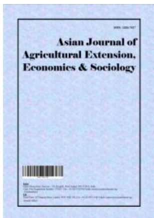

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Factors Affecting the Use of Domestic Gas in Benin: A Comparative Study of Artificial Neural Networks and Logistic Regression

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Author's contribution

The sole author designed, analysed, interpreted and prepared the manuscript.

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ABSTRACT

The strong growth in demand for wood energy in Benin's major cities today represents a real threat to the preservation of forest ecosystems. The promotion of new alternatives such as the use of domestic gas as cooking energy could help to better cope with the adverse effects of climate change resulting from deforestation. The objective of this paper is to analyze the determinants of domestic gas use in Benin. To do so, we used data from 15,000 households collected during the Global Food Vulnerability and Security Analysis Survey of 2017. We then compared the prediction of household gas use determinants by Multilayer Perceptron Neural Networks (MLP) and classical Binary Logistic Regression (BLR). The two approaches have highlighted as important factors of the adoption of Domestic Gas in Benin, the residence department (here department of the Littoral) and the level of education. We also noted that the MLP highlighted more adoption factors than the BLR model (income, ethnicity, and number of wives of the household head). In order to increase the use of domestic gas on a large scale, the Government must put in place a policy that promotes the physical and financial accessibility (through subsidies) of the product to the large mass of the population in our cities which are still dependent on traditional energy sources such as wood fuel and charcoal in order to better protect our forest ecosystems in a sustainable manner. The Government could also strengthen the public-private partnership in this sub-sector by, for example, creating facilities for private economic operators through tax or customs exemption measures.

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Keywords: Domestic gas, adoption; neural networks; multilayer perceptron; binary logistic regression; Benin.

1. INTRODUCTION

Benin's population has grown from 6,769,914 inhabitants in 2002 (National Population and Housing Census 2002) to 10,008,749 inhabitants in 2013 (National Population and Housing Census 2013). It is estimated at 11,496,140 inhabitants in 2018 with a growth rate of 2.77% per year. This strong growth observed especially in Benin's major cities in recent years has resulted in an ever-increasing demand for energy (firewood, charcoal, butane gas, electricity, etc.). As a consequence, enormous pressure is exerted on forest ecosystems each year for the production of wood energy (fuelwood and charcoal) in order to meet increasing urban demand [1]. The deforestation resulting from such over-exploitation is today perceived as a real ecological problem whose repercussions in terms of climate are reflected in recurrent flooding and pockets of drought [2]. Kitoto [3] stressed in his work that deforestation is the main cause of biodiversity loss, desertification, soil erosion and the decline in the productive potential of agricultural land. For Wang et al. [4], the increase in energy demand not only leads to an increase in the consumption of natural resources, but it also leads to the degradation of the climate and the global ecosystem. An alternative today to reduce the high pressure on forest resources used for wood energy is the promotion of the use of domestic gas in several countries. The promotion of access to clean energy for domestic cooking is today an important topic for policy making in low and middle income countries, in the light of the urgent global efforts to achieve universal access to energy by 2030 (Sustainable Development Goal 7) [5]. The Government of Benin, within the framework of the promotion of alternative energy sources to fuelwood and charcoal, decided during the Council of Ministers of March 27, 2009, to implement through certain projects or programs, subsidies to promote the use of domestic gas, by facilitating access to cooking equipment for low-income households. A guarantee fund necessary to secure credits for domestic equipment should also be set up. Despite the numerous efforts made by the Government of Benin, the Technical and Financial Partners [UNDP, UNDP/GEF, World Bank, ECOWAS (West African Gas Pipeline – WAGP), etc.)] and the private sector (PROGAZ Company, Oryx Energies, etc.), the use of domestic gas has not become widespread. Energy consumption is characterized by a strong predominance of wood energy and a low rate of access of the population to electricity (28% in 2012) and modern cooking energy (butane gas and kerosene). In 2010, the consumption of wood energy alone represented 77.5% of total household energy consumption, against 20.3% for kerosene, and only 1.8% for electricity and 0.4% for butane gas. This low penetration of domestic gas was also observed by Mbaka et al. [6] in Kenya and by Wahyudi [7] in Indonesia. This contrasts with the situation in developing and middle-income countries where household gas has already replaced solid fuels for all or some cooking tasks among middle-income households [8]. Knowledge of the factors likely to influence the use of domestic gas in Benin is essential to set up a more offensive policy in favor of the use of domestic gas. The objective of this paper is to analyze the determinants of domestic gas use in Benin through a comparison of Multilayer Perceptron Neural Networks and classical Binary Logistic Regression. Specifically, we will:

- Identify the determinants that significantly affect the probability that a household will use household gas in Benin using the Stepwise and Olden procedures;
- Compare different approaches to selecting determinants for effective prediction of household gas use in Benin;
- and Analyze the determinants of household gas use in Benin using the best approaches obtained.

To achieve this objective, we have organized the paper in three parts: the first part deals with the literature review, the second part presents the methodology used, and the third part identifies the factors likely to influence household energy demand.

2. LITERATURE REVIEW

Several theories are used to explain the mechanisms of adoption of new technologies. These include:

- The theory of diffusion of innovations, which states that adoption is a decision to "fully use an innovation as the best available course of action" and rejection

is a decision to "not adopt an innovation" [9];
- The model of technology acceptance, which looks at the individual characteristics of potential users of a technology or innovation that may influence the decision to adopt or not adopt that technology [10];
- And the theory of innovation diffusion, which considers that through social systems and behavioural processes, people adopt new technologies [11-13].

As a general rule, the decision to adopt an innovation depends on:

- the degree of compatibility of the innovation with the environment of potential adopters [9];
- the dynamics of social networks within the target group and interactions with extension services [9,14,15,16];
- and the social and economic context of the target group [9,17].

Several previous studies on the adoption and sustainable use of household gas highlight the techno-economic, commercial, social, and behavioral challenges that need to be overcome for the efficient dissemination of this technology [18,19,20].

Danlami et al. [21] conducted a review of empirical studies on the determinants of household energy choice and consumption and identified four groups according to the analytical tools used: (1) The first group consists of studies using descriptive statistics tools (frequencies, percentages, graphs, correlation coefficients) to analyze household energy consumption behavior; (2) The second group concerns studies that use Ordinary Least Squares (OLS) to analyze the determinants of energy demand; (3) The third group includes studies that use the ordered Logit or Probit model to analyze factors that may influence the adoption process; and (4) The fourth group includes studies using a multinomial Logit or Probit model to analyze the determinants of household energy choice. According to the same authors, not all explanatory factors are equally important in explaining household consumption behavior in different regions, due to differences in socioeconomic context, cultural and environmental factors, and the level of development of the region.

