoke and heat from polluting cooking energies, notably chronic respiratory diseases and cardiovascular diseases [29–31]. Finally, let $y*$ and z denote the reduced-form of (10) and (11), respectively, k a vector of households' socio-economic and demographic characteristics such as place of residence, health insurance coverage, education level and age of the household head and spouse(s), media exposure and other behavioural factors such as smoking cigarette status. The parameter E is measured by the reliance on polluting cooking energies. Hence, $y*$ and z are specified as follows:

$$y^* = f\left(k_y, E\right), \tag{12}$$

$$z = f\left(y^*, \mathrm{k}_z, \mathrm{E}\right). \tag{13}$$

2.7 Econometric Strategy

Denoting the vector of explanatory variables in Equations 12 and 13 as x_1 and x_2, the estimable form of the preventive adoption equation can be specified as follows:

$$y_1^* = x_1\beta_1 + \varepsilon_1, \tag{14}$$

where $y_1 = \begin{cases} 1 \text{ if } y_1^* > 0 \\ 0 \text{ otherwise} \end{cases}$ and $\varepsilon_1 = a_1 r^* + e$, r^* are risk factors known to the household but not measured in the surveys, such as previous experiences of illness, and $\varepsilon_1$is the composite error term split into estimation error e and unobservable risk factors for pollution exposure$a_1 r^*$. It is assumed that $\partial y_1^* / \partial r^* = a_1 > 0$ to the extent that the risk factors r^* increase the occurrence of illness, households commit more resources to preventive measures. Similarly, Equation 13 to be estimated is as follows:

$$y_2^* = x_2\beta_2 + c y_1^* + \varepsilon_2, \tag{15}$$

where $y_2 = \begin{cases} 1 \text{ if } y_2^* > 0 \\ 0 \text{ otherwise} \end{cases}$ and $\varepsilon_2 = a_2 r^* + u$.

The binary specification of Equation (15) indicates that the illness is observed in the household when y_2^* is greater than zero. The term ε_2 is the error term composed of the estimation error u and the unobservable risk factors for pollution exposure $a_2 r^*$. We assume that $\partial y_2^* / \partial r^* = a_2 > 0$, meaning that a high level of pollution exposure risk increases the probability of illness in the household. In contrast, $\partial y_2^* / \partial y_1^* = c < 0$ reflects that preventive measures reduce the risk of illness in the household.

The reader may note that the estimation of the model in Equation (15) suffers from an endogeneity bias in that one of the explanatory variables in the model (y_1^*) is correlated with the error term ε_2 in Equation 2. We solve this problem by eliminating the endogenous variable y_1^* on the right-hand side of Equation (15) by substituting its expression from Equation (14) as follows:

$$y_2^* = x_2\beta_2 + x_1\left(c\beta_1\right) + \eta, \tag{16}$$

where the composite error term equals to $\eta = c\varepsilon_1 + \varepsilon_2$.

The resulting Equation (16) now consists only of exogenous explanatory variables x_1 and x_2. Consequently, Equations (14) and (16) can be estimated separately. However, this is not possible since the error terms of these two equations are correlated ($\eta = f[\varepsilon_1]$). Such a correlation denotes the nonseparability of the occurrence of the illness and the adoption of preventive measures. Under these conditions, the estimation of Equations (14) and (16) need to take into account the structure of the covariance matrix of the errors of the two equations. Therefore, we assume that the error terms ε_1 and η have a standard normal bivariate joint distribution with mean zero and covariance matrix $\sum = \begin{pmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{pmatrix}$, where σ and $\rho$are the variance and correlation coefficients, respectively.

Since the dependent variables of both Equations 14 and 16 are binary, they can be simultaneously estimated through bivariate probit regression. This can be done using the maximum likelihood method.

Practically, it is worth noting that our model contains both household-level variables and individual-level data. Thus, ignoring the hierarchical structure of the data, that is, individuals nested within households, is likely to bias our results [32]. Hence, we estimated a multilevel mixed-effects biprobit model by assuming (i) that the occurrence of illness may vary from one household to another and (ii) that the effect of an explanatory variable may vary equally from one household to another. The multilevel mixed-effects model uses the control-function approach to simultaneously estimate both the fixed-effect and random effects. By doing so, the multilevel mixed-effects model addresses endogeneity and imbalance [33, 34]. To control for the endogeneity issue, we included restriction exclusion variables in the averting behaviour equation, that is, access to information through television ownership and access to credit. Indeed, it showed that better access to information is likely to increase household awareness of health hazards associated with polluting energies [35], so that it may increase the adoption of averting measures. Equally, as the adoption of averting measures such as the use of improved cookstoves is associated with an upfront investment cost, it showed that access to credits reduces the barriers to the adoption of improved cookstoves [36, 37]. Nonetheless, it is unlikely that access to credit directly affects the occurrence of illness. The multilevel mixed-effects model was estimated using the maximum likelihood estimator.