It appears, from our literature review, that several methods are used to analyze the determinants of household gas adoption. These are:

❖ *Studies that used logistic regression (binary or multinomial) :*

- Kumar et al. [22] in a study carried out in Rural India, found that there are disparities in the adoption of household gas due to affordability, accessibility, and awareness. Household income positively influences its adoption, while easy of access to biomass discourages households from adopting it. Concerns about the safety of household gas reduce the likelihood of adoption, while participation in awareness campaigns on the benefits of clean cooking is strongly associated with household gas adoption.
- Pye et al. [23] in a study carried out in southwest Cameroon, found that factors affecting the adoption and sustainable use of household gas include higher levels of education, rising incomes, and younger age, while rural location, availability problems, rising fuel costs, and larger household size (increasing number of residents) appear to hinder Liquefied Petroleum Gas (LPG) use. Stanistreet et al. [24] in a study carried out in the same region, found that accessibility, safety, convenience, and health awareness are determinants in the adoption and sustainable use of household gas. Pope et al. [25] in their research always carried out in the Southwest of Cameroon, found that in rural households, higher levels of education, access to sanitation and drinking water, and household wealth (income and asset ownership) were all associated with household gas use.
- Uhunamure et al. [26] in a study carried out in South Africa, found that level of education of the household head, age of the household head, number of cattle owned, distance to fuelwood source, crop production, credit, loans and grants, income, water availability, and gender awareness were factors that had statistical significance. Household size, availability of technology, and distance from the fuelwood source therefore have a positive influence on the adoption and use of biogas technology.
- Soltani et al. [27] in their research carried out in Mahabad City in Iran, found that

income can lead to variation in household gas consumption.

- Puzzolo et al. [5] in their study carried out in Low- and Middle-Income Countries, found that several factors influence the adoption and use of clean energy. These include:

  - ✓ the structure of industry and services;
  - ✓ the institutional environment that influence the viability of different supply chains;
  - ✓ the energy costs and prices;
  - ✓ the integrity and sustainability of the energy supply chain;
  - ✓ and finally socio-cultural norms and current energy preferences and availability.

- Ogwumike et al. [28] in their research carried out in Nigeria, found that factors that significantly influence household energy use for cooking include parental education levels, per capita expenditure and household size.

❖ *Studies that used regression model (linear or multiple):*

- Bisu et al. [2] carried out a study in Bauchi metropolis, Nigeria and found that changes in household size, home ownership status, income, education level, housing location and availability of gas are the factors that influence household cooking energy choice.
- Makonese et al. [29] in their research carried out In Southern Africa, showed that socio-demographic factors such as access to electricity, household size, education level and wealth index have a positive influence on the type of cooking fuel used in the region. However, access to electricity does not imply that households will forego the use of traditional fuels.
- Dewoolkar et al. [30] in a research carried out in Chandpur district in India, found that in addition to household income level, other factors such as improved education of women influence the rate of adoption of household gas.
- Mgimba et al. [31] in their research in Tanzania found that a number of factors influences household adoption: The price of gas, household size, and denial of access to the forest are inversely associated with the adoption of modern energy by households. The education level and the availability of extension services positively affect the household adoption of modern energy.

❖ *Studies that used descriptive statistics and other analysis tools :*

- Rao et al. [32] in a study carried out in Rural India, pointed out that policy to promote household gas for the poor will have limited success in the absence of a corresponding infrastructure for dissemination and awareness of household gas. Goulda and Urpelainenb [33] in a study carried out in the same region, found that:

  - ✓ the cost of household gas is a major barrier to its widespread adoption;
  - ✓ combining fuels is the dominant norm because few households stop using wood energy when they switch to domestic gas;
  - ✓ and both users and non-users have a very positive view of household gas as clean cooking fuel.

- The research of Mbaka et al. [6] in Kenya, showed that the preference and intensity of household energy consumption are mainly influenced by location (rural or urban), the household's energy consumption decision maker, level of education, age of the household head and average monthly income.
- The study carried out by Wahyudi [7] in Indonesia, clearly showed that the socio-economic profiles of potential biogas adopters play a key role in the sustainable adoption of biogas technology:

  - ✓ Individuals with high social status adopt biogas earlier than other members of the social system;
  - ✓ Individuals with higher income and education have the opportunity to purchase biogas digesters with their own money;
  - ✓ Installation of a biogas digester increases the biogas adoption rate.

Therefore, we see that the adoption of a new technology is often modeled as a choice between two alternatives: to adopt or not to adopt. The logistic regression model is often used to analyze the process of technology adoption. In recent years, the use of Artificial Neural Networks has been developed in many fields including economics, ecology, environment, biology and medicine. They are often used to solve problems of classification, prediction, optimization, categorization [34]. Chong [35] analyzed the factors related to the adoption of m-commerce by testing two models, namely the regression model and the neural network model. Other authors such as Gregova et al. [36] and Hajmeera and Basheerb [37] have compared Artificial Neural Networks and Logistic Regression in their studies. Although they constitute a new alternative to traditional statistics for data processing, Artificial Neural Networks are not sufficiently used in social sciences [38]. However, they represent a method for approximating complex systems that are difficult to model using classical statistical methods. They are used where there is a non-linear relationship between a predictive variable and a predicted variable [38].

In the present study, we will make a comparative study of Artificial Neural Networks and Logistic Regression in the analysis of determinants of household gas use in Benin.

3. METHODOLOGY

3.1 Sampling and Data Collection

The primary data used in this study come from the Global Food Vulnerability and Security Analysis survey data conducted in 2017. The survey was conducted among 15,000 households throughout the country. These households were drawn according to a two-stage sampling design with a 5% margin of error. In the first stage, 750 clusters were drawn from the 920 clusters surveyed in the EMICoV-2015 survey, and in the second stage, 20 households were drawn, in a systematic way, in each cluster. The sample was drawn by urban/rural stratum in each commune. A total of 148 strata were thus defined. Sample households were distributed in each department in proportion to their size in terms of number of households. This survey did not specifically focus on household energy demand. But it did collect information on the socio-economic characteristics and energy preferences of households. The data used in this study were drawn from this survey. The data are recorded in a 27x4246 table. The description of the data was done by calculating certain parameters of descriptive statistics such as the mean, standard error (for quantitative variables), absolute frequency and relative frequency (for qualitative variables) (Appendix 1). After transforming the ordinal and nominal qualitative variables into dummy variables, the size of the table submitted for analysis becomes 93x4246.

3.2 Model Specification

3.2.1 Binary Logistic Regression Model (BLR)

Binary Logistic Regression is a statistical modeling technique that aims here to predict and explain the use of household gas by households in Benin from a collection of continuous, discrete and binary predictor variables $X=(X_1,\ldots,X_a)\in R^a$ with $a \in N^*$.

Let Y be this binary variable, Y = 1 if the household uses household gas; or Y = 0 if the household uses other types of household energy. For k predictor variables, the logistic function is written as:

$$p(Y=1|X=x)=\frac{e^{x\beta}}{1+e^{x\beta}} \tag{1}$$

With $p(Y=1|X=x)\in[0,1]$, the probability that a household uses household gas in Benin; $x\beta=\beta_0+\beta_1x_1+\cdots+\beta_ax_a$ is a linear combination between the observed predictor variables $x=(x_0,x_1,\cdots,x_a)'\in R^{a+1}$ and the vector of parameters of the logistic regression model $\beta=(\beta_0,\beta_1,\cdots,\beta_a)'\in R^{a+1}$; x_0 is an additional unit vector component and β_0 is the original ordinate in the model. Applying the logistic transformation and using equation (1), we obtain the linear relationship between the log odds ratio (odds = $e^{x\beta}$) and the predictive variables (Equation 2).

$$\log it(y)=\ln\left(\frac{p(Y=1|X=x)}{1-p(Y=1|X=x)}\right)=\beta_0+\beta_1x_1+\cdots+\beta_kx_k \tag{2}$$

For the sample of households selected in Benin of size $n \in N^*$ and for each household $i=1,\cdots,n$ and considering that the examples $(x_i,y_i)_{1\le i\le n}$ are independent, the probability density function of Y is :

$$f(y_i|\beta) = p(Y_i = 1|X_i = x_i)^{y_i}(1 - p(Y_i = 1|X_i = x_i))^{1-y_i} \quad (3)$$

and the conditional likelihood function to x_i is written :

$$L(\beta|y) = \prod_{i=1}^{n} p(Y_i = 1|X_i = x_i)^{y_i}(1 - p(Y_i = 1|X_i = x_i))^{1-y_i} \quad (4)$$

To simplify the maximization of equation (4), which allows to obtain the values of β, its logarithm is used.

$$\ln L(\beta|y) = \sum_{\{Y_i=1\}} \ln p(Y_i = 1|X_i = x_i) + \sum_{\{Y_i=0\}} \ln(1 - p(Y_i = 1|X_i = x_i)) \quad (5)$$

And by replacing the expression $p(Y = 1|X = x)$ (see Eq. 1) in Equation 5 we get:

$$\ln L(\beta|y) = -\sum_{i=1}^{n} \ln(1 + e^{(1-2Y_i)x_i\beta)}) \quad (6)$$

Maximizing the relationship (Equation 6) gives the estimate of β and this includes partial differentiations using iterative procedures [39].

3.2.2 Perceptron Multilayer Neural Networks model (MLP)

Multilayer Perceptron Neural Networks models are mathematical models inspired by the function of the hate brain and represented as an oriented graph (Fig. 1). They are made up of neurons organized in successive layers. The first layer is called the "Input layer", the last layer is called the "Output layer", and the intermediate layers are called the "Hidden layers". The neurons are interconnected by synatic weights (model parameters) and on the same layer, neurons cannot interconnect.

Considering $n \in N^*$ randomly selected households in Benin, and i (i = 1,…, n) any household, after the passage of the examples $(x_i, y_i)_{1\le i\le n}$ in the network, the output (the probability of household gas use by households in Benin) is calculated using the following equation [40]:

$$F(\theta, x) = f(\sum_{k=1}^{m} \alpha_i f(\sum_{l=1}^{a} w_{kl}x_l + w_{k0}) + \alpha_0) \quad (7)$$

where:

$F(.): R^{m(a+2)+1} \times R^{a+1} \rightarrow [0,1]$

$\theta = (w_{10}, \cdots, w_{m0}; w_{11}, \cdots, w_{1a}, \cdots, w_{ml}, \ldots, w_{ma}; \alpha_0; \alpha_1, \cdots, \alpha_m) \in R^{m(a+2)+1}$

and $f(.) : R \rightarrow [0,1]$ (real value function) are respectively the parameter vector of the model and the activation function of the output unit and the hidden unit ($f(z) = \frac{1}{1+e^{-z}}$). $w_k = (w_{k0}, \ldots, w_{ka})' \in R^{a+1}$ is a vector of parameters for the hidden k-unit $(1 \le k \le m); m \in N$ and $\alpha = (\alpha_0, \ldots, \alpha_m)' \in R^{m+1}$ a vector of parameters for the output unit only.

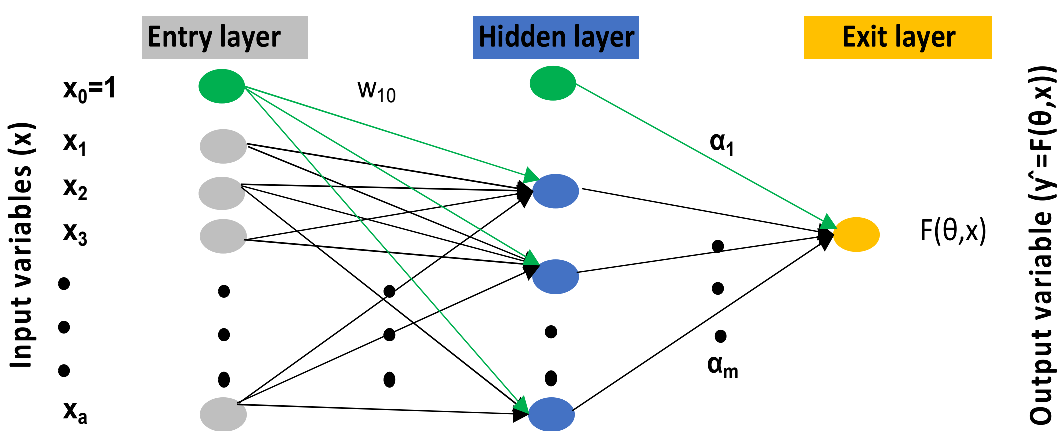

Fig. 1. Multilayer perceptron-like neural networks with one hidden layer MLP (a,1,1)

The parameter θ is estimated by minimizing the cross Entropy error function defined by:

$$E(\theta) = \sum_{i=1}^{n} y \log(F(\theta, x) + (1-y)\log(1-(F(\theta, x)) \quad (7)$$

For this purpose, different algorithms are used based on the descending gradient procedure. The basic idea is to compute the partial derivatives $(\theta)/\partial w_k$ and $(\theta)/\partial \alpha_k$ using the string rule. There are two steps: The first one is the propagation learning, which allows to calculate the error and the partial derivatives; and the second is the reverse propagation learning which allows to calculate the update of the resulting weight.

From one algorithm to another, only the second step changes. We briefly present the one used in this work, the Resilient backpropagation algorithm (Rprop). It is a local adaptive learning program [41].

$$\theta(k+1) = \theta(k) + \Delta\theta(k) \quad (8)$$

$$\Delta\theta(k) = \begin{cases} \eta^{+} \times \Delta(\mathrm{k}-1) \; if \; \frac{\partial E(\theta)}{\partial \theta}(k-1) \times \frac{\partial E(\theta)}{\partial \theta} > 0 \\ \eta^{-} \times \Delta(\mathrm{k}-1) \; if \; \frac{\partial E(\theta)}{\partial \theta}(k-1) \times \frac{\partial E(\theta)}{\partial \theta} < 0 \\ \Delta\theta(k-1) \quad else \end{cases} \quad (9)$$

where:

k = number of iterations;

η^{-} = decreasing factors; η^{+} = increasing factors; and $0 < \eta^{-} < 1 < \eta^{+}$.

These factors are set at η^{+}= 1, 2 and η^{-}= 0.5 on the basis of theoretical considerations and empirical evaluations. This reduces the number of free parameters to two, namely Δ_0 and Δ_{max}. The calculation is slightly more expensive than ordinary backpropagation but is an answer to the problems of convergence and over-adjustment.

3.2.3 Variables selection

The selection of variables allows for the elimination of impertinent covariates from the model to improve its accuracy and also to reduce the risk of over-fitting the model [42]. For logistic regression models, it is possible to test the statistic of the coe□cients associated with the covariates in the model [43]. These tests can be used to build models in a stepwise fashion. The three most common approaches are to start with an empty model and successively add covariates (forward selection), to start with the complete model and remove covariates (backward selection), or by adding and removing covariates (stepwise selection).

Due to the non-linear nature of Multilayer Perceptron Neural Networks, the statistical tests for the coe□cients that are used in logistic regression cannot be applied here. Instead, automatic relevance determination or sensitivity analysis can be used to heuristically evaluate the importance of the input variables on the target variable [44,45,46].