2.8 Monetization of Health Damage

The evaluation of the health damage of the use of polluting energies takes into account the direct costs related to the medical expenses of the household and the opportunity costs in terms of loss of income due to the time of inactivity by the household members. To estimate the average monthly cost of illness for a representative household, we divided the sample into three groups, namely, children (0-14 years), adults (15-64 years) and elderly individuals (over 64 years). This distinction is justified by two arguments. First, health expenditures may differ among these three groups of individuals. In particular, health expenditures are likely to be higher among children and the elderly compared to the adult group. Thus, this distinction helps limit bias in the estimation of direct costs. Second, we distinguish the three population groups because children and the elderly are not counted in the labour force. As a result, this distinction has the advantage of limiting bias in the estimation of indirect costs.

2.8.1 Estimation of Direct Costs

Let ψ_h be the probability that a household is affected by the illness due to exposure to energy pollution, ψ_c, ψ_a and ψ_e respectively be the probability of being a child, an adult and an elderly from an affected household. Let us also denote by ξ_c, ξ_a, and ξ_e the respective probability that a child, an adult, and an elderly person are sick knowing that they come from an affected household. Finally, let us denote by c_h, c_c, c_a, and c_e the average monthly treatment cost of a household, child, adult, and elderly as follows:

$$c_h = n \times \psi_h \sum_{i=1}^{3} \psi_i \xi_i c_i, \tag{17}$$

where i= c, a, e; and n refers to the average household size. The parameter ψ_h can be predicted from the estimation of the biprobit model Equations 14 and 16 as the mean probability of a household being sick. The probability of being a child, adult, or elderly from an affected household ψ_i is equal to the ratio between the total number of children, adults, and elderly in the affected households and the total number of individuals in the affected households. The parameter ξ_i can be calculated by dividing the total number of child, adult, and elderly sick individuals over the total number of child, adult, and elderly individuals in the affected households.

2.8.2 Estimating Opportunity Costs

The opportunity cost of illness can be measured for an adult through the loss of income caused by the inability of the individual affected by the illness to work during the entire period of illness. The estimation of the economic costs is based on the following assumptions:

- We only consider labour income;
- Only adults aged 15–64 years old participate in the labour market;
- The illness of a household member does affect the working time of the household head.

Accordingly, the average monthly cost (oc) in terms of lost income due to illness from polluting cooking energy for a representative household is obtained by multiplying the probability ($\psi_h \psi_a \xi_a$) that an adult is affected by illness in a representative household by the average wage rate in sample w, the employment rate in sample W, and the average time lost from work T^i in illness as follows:

$$oc = \psi_h \psi_a \xi_a \times w \times W \times T^i. \tag{18}$$

2.8.3 Estimating Health Damage

Finally, the average total monthly health damage (AMD) for a representative household from polluting cooking energy dependence is given by the sum of direct costs and opportunity costs as follows:

$$AMD = \psi_h \left(n \times \sum_{i=1}^{3} \psi_i \xi_i c_i + c_h \psi_a \xi_a \times w \times W \times T^i \right). \tag{19}$$

2.9 Data and Model Flow

This work used a secondary household data source from Benin's Harmonized Survey on Living Conditions of Households in Benin (EHCVM, 2019). This survey was conducted in the eight countries of the West African Economic and Monetary Union (WAEMU) between 2018 and 2019 with joint funding from the World Bank and the UEMOA Commission and carried out by the National Institute of Statistics and Economic Analysis of Benin (INSAE). The EHCVM was based on a nationally representative household survey taking into account the 12 administrative zones and the area of residence (urban and rural). The selection of the sample was based on a two-stage sampling design, consisting of selecting at the first stage 670 clusters with probability proportional to size (number of households) using the household sampling frame from the 2013 General Census of Population and Housing of Benin (RGPH 4). In the second stage, 12 households were selected randomly in each of the 670 clusters. Finally, the sample selected encompasses 8040 households. The EHCVM has two modules, the community module and the household-individual module. The latter provides information on households' socio-economic and demographic characteristics, including the types of cooking energies used, health status, health expenditures, and income. Household-individual data were used in this study. The dataset is freely available on the website of the Program for the Harmonization and Modernization of Household Living Conditions Surveys in WAEMU countries.