3.2.4 Statistical performance criteria

To evaluate the models and select the best performing one, model evaluation techniques such as sensitivity, precision, F-measurement, accuracy and Area Under the Receiver Operating Characteristic (AUC ROC) curve are used. The closer the values of these criteria are to 1, the better the model. They are calculated from a Confusion Matrix (Table 1). The notations in this table are as follows: all True Positives (VP), False Negatives (FN), False Positives (FP) and True Negatives (VN) [47]. True Positive are those observations that have been classified as positive and are actually positive. False Positives are the individuals who were classified as positive and who are actually negative. Similarly, False Negatives are the observations that were classified as negative but are actually positive, and True Negatives are the observations that were classified as negative and are actually negative.

Table 1. Confusion matrix

	Predicted No(0)	Predicted Yes(1)
Current: No (0)	True Negatives (VN)	False Positives (FP)
Current: Yes (1)	False Negatives (FN)	True Positive (VP)

3.2.5 Method of data analysis and processing

The analysis and processing of the data was done in 5 steps:

❖ *First step: Preparation of the data*

The initial data (X_{ij}, Y_i, with 1 ≤ i ≤ 4246 and 1 ≤ j ≤ 93) are normalized using the relationship (10). They are then partitioned into learning data (70%) and test data (30%). The learning data are used for modeling and the test data are used to assess its generalization capabilities.

$$new_v = \frac{v - min_z}{max_z - min_z} \quad (10)$$

where v is an observation of the z vector and new_v is a normalized observation.

❖ *Second step: Establishment of models*

Two different models have been considered for the prediction of domestic gas use:

- First, the Binary Logistic Regression (BLR) model using regression (2) with the "glm" function of the default package "stat" and based on the binomial distribution ;
- Second, neural networks of the multilayer perceptron type, MLP (see Eq. 7) were used by varying the number of hidden neurons (2, 5, 8, 11, 15, 20 and 25). The Rprop algorithm was applied. The "neuralnet" function of the "neuralnet" package (Fritsch et al., 2019) is used. The best MLP architecture is obtained based on the value of the performance criteria close to 1.

❖ *Third step : Selection of variables (identification of the determinants of domestic gas use)*

Methods are used to select determinants for efficient prediction of domestic gas use in Benin:

- The Stepwise method is applied on the BLR model with the "stepAIC" function of the "MASS" package (Venables and Ripley, 2002). The AIC fit statistic is used to measure the fit of the model during the variable selection process. The best model is the one with the lowest value.
- The Olden method is applied to the MLP identified in step 2 as best. The "olden" function of the NeuralNetTools package (Beck, 2018) is used and the higher the Importance value of an explanatory variable, the better this variable affects the response variable.

❖ *Fourth step : Efficient prediction of domestic gas use in Benin with selected variables and identification of the best models approaches*

Four types of models have been developed, but with regard to the use of MLPs, the number of hidden neurons has always varied. These models are:

- MLP on selected variables from the Olden procedure ;
- MLP on selected variables from the Stepwise procedure;
- BLR on selected variables from the Olden procedure;
- BLR on selected variables from the Stepwise procedure.

Based on the value of the performance criteria close to 1, the best models are identified.

❖ *Fifth step: Analysis of the determinants of domestic gas use in Benin according to the best approaches*

Software R 3.3.6: (R Develpment Core Team, 2019) [1] was used for data processing and analysis in this work.

4. RESULTS AND DISCUSSION

4.1 Determining the Best Architecture for Multilayer Perceptron Neural Networks (MLP) and Classical Binary Logistic Regression

The Table 2 presents the results of the performance criteria calculated for the binary classification model for prediction purposes. The analysis shows that the Multilayer Perceptron Neural Network model with 15 hidden layers presents the best predictive performance of the use or non-use of domestic gas in Benin. Whatever the architecture of the PMCs considered, these models are better than the classical binary logistic regression model (high values of sensitivity, precision, F-measurements, accuracy, with the exception of the area under AUC (Area Under The Curve) ROC (Receiver Operating Characteristics) curve.

4.2 Identification of the Determinants of the Use of Domestic Gas in Benin According to the Olden and Stepwise Procedure

Of the initial 93 explanatory variables, 58 were identified by Olden's procedure (Importance ≤ 100 in absolute terms) as those that significantly affect the probability that a household uses household gas in Benin (Table 3; Fig. 2) versus

[1] *R Core Team, 2019. R 3.3.6: A Language and Environment for Statistical Computing, R Foundation for Statistical Computing, Vienna, Austrian. https://www.R-project.org/*

Table 2. Performance parameters of PMC and classical binary logistic regression models

	Performance parameters				
Models	**Sensitivity**	**Precision**	**F-mesures**	**Accuracy**	**AUC ROC**
PMC (93, 2, 1)	0.42	0.63	0.50	0.96	0.97
PMC (93, 5, 1)	0.45	0.47	0.46	0.95	0.93
PMC (93, 8, 1)	0.47	0.59	0.52	0.96	0.94
PMC (93, 11, 1)	0.48	0.58	0.52	0.96	0.95
PMC (93, 15, 1)	0.55	0.59	0.55	0.96	0.96
PMC (93, 20, 1)	0.47	0.50	0.48	0.95	0.95
PMC (93, 25, 1)	0.40	0.51	0.47	0.95	0.96
Classic Binary Logistic Regression	0.18	0.14	0.16	0.9	0.96

33 identified by the Stepwise procedure (Table 4) based on the lowest AIC of a more significant set of variables. The AIC of the BLR before selection of determinants is 8722.39 and after selection is 468.31.

4.3 Comparison of Methods for Better Prediction of Household Gas Use in Benin

MLP on selected variables from the Stepwise procedure is the approach for selecting determinants for efficient prediction of household gas use in Benin compared to the other three approaches (Table 5), namely:

- MLP on selected variables from the Olden procedure;
- BLR on selected variables from the Stepwise procedure;
- And BLR on selected variables from the Olden procedure (high values of sensitivity, precision, F-measurements, accuracy and AUC of ROC).

The best model is an MLP with 33 variables (selected variables from the Stepwise procedure) in the input layer, 8 neurons in the hidden layer and 1 neuron in the output layer (Fig. 3). The graphical representation shows the input

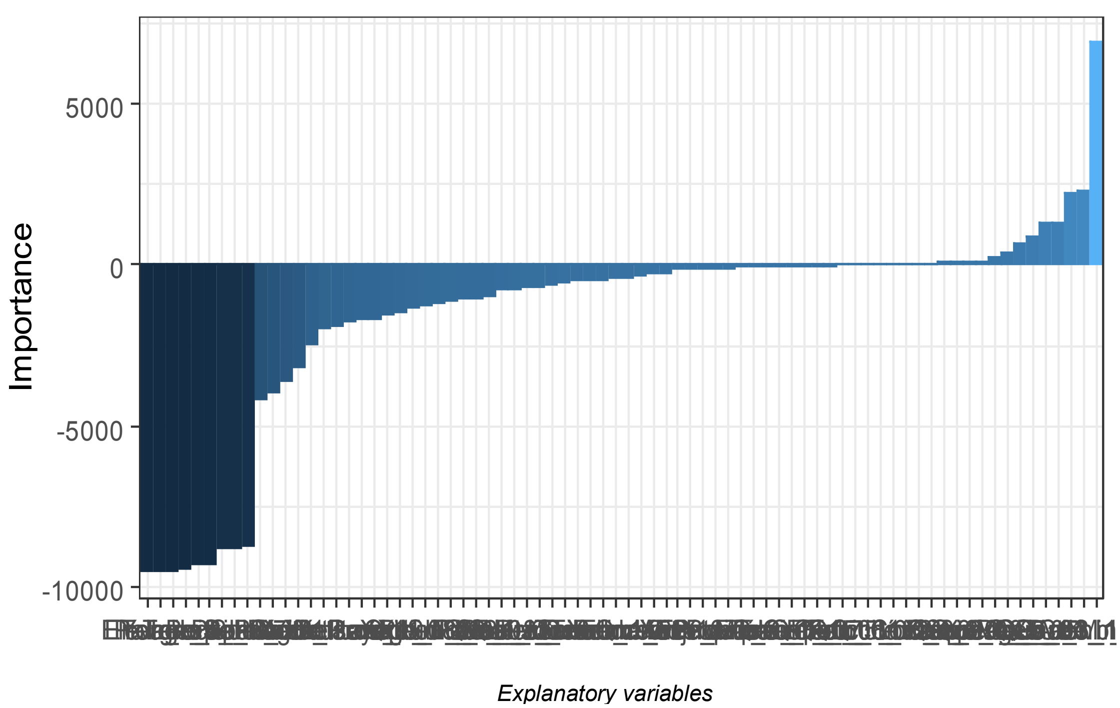

Fig. 2. Importance of the explanatory variables in relation to the use of domestic gas in Benin according to Olden's procedure

Table 3. Determinants of domestic gas use in Benin according to Olden's procedure (in blue) and non-determinants (in red)

Variable	Importance	Variable	Importance	Variable	Importance
Elevage	-9527,17	X12	-1016,99	Transport	-53,05304
Torche	-9499,14	Primaire	-959,63	Ciment	-46,844755
Terre	-9475,287	Travail_Jour	-783,55	Q_1_07	-45,775854
Yoa_Lokpa	-9424,57	Q_1_06	-761,07	Fon	-35,997734
Energie_Solaire	-9285,47	Q_1_08_mcal	-659,91	Electricité	4,07396
Palme_Bambou	-9258,13	Puits_Trad	-646,450588	Q_5_01	4,805396
Lampe_Gaz	-8791,25	Gros_commerce	-578,282015	Q_1_08_tcal	6,763752
Paille,1	-8784,19	Tuile	-534,54428	Fonctionnaire	8,24376
Bois_Planche	-8718,15	Dendi	-475,082772	Eau_Courante	9,765633
Semi_dur	-4179,65	Petit_commerce	-440,508831	Q_5_03_1_2	29,540399
X7	-3929,88	Secondaire	-433,996012	X3	42,010073
Bariba	-3560,97	Yorouba	-402,873835	Locataire	42,312214
X2	-3161,12	Feminin	-375,538815	Brique	72,466394
X1	-2435,92	Q_1_02	-298,465223	X8	114,775916
Agriculture	-1995,73	X5	-258,152694	Carrelage	131,358689
Puits_Protégé	-1896,80	Borne_Fontaine	-241,944464	Supérieur	135,512238
Artisanat	-1756,25	Adja	-143,85009	Q_6_09_Cr_tel	217,469653
Betamaribe	-1707,94	Divorce	-132,561502	Marie	414,069531
X4	-1688,28	X10	-123,662555	Rev_An	638,46768
Pays_Lim	-1547,28	Autre_Ethnie	-98,543069	Q_3_05	858,905295
X11	-1489,65	Pompe	-97,167235	Q_6_09_Comb_CE	1305,26237
Peulh	-1297,36	Propriétaire	-66,888642	Dalle	1309,72685
Lampe_Pétrole	-1242,95	Tole	-61,598979	Q_5_03_1_1	2267,09093
Q_1_08_fcal	-1175,82	Masculin	-54,641541	Q_5_03_1_1,1	2300,09438
Sol_Nu	-1111,44	Q_3_14	-53,557983	Eau_Minérale	6902,69888
X9	-1070,15				

Table 4. Determinants of the use of domestic gas in Benin according to the stepwise procedure

Variable	Df	Deviance	AIC	Variable	Df	Deviance	AIC
<none>		400.31	468.31	X3	1	406.67	472.67
Yoa_Lokpa	1	403.06	469.06	X10	1	407.29	473.29
X1	1	403.26	469.26	Q_1_06	1	408.24	474.24
Bariba	1	403.55	469.55	Q_1_07	1	409.32	475.32
Petit_commerce	1	403.68	469.68	Q_1_08_mcal	1	410.36	476.36
Locataire	1	403.71	469.71	Fonctionnaire	1	412.97	478.97
Yorouba	1	404.61	470.61	Brique	1	413.83	479.83
Carrelage	1	405.06	471.06	Eau_Courante	1	414.35	480.35
Q_3_05	1	405.08	471.08	Borne_Fontaine	1	415.21	481.21
Q_6_09_Comb_CE	1	405.20	471.20	Divorce	1	415.54	481.54
Primaire	1	405.39	471.39	Pompe	1	416.04	482.04
Lampe_Pétrole	1	405.72	471.72	Q_5_03_1_1	1	416.45	482.45
Secondaire	1	406.18	472.18	Supérieur	1	416.63	482.63
Gros_commerce	1	406.29	472.29	Puits_Trad	1	416.79	482.79
Q_1_08_fcal	1	406.48	472.48	Puits_Protégé	1	417.97	483.97
Transport	1	406.61	472.61	Electricité	1	427.47	493.47
Tôle	1	406.66	472.66	X8	1	434.16	500.16

variables, the synaptic weights (between the input layer and the output layer via the hidden layer) and the output layer. For the interpretation diagram of an MLP, no weight values are displayed but rather, black lines indicate positive weights while grey lines indicate negative weights. The thickness of the connections is proportional to the importance of the weights.

The MLP is followed by the BLR model on selected variables from the Olden procedure (58 variables) presented by the following relation (2):

$$\ln(\frac{p(Y=1|X=x)}{1-p(Y=1|X=x)}) =$$

-2.043e+00 -18.30 Elevage -4.539 Torche-15.10 Terre -16.74 Yoa_Lokpa -21.27 Energie_Solaire -19.11 Palme_Bambou -17.22 Lampe_Gaz -14.61 Paille.1 -19.10 Bois_Planche -0.30 Semi_dur +19.14 X7 -21.82 Bariba -22.16 X2 + 5.4 X1 + 0.31 Agriculture -0.98 Puits_Protégé -0.07 Artisanat +2.16 Betamaribe -14.60 X4 +29.31 Pays_Lim -21.61 X11-28.90 Peulh-2.06 Lampe_Pétrole -4.50 Q_1_08_fcal-17.03 Sol_Nu -0.69 X9 +0.33 X12 +0.6 Primaire +1.24 Travail_Jour +0.78 Q_1_06 -6.86 Q_1_08_mcal - 0.09 Puits_Trad -0.02 Gros_commerce +1.17 Tuile -8.99 Dendi-0.31 Petit_commerce +0.73 Secondaire -0.94 Yorouba +0.24 Feminin -1.42 Q_1_02+0.58 X5 -0.14 Borne_Fontaine +0.59 Adja -1.64 Divorcé +0.94 X10 +1.83 X8 -0.27 Carrelage +2.87 Supérieur -2.42 Q_6_09_Cr_tel +0.25 Marié + 8.16 Rev_An -0.97 Q_3_05 + 6.2 Q_6_09_Comb_CE +0.71 Dalle + 37.42 Q_5_03_1_1 +0.001 Q_5_03_1_1.1 +16.85 Eau_Minérale

4.4 Analysis of the Determinants of Domestic Gas Use in Benin According to the Best Approaches

The MLP procedure on the variables selected following the Stepwise procedure reveals that household use of household gas in Benin depends essentially on the department (Alibori, Littoral and Ouémé), the households rented, the ethnic group (Yoruba), the level of education (primary and higher), the number of wives of the household head, and the monthly income from the activity carried out (Table 6). As for the BLR procedure on the variables selected from the Olden procedure, only the department (Littoral) and the level of education (Superior) significantly explain household use of household gas in Benin (Table 7).