Figure 2 illustrates the analysis flow, which can be divided into three parts. The first part represents the mathematical and econometric modeling (depicted as white font rectangles). The second part highlights the data used to estimate the econometric model (represented by dotted circles on the left-hand side). The final part demonstrates the process of transforming key parameters estimated from the econometric model into direct and economic costs, in conjunction with additional data (shown as black font rectangles).

2.10 Summary Statistics

This study involved two dependent variables, namely, illness occurrence and adoption of averting measures. Illness occurrence is a binary variable taking the value of 1 if at least one of the household members reported any of the following diseases: chronic respiratory diseases, infectious respiratory diseases, cardiovascular diseases, and lung cancer; and 0 otherwise. The adoption of averting behaviour is measured through a dummy variable taking the value 1 if the household uses improved cookstoves or open cooking and 0 otherwise. The main independent variable was the use of polluting cooking energy, which is measured through a dummy variable taking the value 1 if the household uses at least one of the following cooking energies as the main source: firewood, charcoal, agricultural residues, and kerosene; and 0 otherwise. We further included a vector of control variables at the individual level and household level in both the illness equation and the averting measures adoption equation, such as health insurance; smoking status; Alcohol consumption status; access to credit; access to information through acess to television with subscribed to cable, satellite, or ADSL television channels; gender, education of household head and spouse; household size; place of residence; and monthly income. Access to health insurance is measured through a dummy variable taking the value 1 if the household has health insurance and 0 otherwise; the smoking and Alcohol consumption status are measured through a dummy variable that takes the value 1 if the individual smokes cigarettes/consume alcohol and 0 otherwise. Table 1 presents the descriptive statistics of the study variables. It is worth noting that, because we had insufficient degrees of freedom for the higher education category, we narrowed down the education variable categories to three (none, primary, secondary/higher) when estimating our model (Table 2) instead of the originally reported four in the descriptive statistics (Table 1).

The descriptive statistics presented in Table 1 show that most households (96%) rely on polluting cooking energies. At the same time, the incidence of illnesses related to the use of polluting energies was 76 per thousand inhabitants, while 361 per thousand households adopted measures to avoid these diseases.

3 Results and Discussion

3.1 Results of the Multilevel Mixed-Effects Bivariate Probit

The results of the estimation of the multilevel mixed-effects bivariate probit model are presented in Table 2. It appears from these results that the quality of the model is globally satisfactory regarding the variance and covariance matrix structures. Notably, the covariance coefficient of the error terms of the illness equation and averting measures equation was negative (−0.002) and statistically significant at the 1% level. This result confirms the validity of simultaneously estimating the two equations instead of estimating each separately. The presence of a negative sign in the covariance coefficient signifies that an increase in the adoption

Table 1 Descriptive statistics

Variables	Coef.	Std. err.	[95% Conf. interval]	
Dependant variables				
Incidence of illness (1=yes)	0.076	0.002	0.073	0.079
Averting behavior (1=yes)	0.361	0.006	0.350	0.372
Explanatory variables				
Household-level				
Polluting energies (1=yes)	0.962	0.002	0.957	0.966
Gender of household head (1=male)	0.726	0.009	0.708	0.744
Education of household head (1–4 scale)	1.514	0.011	1.492	1.536
Education of spouse (1–4 scale)	1.178	0.007	1.164	1.192
Household size	6.747	0.042	6.664	6.831
Residence (1=urban)	0.471	0.003	0.464	0.477
Access to television (1=yes)	0.056	0.003	0.050	0.061
Job in agriculture	0.516	0.011	0.493	0.539
Monthly income (Francs CFA)	93721	5203	83513	103929
Individual level				
Access to credit (Francs CFA)	8982	1066	6893	11072
Health insurance (1=yes)	0.007	0.001	0.005	0.009
Smoke (1=yes)	0.003	0.001	0.026	0.336
Alcohol consumption (1=yes)	0.086	0.028	0.080	0.912

Table 2 Multilevel mixed-effects biprobit estimates

Dependant variable: occurrence of illness					
Independent variables	Coefficient.	Robust adjusted Std. err.	z	[95% Conf. interval]	
Fixed-effects					
Use of polluting energies (ref.=no)	0.423**	0.223	1.90	-0.014	0.859
Head of household education (ref.=no educ)					
Primary	−0.435**	0.243	−1.79	−0.912	0.041
Secondary	−0.157	0.218	−0.72	−0.584	0.269
Spouse education (ref.=no education)	−0.437	0.230	−1.90	−0.887	0.014
Primary	−0.035	0.249	−0.14	−0.523	0.454
Secondary	0.035	0.314	0.11	−0.580	0.651
Gender of head of household (ref.=female)	0.230	0.207	1.11	−0.175	0.635
Log (income)	−0.066	0.059	−1.13	−0.182	0.049
Health insurance (ref.=no)	−0.731**	0.386	−1.89	−1.488	0.026
Residence (ref.=rural)	0.086	0.161	0.53	−0.231	0.402
Log (household size)	0.023	0.112	0.20	−0.196	0.242
Smoke (ref.=no)	0.229	0.468	0.49	−0.688	1.145
Alcohol consumption (ref.=no)	0.133	0.209	0.64	−0.276	0.543
Access to television (ref.=no)	0.181	0.223	0.81	−0.256	0.617
Intercept	−0.865	0.815	−1.06	−2.462	0.733
Dependant variable: adoption of averting behaviours					
Independent variables	Coef.	Std. err.	z	[95% Conf. interval]	
Fixed-effects					
Use of polluting energies (ref.=no)	0.536**	0.222	2.42	0.101	0.971
Head of household education (ref.=no educ)					
Primary	−0.146	0.145	−1.01	−0.429	0.138
Secondary	−0.038	0.178	−0.21	−0.387	0.311
Spouse education (ref.=no education)					
Primary	−0.622***	0.227	−2.73	−1.067	−0.176
Secondary	−0.156	0.313	−0.50	−0.769	0.457
Gender of head of household (ref.=female)	0.147	0.152	0.97	−0.151	0.444
Log (income)	−0.153***	0.045	−3.37	−0.242	−0.064
Residence (ref.=rural)	−0.510***	0.111	−4.60	−0.727	−0.293
Log (household size)	−0.165**	0.075	−2.21	−0.312	−0.019
Access to television (ref.=no)	−0.274	0.206	−1.33	−0.678	0.130
Log (access credit)	0.039*	0.022	1.76	−0.005	0.084
Intercept	0.934	0.490	1.90	-0.027	1.895
Random-effects household-level					
Variance (illness)	0.194	0.000		0.194	0.194
Variance (averting behaviour)	0.047	0.000		0.047	0.047
Covariance (illness, averting)	0.096	0.000		0.096	0.096
Number observation	23,801				
Error terms					
var(e.Illness)	0.070***	0.001	47.64	0.067	0.073
var(e.Averting)	0.231***	0.001	264.08	0.229	0.232
cov(e.Illness,e.Averting)	−0.002**	0.001	−2.04	−0.003	−0.000

of averting measures has a substantial effect in decreasing the likelihood of illness. Furthermore, the household-level random intercepts for the illness and averting behaviors equations were determined to be 0.195 and 0.047, respectively, and were found to be statistically significant. This lends support to the estimation of a multilevel model. These results imply that there is greater heterogeneity within households regarding illness compared to households that adopt averting measures. Equally, the coefficients of the exclusion restriction variables in the averting behaviour equation, notably access to credit was significant, supporting the validity of the structural model. We additionally employed the likelihood ratio (LR) test to assess the superiority of the multilevel mixed-effects bivariate probit model, estimated both with and without the exclusion restriction variables. The results of the LR test strongly rejected the null hypothesis that the multilevel mixed-effects biprobit model without exclusion restriction variables (Table 7 in Appendix 3) is superior to the one with exclusion restriction variables, as indicated by the LR statistic, chi-2(2)=5.58 with p value=0.061. Before interpreting the estimation results, it is worth noting that the coefficients cannot be directly interpreted but rather their sign concerning the dichotomous nature of the dependent variables. Hence, we calculated the marginal effects (Table 3). We only reported in this table the marginal effects of significant variables.