Several determinants of household gas adoption identified by the different approaches used in this work have also been confirmed by other researchers who have carried out research elsewhere:

Table 5. Determinants of the use of domestic gas in Benin according to the stepwise procedure

Approaches	Models	Performance parameters				
		Sensibility	Precision	F-mesures	Accuracy	AUC ROC
MLP on selected variables from the Olden procedure	MLP (58, 2, 1)	0.47	0.71	0.57	0.96	0.95
	MLP (58, 5, 1)	0.44	0.56	0.49	0.95	0.93
	MLP (58, 8, 1)	0.4	0.51	0.45	0.95	0.93
	MLP (58, 11, 1)	0.53	0.60	0.56	0.96	0.96
	MLP (58, 15, 1)	0.45	0.60	0.51	0.96	0.96
	MLP (58, 20, 1)	0.39	0.51	0.44	0.95	0.94
	MLP (58, 25, 1)	0.44	0.51	0.47	0.95	0.95
MLP on selected variables from the Stepwise procedure	MLP (33, 2, 1)	1	0.77	0.87	0.98	0.98
	MLP (33, 5, 1)	1	0.98	0.99	0.99	0.97
	MLP (33, 8, 1)	1	1	1	1	0.99
	MLP (33, 11, 1)	1	1	1	1	0.99
	MLP (33, 15, 1)	1	1	1	1	0.99
	MLP (33, 20, 1)	1	1	1	1	0.99
	MLP (33, 25, 1)	1	1	1	1	0.99
BLR on selected variables from the Stepwise procedure	BLR	1	0.73	0.84	0.97	0.98
BLR on selected variables from the Olden procedure	BLR	1	0.78	0.88	0.97	0.98

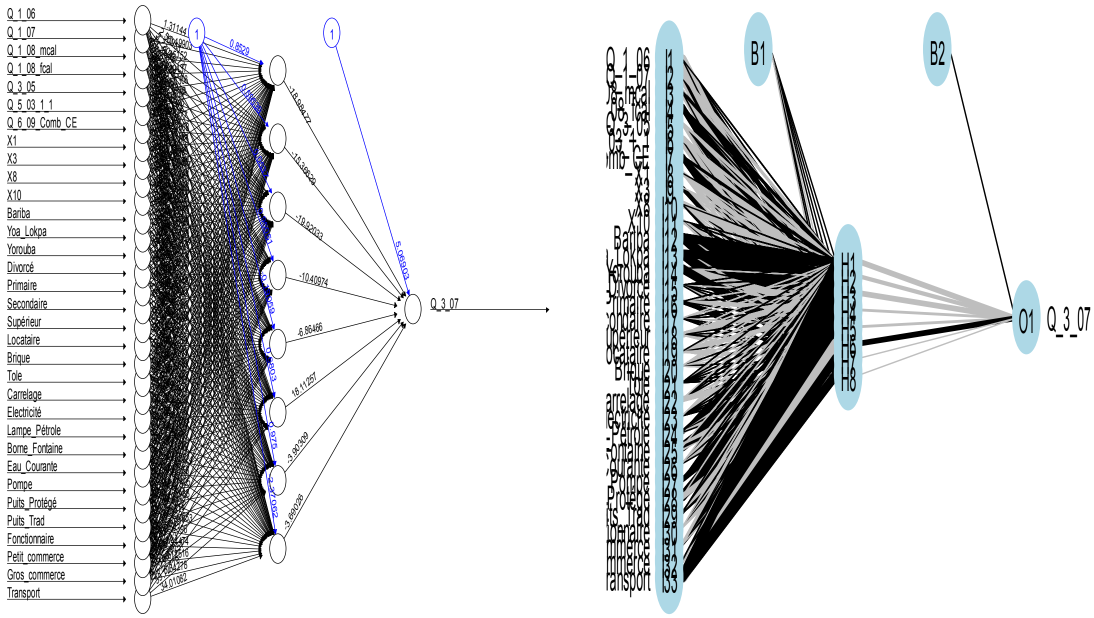

Fig. 3. Graphical representation of the MLP (33, 8, 1) on the left and the interpretation diagram of an MLP (33, 8, 1) on the right

- The research work of Bisu et al. [2], Mbaka et al. [6], Wahyudi [7], Pye et al. [23], Uhunamure et al. [26], Makonese et al. [29], Pope et al. [25], Ogwumike et al. [28], Dewoolkar et al. [30] and Mgimba et al. [31], have identified the level of education as a factor likely to influence the adoption of household gas or modern energy.
- Geographic location of residence, which conditions physical accessibility to the product and extension services, was confirmed as a determinant of household gas adoption in the research work of Bisu et al. [2], Puzzolo et al. [5], Mbaka et al. [6], Stanistreet et al. [8], Uhunamure et al. [26], Makonese et al. [29], Dewoolkar et al. [30], Mgimba et al. [31] and Rao et al. [32].
- Income, which determines household purchasing power and hence affordability, has been identified as a key factor of household gas adoption in the research work of Mbaka et al. [6], Wahyudi [7], Stanistreet et al. [8], Kumar et al. [22], Pye et al. [23], Uhunamure et al. [26], Makonese et al. [29], Soltani et al. [27], Pope et al. [25], Dewoolkar et al. [30] and Goulda and Urpelainenb [33].

We also noted that some determinants of the adoption of domestic gas found elsewhere were not identified for the case of Benin. It is the case of:

Table 6. Importance of the explanatory variables relative to the MLP on the selected variables from the stepwise procedure

Variables	Importance	Variables	Importance	Variables	Importance
Transport	-3297,87568	Petit_commerce	-71,700969	Q_3_05	94,758026
Yoa_Lokpa	-3257,86499	Divorcé	-50,13837	Electricité	96,547112
Bariba	-3245,58688	Tole	-32,677166	X10	116,59886
Q_1_08_fcal	-849,211692	Fonctionnaire	-23,424611	Primaire	135,856998
Puits_Protégé	-346,216754	Eau_Courante	-17,218223	Yorouba	170,734507
Borne_Fontaine	-341,933419	Q_1_06	5,752937	Locataire	203,110015
Puits_Trad	-249,587578	Brique	53,046897	X1	353,103847
Lampe_Pétrole	-239,125241	Gros_commerce	56,851111	X8	422,831828
Q_1_08_mcal	-222,908905	Carrelage	67,967452	Supérieur	498,874679
Pompe	-206,657767	Secondaire	73,421292	Q_1_07	625,544452
Q_6_09_Comb_CE	-155,204578	X3	75,599741	Q_5_03_1_1	1559,06783