The results of the illness equation show that the type of cooking energy used was positively and significantly associated with the occurrence of illness. In particular, relying on polluting cooking energies increases the probability of being sick by 4.9% (Table 3). These results confirm those of existing studies in Africa and Asia. For instance, Ofori et al. [38] investigated the association between biomass cooking fuels and cardiovascular diseases in rural Nigerian women aged 18 years and above and concluded that women using biomass fuels as the primary source of cooking energy were more likely (1.2 times) to suffer from cardiovascular diseases than those who use liquefied petroleum gas. In Pakistan, Imran, and Ozcatalbas [22] found that reliance on charcoal as the main source of cooking energy increases the risk of illness by 25% among households compared to those who use liquefied petroleum gas. Similarly, Zheng et al. [39] analysed the health hazards of biomass cooking fuels among Chinese rural women and revealed that the odds of suffering from blood pressure, triglycerides, high-density lipoprotein cholesterol, and overweight were at least 5 times higher among women who relied on biomass cooking fuels. Patel et al. [40] focused on Indian children under 3 years old and revealed that children from households who used cake dung and kerosene as the main cooking energy sources were 21–25% more likely to suffer from acute respiratory infections. Alharthi and Hanif [41] and Hani [42] reached the same conclusions when adopting a country-level approach through longitudinal data using a sample of Asian and sub-Saharan African countries. Furthermore, the results showed that the education of the head of household and that of the spouse, health insurance, and income negatively reduce the probability of being sick. These findings align with our expectations and confirm those of previous studies that indicated that in developing countries.

Equally, the results from the averting behaviours equation indicated that the quality of cooking energy, income, place of residence, access to information, and access to credit were significantly associated with the adoption of averting measures. Thus, the reliance on polluting energies increases the probability of adopting averting measures by 15.3% (Table 3). These results are consistent with our expectations because households using clean energies are generally less exposed to smoke and heat during cooking. For instance, it is less likely that households use liquefied petroleum gas as cooking energy outdoors. The results also indicated that the economic status of households measured by the level of income significantly decreases the probability of

Table 3 Marginal effects

Dependant variable: occurrence of illness					
Independent variables	Coef.	Std. err.	z	[95% Conf. interval]	
Fixed-effects					
Use of polluting energies (ref.=no)	0.049*	0.026	1.84	−0.003	0.100
Head of household education (ref.=no education)					
Primary	−0.043**	0.02	−2.12	−0.826	−0.003
Health insurance (ref.=no)	−0.128*	0.092	−1.38	−0.309	0.053
Dependant variable: adoption of averting behaviours					
Independent variables	Coef.	Std. err.	z	[95% Conf. Interval]	
Fixed-effects					
Use of polluting energies (ref.=no)	0.153***	0.062	2.45	0.031	0.276
Education of spouse (ref.=no education)					
Primary	−0.154***	0.046	−3.35	−0.244	−0.064
Log (income)	−0.044***	0.013	−3.49	−0.068	−0.019
Residence (ref.=rural)	−0.155***	0.035	−4.43	−0.224	−0.086
Log (size of household)	−0.047**	0.021	−2.25	−0.088	−0.006
Log (access credit)	0.011*	0.006	1.77	−0.001	0.0294

adopting aversion measures. This result may imply that households tend to move away from the use of polluting energies to clean cooking energies, as argued in the energy ladder and energy stacking hypotheses. In contrast, households residing in rural areas are more likely to adopt averting mitigation measures than households in urban areas. This result may be explained by the fact that the direct costs of averting measures such as cooking outdoors are less than those in urban areas, holding the costs of adopting improved cookstoves equal in both rural and urban areas. Indeed, rural residents have access to spacious housing, allowing for open-air space for cooking.

3.2 Monetization of Health Damage

Recall that the main objective of this study was to monetize the health damage due to households' exposure to pollution from polluting cooking energies. As presented in the valuation methodology (section 3.3), the value of health damage is equal to the sum of direct costs (medical expenses) and indirect costs (opportunity costs in terms of lost wages). The results of the estimation of the multilevel mixed-effects bivariate probit model presented in Table 2 allow us to derive the predicted probabilities of being ill by population groups (child, adult, elderly). The average monthly direct cost of illness for a representative household is then calculated using the formula in Equation 17. The average monthly health expenses by population groups and the average household size presented in Table 4 are those calculated directly from our data. The results presented in Table 4 show that illness that could be attributed to exposure-related polluting cooking energies costs an average of 331 CFA francs (0.560 USD) per month. This value represents the average monthly cost of treatment and prevention of illness for a representative household. Although this amount seems to be low, it represents 4.95% of household monthly health expenditures in Benin. Indeed, the Benin National Institute of Statistics (INSAE) estimated an average household monthly health expenditure of 6682 CFA francs (11 USD) [43].

Table 4 Cost of treatment of illness

Parameter	Child	Adult	Elderly	Total
ψ_i	0.840	0.062	0.099	-
ξ_i	0.161	0.186	0.224	-
c_i	1552	2719	2858	-
Prob sick ($\psi_h \psi_i \xi_i$)	0.029	0.002	0.005	
$\sum_{i=1}^{3} \psi_i \xi_i c_i$	210	31	63	305
n				5.14
ψ_h				0.212
$c_h = n \times \psi_h \sum_{i=1}^{3} \psi_i \xi_i c_i$				331

Table 5 Opportunity cost (wage lost)

Variable	Value
Probability of being sick/adult	0.002
Average monthly time spent on illness (day)	1.8
Employment rate	0.974
Wage rate/adult	95203
Average monthly wage lost/household	1153

Table 5 presents the results of the monetization of lost wages due to illness from the use of polluting cooking energies. The predicted probabilities of illness for an adult are derived from the estimation of the multilevel mixed-effects bivariate probit model. The remaining parameters (average time in illness, employment rate, monthly wage rate) were obtained directly from our data. These results showed that the average monthly loss of income due to the use of polluting cooking energies was estimated at 1153 CFA francs (1.95 USD) for a representative household. This amount is three times higher than the direct costs of illness, indicating the importance of economic losses, which are generally not evaluated by households or even public authorities. The economic costs of polluting cooking energies represent 17.25% of households' monthly health expenditures in Benin.

Overall, the average monthly health damage associated with the reliance on polluting cooking energies for a representative household was estimated at 1484 CFA Francs (2.51 USD), representative of an annual cost of 17,808 CFA Francs (30.13 USD) per household (Table 5). This amount is equivalent to 22.21% of households' monthly health expenditures. These results have many implications for poverty reduction policies in Benin. For instance, the annual costs of polluting cooking energies are equivalent to 44% of the minimum wage in Benin, which was 40,000 FCFA (68 USD) in 2019. More importantly, the Benin National Institute of Statistics [44] reported that a shrinkage in household consumption expenditures by 1.3% led to an increase in poverty by 3.9% in Benin between 2011 and 2015. Hence, as our estimated costs of polluting cooking energies represent 1.5% of household monthly consumption expenditures, it could be inferred that the promotion of clean cooking energies could contribute to reducing poverty by 5% *ceteris paribus* in Benin.

From a country-level perspective, the Benin Fourth General Population and Housing Census (RGPH 4) conducted in 2013 indicated a total of 1,803,123 households. Aggregating the average monthly health damage for a representative household to all Benin's households yields an annual cost equivalent to 0.51% of Benin's real gross domestic product, including 0.11% of direct costs and 0.39% of economic costs (Table 6). Our results align with previous findings in Africa and Asia. Notably, our findings on the economic costs of

Table 6 Total health damage per year

Costs (FCFA)	Household	Benin	% Benin's GDP[a]
Direct costs	3972	7,167,081,092	0.11
Economic costs	13,836	24,943,482,154	0.39
Total health damages	17,808	110,948,455,262	0.51

[a]The Benin's Gross domestic product (GDP) in 2019 was 6,330 Billion (FCFA) (https://edenpub.bceao.int)