Table 7. Importance of BLR explanatory variables on selected variables from the olden procedure

	Estimate	Std.Error	z value	Pr(>|z|)
(Intercept)	-2.043e+00	1.452e+00	-1.407	0.15945
Elevage	-1.830e+01	7.547e+03	-0.002	0.99807
Torche	-4.539e+00	2.659e+00	-1.707	0.08781
Terre	-1.512e+01	2.071e+03	-0.007	0.99417
Yoa_Lokpa	-1.674e+01	6.744e+03	-0.002	0.99802
Energie_Solaire	-2.127e+01	5.172e+03	-0.004	0.99672
Palme_Bambou	-1.911e+01	9.015e+03	-0.002	0.99831
Lampe_Gaz	-1.722e+01	3.014e+04	-0.001	0.99954
Paille.1	-1.461e+01	4.637e+03	-0.003	0.99749
Bois_Planche	-1.910e+01	2.611e+04	-0.001	0.99942
Semi_dur	-3.038e-01	1.167e+00	-0.260	0.79471
X7	-1.914e+01	7.717e+03	-0.002	0.99802
Bariba	-2.182e+01	2.545e+03	-0.009	0.99316
X2	-2.216e+01	6.705e+03	-0.003	0.99736
X1	5.454e+00	3.122e+00	1.747	0.08059
Agriculture	3.119e-01	1.362e+00	0.229	0.81888
Puits_Protégé	-9.753e-01	1.214e+00	-0.803	0.42183
Artisanat	-6.847e-02	1.258e+00	-0.054	0.95658
Betamaribe	2.158e+00	8.098e+03	0.000	0.99979
X4	-1.460e+01	2.551e+03	-0.006	0.99543
Pays_Lim	2.931e+01	7.956e+04	0.000	0.99971
X11	-2.161e+01	8.846e+03	-0.002	0.99805
Peulh	-2.089e+01	3.280e+03	-0.006	0.99492
Lampe_Pétrole	-2.060e+00	1.189e+00	-1.732	0.08325
Q_1_08_fcal	-4.498e+00	1.315e+01	-0.342	0.73234
Sol_Nu	-1.703e+01	2.127e+03	-0.008	0.99361
X9	-6.907e-01	1.324e+00	-0.522	0.60184
X12	3.255e-01	1.033e+00	0.315	0.75255
Primaire	6.444e-01	1.018e+00	0.633	0.52686
Travail_Jour	1.240e+00	7.895e-01	1.570	0.11639
Q_1_06	7.826e-01	7.965e-01	0.983	0.32581
Q_1_08_mcal	-6.863e+00	5.433e+00	-1.263	0.20653
Puits_Trad	-8.925e-02	9.316e-01	-0.096	0.92368
Gros_commerce	-2.250e-02	9.526e-01	-0.024	0.98116
Tuile	1.171e+00	7.517e-01	1.558	0.11924
Dendi	-8.991e+00	1.823e+01	-0.493	0.62184
Petit_commerce	-3.148e-01	7.200e-01	-0.437	0.66198
Secondaire	7.261e-01	9.931e-01	0.731	0.46468
Yorouba	-9.410e-01	8.393e-01	-1.121	0.26222
Feminin	2.419e-01	6.807e-01	0.355	0.72229
Q_1_02	-1.417e+00	2.296e+00	-0.617	0.53719
X5	5.759e-01	1.138e+00	0.506	0.61287
Borne_Fontaine	-1.398e+00	1.013e+00	-1.381	0.16729
Adja	5.881e-01	6.912e-01	0.851	0.39485
Divorcé	-1.638e+00	9.954e-01	-1.646	0.09979
X10	9.361e-01	7.480e-01	1.251	0.21080
X8	1.833e+00	6.763e-01	2.711	0.00671 **
Carrelage	-2.660e-01	6.860e-01	-0.388	0.69824
Supérieur	2.873e+00	1.081e+00	2.657	0.00788 **
Q_6_09_Cr_tel	-2.420e+00	5.035e+00	-0.481	0.63077
Marié	2.472e-01	1.095e+00	0.226	0.82145
Rev_An	8.159e+00	1.955e+01	0.417	0.67640
Q_3_05	-9.721e-01	5.250e+00	-0.185	0.85310

	Estimate	Std.Error	z value	Pr(>|z|)
Q_6_09_Comb_CE	6.258e+00	4.486e+00	1.395	0.16303
Dalle	7.133e-01	9.141e-01	0.780	0.43517
Q_5_03_1_1	3.742e+01	2.474e+01	1.512	0.13048
Q_5_03_1_1.1	0.001e+00	5.035e+00	-0.481	0.63077
Eau_Minérale	1.685e+01	7.952e+04	0.000	0.99983

- the size of households, which emerges from the work of Uhunamure et al. [26] and Makonese et al. [29];
- and the age of the household head, which emerges from the work of Mbaka et al. [6], Pye et al. [23], Uhunamure et al. [26] and Pope et al. [25].

On the other hand, some of the determinants found by this study are specific to the case of Benin. These include ethnicity and the number of wives of the household head.

5. CONCLUSIONS AND RECOMMENDATIONS

The two approaches in particular the MLP (model based on neural networks of the Perceptron Multilayer type) and the Binary Logistic Regression (BLR) have highlighted as important factors of the adoption of Domestic Gas in Benin, the residence department (here department of the Littoral) and the level of education. When one considers that the Littoral Department contains only one Municipality namely Cotonou, the most populous Municipality of Benin, which is the economic capital of Benin and which has a port, airport and most of the ministries, it is easy to understand that residing in this department increases the likelihood of adopting Domestic Gas. We also noted that the MLP highlighted more adoption factors than the BLR model (income, ethnicity, and number of wives of the household head). For the future, it would be interesting to analyze other adoption phenomena by making a comparative study of the MLP model with the models traditionally used in the social sciences.

In order to increase the use of domestic gas on a large scale, the Government must put in place a policy that promotes the physical and financial accessibility (through subsidies) of the product to the large mass of the population in our cities which are still dependent on traditional energy sources such as wood fuel and charcoal in order to better protect our forest ecosystems in a sustainable manner. The Government could also strengthen the public-private partnership in this sub-sector by, for example, creating facilities for private economic operators through tax or customs exemption measures.

CONSENT

As per international standard or university standard, participant’s written consent has been collected and preserved by the authors.

COMPETING INTERESTS

Author has declared that no competing interests exist.