cooking energies align with those of Fisher et al. [16] in three selected African countries (Ethiopia, Ghana, and Rwanda). These authors estimated that economic output lost 0.93% of Ethiopian GDP, 0.38% of Ghana's GDP, and 0.85% of Rwanda's GDP. Similarly, Zhang et al. [23] valued the health damage associated with households' reliance on coal for heating in the Beijing region. Their estimates indicated health costs equivalent to 3.71% of the region's GDP. Huang and Zhang [45] previously used results from a meta-analysis of epidemiological studies to evaluate the health costs associated with air pollution in China. Using data from a sample of three regions, they estimated an annual cost equivalent to 4.68% of the region's GDP. Although the estimated costs of these studies are higher than our findings, the difference can be attributed to confounding factors, notably the difference in outdoor air pollution levels. China's air pollution is higher than that of Benin. Our findings have policy implications for poverty reduction financing in Benin. Indeed, the Benin sustainable development plan estimated 70 billion FCFA per year as the needed investments to reach SDG 1, aiming to reduce poverty by half by 2030, while the effective investments for SDG 1 were 13 billion FCFA in the government budget in 2018 [46]. It could be concluded from our results that the costs of polluting cooking energies (55 billion FCFA per year) may finance 79% of the resources needed (70 billion FCFA) to reach the poverty reduction goal in Benin.

4 Conclusion

Households' reliance on polluting cooking energies has many environmental and health implications. The literature has largely focused on the effects of the use of polluting cooking energies on air quality and forest sustainability in developing countries. Similarly, there is emerging evidence on the effects of polluting cooking energies on human health in developing countries, including sub-Saharan African countries. Despite this evidence, little attention has been given to the monetary valuation of the health damage associated with the use of polluting cooking energies. This paper contributed to filling this literature gap by valuing the direct and indirect costs associated with the use of polluting cooking energies in Benin using a nationally representative dataset from the Harmonized Survey on Household Living Conditions in Benin implemented in 2019. Based on the health production function approach, direct costs (medical expenses) and indirect costs (wage loss) were derived from the estimation of a structural model that takes into consideration the adoption of averting measures. The total health damage was estimated at 22% of households' monthly health expenditures in Benin. More importantly, we showed that the economic costs were approximately three times higher than the direct costs. Our findings have many policy implications. First, the results of this study may help policymakers in designing clean cooking energy policies aiming to increase households' awareness of the use of polluting cooking energies. Second, the amount of health costs estimated could be used by policymakers to appreciate households' willingness to pay or receive to switch from polluting cooking energy sources to clean cooking energies. Finally, these findings could be used to design targeted poverty reduction policies. Nonetheless, this study is not free from limitations. For instance, we used cross-sectional data that cannot control for transient health factors. Equally, we did not control for outdoor air pollution in our estimations. Further research may improve the quality of the valuation by addressing the issue of household-level longitudinal data. In addition, cost–benefit analyses of the use of clean cooking energies and technologies could also be more informative for policymakers.

Appendix 1

The first and second partial derivatives of Equation 2 are as follows:

$$\partial U / \partial X > 0, \partial^2 U / \partial X^2 < 0, \tag{20}$$

$$\partial U / \partial T^l > 0, \partial^2 U / \partial T^{l2} < 0, \tag{21}$$

$$\partial U / \partial B > 0, \partial^2 U / \partial B^2 < 0. \tag{22}$$

From the household problem in Equation 6, let ℓ denote the Lagrangian, with λ the multiplier as:

$$\begin{aligned} &\ell\left(T^l, T^i, T^p, \lambda, \mu\right) = U\left[X, T^l, T^i(\mathrm{E}, T^p; B)\right] \\ &+ \lambda\left[R_0 + w\left(T - T^l - T^i(\mathrm{E}, T^p; B) - T^p\right) - X - P.T^p\right]. \end{aligned} \tag{23}$$

Assuming interior solutions, the first-order conditions with respect to X, T^l, T^i,T^p, and λ lead to:

$$\partial\ell \big/ \partial X = 0 \iff U'_x = \lambda, \tag{24}$$

$$\partial\ell \big/ \partial T^l = 0 \iff U'_{T^l} - w\lambda = 0, \tag{25}$$

$$\partial \ell / \partial T^p = 0 \iff U'_{T^i}.T^{i'}_{T^p} - w\lambda T^{i'}_{T^p} - w\lambda - \lambda P = 0, \quad (26)$$

$$\partial \ell / \partial \lambda = 0 \iff R_0 + w\left[T - T^l - T^i - T^p\right] - X - P.T^p = 0. \quad (27)$$

Appendix 2

Proof of proposition *The net marginal cost of the preventive measures is* $p + w + wT^{i'}_{T^p}$.

The marginal rate of substitution can be derived from the first-order conditions as:

$$MRS\left(T^p / X\right) = -dT^p / dx \iff \left[\frac{U'_{T^i}.T^{i'}_{T^p}}{U'_x}\right] = \frac{w\lambda T^{i'}_{T^p} - w\lambda - \lambda p}{\lambda} \quad (28)$$

$$\iff MRS\left(T^p / X\right) = p + w + wT^{i'}_{T^p} \quad (29)$$

Equation 29 is straightforward when dividing Equation (26) by Equation (24) side by side.

Appendix 3

Table 7 Multilevel mixed-effects biprobit without restriction exclusion variables

	Coef.	Std. err.	*t*	*P* > |*t*|	[95% Conf. interval]	
Dependant variable: occurrence of illness						
Use of polluting energies (ref.=no)	0.329	0.309	1.07	0.29	-0.277	0.935
Head of household educ (ref.=no educ)						
Primary	−0.422	0.251	−1.68	0.09	−0.913	0.070
Secondary	−0.143	0.260	−0.55	0.58	−0.652	0.366
Spouse education (ref.=no education)						
Primary	−0.036	0.304	−0.12	0.90	−0.632	0.559
Secondary	0.042	0.406	0.10	0.92	−0.754	0.837
Gender of head of household (ref.=female)	0.196	0.240	0.82	0.41	−0.274	0.666
Log (income)	−0.058	0.065	−0.90	0.37	−0.186	0.069
Health insurance (ref.=no)	−0.746	0.424	−1.76	0.08	−1.576	0.085
Residence (ref.=rural)	0.068	0.173	0.39	0.70	−0.272	0.407
Log (household size)	0.018	0.116	0.15	0.88	−0.209	0.245
Smoke (ref.=no)	0.197	0.469	0.42	0.67	−0.722	1.116
Alcohol consumption (ref.=no)	0.121	0.217	0.56	0.58	−0.304	0.547
M1[household] (constrained)	1.000	0.000			1.000	1.000
_cons	−0.804	0.837	−0.96	0.34	−2.445	0.836
Dependant variable: adoption of averting behaviours						
Use of polluting energies (ref.=no)	0.593	0.212	2.80	0.01	0.177	1.009
Head of household educ (ref.=no educ)						
Primary	−0.158	0.145	−1.09	0.27	−0.442	0.125
Secondary	−0.065	0.173	−0.37	0.71	−0.404	0.275
Spouse education (ref.=no education)						
Primary	−0.646	0.229	−2.82	0.00	−1.096	−0.197
Secondary	−0.219	0.289	−0.76	0.45	−0.786	0.348
Gender of head of household (ref.=female)	0.154	0.145	1.06	0.29	−0.131	0.439
Log (income)	−0.154	0.042	−3.65	0.00	−0.237	−0.072
Residence (ref.=rural)	−0.504	0.108	−4.65	0.00	−0.716	−0.291
Log (household size)	−0.187	0.074	−2.55	0.01	−0.331	−0.043
M2[household] (constrained)	1.000	0.000			1.000	1.000
_cons	0.920	0.502	1.83	0.07	−0.063	1.903
var(M1[household])	0.229	0.000			0.229	0.229
var(M2[household])	0.019	0.000	44.86	0.00	0.018	0.020
cov(M1[household],M2[household])	0.066	0.001	63.75	0.00	0.064	0.068

Acknowledgements The authors thank participants at the second University of Pretoria Economics PhD workshop, in June 2022, South Africa and participants at the second PhD students workshop of the Ecole Nationale Supérieure de Statistique et d'Economie Appliquée (ENSEA), August 2022, Abidjan, Côte d'Ivoire.

Author Contribution All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Nassibou Bassongui and Albert N. Honlonkou. The first draft of the manuscript was written by Nassibou Bassongui. All the authors have read and approved the final manuscript.

Funding Nassibou Bassongui received financial support from the African Economic Research Consortium (AERC) through the doctoral thesis research grant number REF: PH/TH/21-022 (award –1992). The opinions expressed in this paper are those of the authors and do not necessarily reflect the point of view of AERC.

Code Availability Code will be made available by the corresponding author upon request.

Data Availability The datasets generated during the current study are available at *Programme d'Harmonization et de Modernization des Enquêtes sur les Conditions de Vie des ménages dans les Etats membres de l'UEMOA*, https://phmecv.uemoa.int.

Declarations

Ethics Approval Not applicable.

Consent to Participate Not applicable.

Consent for Publication Not applicable.

Conflict of Interest The authors declare no competing interests.

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