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APPENDIX

Appendix 1. Data description (n=4646)

Variables	Label	Type of variables	Modalities	Statistical parameters
Departement	Dep	Qualitative / nominale	X1=ALIBORI X2=ATACORA X3=ATLANTIQUE X4=BORGOU X5=COLLINES X6=COUFFO X7=DONGA X8=LITTORAL X9=MONO X10=OUEME X11= PLATEAU X12=ZOU	N(1)=570; P(1)=13,4244 N(2)=223; P(2)=5,2520 N(3)=405; P(3)=9,5384 N(4)=640; P(4)=15,0730 N(5)=554; P(5)=13,0476 N(6)=79; P(6)=1,8606 N(7)=193; P(7)=4,5455 N(8)=254; P(8)=5,9821 N(9)=329; P(9)=7,7485 N(10)=490; P(10)=11,5403 N(11)=172; P(11)=4,0509 N(12)=337; P(12)=7,9369
Gender Head of household (CM)	Q_1_01	Qualitative / binary	1 = Male 2 = Female	N(1)=3692; P(1)=86,81 N(2)=561; P(2)=13,19
Age of the head of household	Q_1_02	Quantitative / Continuous		Average = 44,427 Standard error = 0,199
Ethnicity of the head of household	Q_1_03	Qualitative / nominale	1 = Adja 2 = Bariba 3 = Dendi 4 = Fon 5 =Yoa_Lokpa 6 = Betamaribe 7 = Peulh 8 = Yorouba 9 = Autre_ethnie 10 = Pays_limitrophe	N(1)=442; P(1)=10,39 N(2)=685; P(2)=16,11 N(3)=224; P(3)=5,27 N(4)=1698; P(4)=39,92 N(5)=159; P(5)=3,74 N(6)=111; P(6)=2,61 N(7)=419; P(7)=9,85 N(8)=465; P(8)=10,93 N(9)=41; P(9)=0,96 N(10)=9;

Variables	Label	Type of variables	Modalities	Statistical parameters
				P(10)=0,21
Marital status CM	Q_1_04	Qualitative / nominale	1 = Married 2 = Divorced 3 = Widow(er) 4 = Single	N(1)=207; P(1)=4,87 N(2)=3864; P(2)=90,85 N(3)=100; P(3)=2,35 N(4)=82; P(4)=1,93
Is the head of household (CM) polygamous ?	Q_1_06	Qualitative binary	0 = No 1 = Yes	N(0)=3154; P(0)=74,16 N(1)=1099; P(1)=25,84
Number of wives of the head of household	Q_1_07	Quantitative / discreet		Average = 0,5883; Standard error = 0,0161
Number of men	Q_1_08_mcal	Quantitative / discreet		Average = 3,7597; Standard error = 0,042
Number of women	Q_1_08_fcal	Quantitative / discreet		Average = 3,4726; Standard error = 0,0434
Total number of people in the household	Q_1_08_tcal	Quantitative / discreet		Average = 7,2323; Standard error = 0,0724
Level of education of the Head of household	Q_1_09	Qualitative / ordinal	1 = None 2 = literacy 3 = Primary school 4 = Secondary school 5 = University 6 = Cursus_Arabic	N(1)=2012; P(1)=47,31 N(2)=123; P(2)=2,89 N(3)=972; P(3)=22,85 N(4)=806; P(4)=18,95 N(5)=284; P(5)=6,68 N(6)=56; P(6)=1,32
Occupancy status of the dwelling	Q_3_01	Qualitative / nominale	1 = Owner 2 = Family_Property 3 = Tenant 4 = Free accommodation	N(1)=1998; P(1)=46,98 N(2)=1721; P(2)=40,47 N(3)=455; P(3)=10,70 N(4)=79; P(4)=1,86
Nature of the walls of the dwelling	Q_3_02	Qualitative / nominale	1 = Straw 2 = Bamboo_Palm 3 = Bois_Plank 4 = Earth 5 = Semi-hard	N(1)=38; P(1)=0,89 N(2)=139; P(2)=3,27 N(3)=27;

Variables	Label	Type of variables	Modalities	Statistical parameters
			6 = Stone 7 = Brick	P(3)=0,63 N(4)=1294; P(4)=30,43 N(5)=1060; P(5)=24,92 N(6)=107; P(6)=2,52 N(7)=1588; P(7)=37,34
Nature roof of the household	Q_3_03	Qualitative / nominale	1 = Sheet metal 2 = Tile 3 = Straw 4 = Slab	N(1)=3796; P(1)=89,25 N(2)=107; P(2)=2,52 N(3)=258; P(3)=6,07 N(4)=92; P(4)=2,16
Nature of the soil habitats	Q_3_04	Qualitative / nominale	1= Cement 2= Tile 3 = Sol_Nu	N(1)=3011; P(1)=70,80 N(2)=163; P(2)=3,83 N(3)=1079; P(3)=25,37
Number of rooms occupied by the household?	Q_3_05	Quantitative / discreet		Average =3,3496; Standard error = 0,0354
Main source of household lighting	Q_3_06	Qualitative / nominale	1 = Electricity 2 = Oil_Lamp 3 = Gas_Lamp 4 = Torch 5 = Solar_Energy 6 = Candle 7 = Fires (wood, straw, etc.)	N(1)=1500; P(1)=35,27 N(2)=912; P(2)=21,44 N(3)=13; P(3)=0,31 N(4)=1531; P(4)=36,00 N(5)=275; P(5)=6,47 N(6)=6; P(6)=0,14 N(7)=16; P(7)=0,38
Main source of energy for cooking and processing household food	Q_3_07	Qualitative / binary	1=Gaz ; 0 = Autre (Charbon de bois, Electricité, Déchets animaux, Réchaud à pétrole)	N(0)=4050; P(0)=95,23 N(1)=203; P(1)=4,77
Main source of drinking water for the household	Q_3_10	Qualitative / nominale	1 = Running water at home (Soneb) 2= Borne_Fountain 3= Pump 4= Protected_Well	N(1)=860; P(1)=20,22 N(2)=649; P(2)=15,26 N(3)=1367; P(3)=32,14 N(4)=352;

Variables	Label	Type of variables	Modalities	Statistical parameters
			5 = Traditional_Well 6 = Surface water (marigot, river, lake, rain...) 7 = Mineral water	P(4)=8,28 N(5)=747; P(5)=17,56 N(6)=274; P(6)=6,44 N(7)=4; P(7)=0,09
Has Phone/Cellular	Q_3_14.14	Qualitative / binary	0 = No 1 = Yes	N(0)=1418; P(0)=33,34 N(1)=2835; P(1)=66,66
How many household members contribute to the income?	Q_5_01	Quantitative / discreet		Average = 1,6040; Standard error = 0,0136
Main household activity	Q_5_02_1	Qualitative / nominale	01. Agriculture 02.Transport 03.Elevage 04.Artisanat 05.Fonctionnaire 06.Gros_Commerce 07.Pêche 08.Chasse 09.Maraîchage 10.Petit_Commerce 11. Travail_Jour	N(1)=1743; P(1)=40,98 N(2)=379; P(2)=8,91 N(3)=160; P(3)=3,76 N(4)=203; P(4)=4,77 N(5)=560; P(5)=13,17 N(6)=104; P(6)=2,45 N(7)=92; P(7)=2,16 N(8)=2; P(8)=0,05 N(9)=16; P(9)=0,38 N(10)=729; P(10)=17,14 N(11)=265; P(11)=6,23
Monthly value (in CFA francs) Main household activity	Q_5_03_1_1	Quantitative / continues		Average = 129585; Standard error = 4299
Number of months of Main activity carried out during the year	Q_5_03_1_2	Quantitative		Average = 9,4195; Standard error = 0,0562
Estimated spending in the last 30 days on Cooking Fuel / Lighting	Q_6_09_Comb_CE	Quantitative continue		Average = 2052; SE= 74,9
Estimated	Q_6_09_Cr_tel	Quantitative continue		Average = 5444;

Variables	Label	Type of variables	Modalities	Statistical parameters
spending in the last 30 days on Telephone Credit (fixed and mobile/Internet)				SE= 146
Calculated annual household income (in FCFA)	Rev_An	Quantitative continue		Average = 1506517; SE= 52987

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