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Research Paper

Modeling and Household Profiles of Women Agripreneurs in Kisangani in the Face of Poverty and Resilience.

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Abstract
This research aimed to characterize the profiles of women agripreneurs' households in the city of Kisangani in terms of poverty and resilience. This involved determining the possible relationships between variables taken from household status and poverty and resilience in order to identify the profiles of each household type. Multinomial logistic regression showed that the poverty of these households depended on total household income and household size, while household resilience varied with total household income and the education level of women agripreneurs.
The mixed factor analysis of data showed that the profile of poor households is: High household size, low total income and no diversification of income sources and the profile of non-poor households is: small household size, high total income and diversification of income sources concomitantly with this the profile of very resilient households is: higher level of education of women agripreneurs, diversification of income sources and high total income, however the profile of resilient households is: average level of education of women agripreneurs and no diversification of income sources and finally the profile of non-resilient households is: Low level of education of women agripreneurs.

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I. Introduction

The DRC is one of the poorest countries in the world, ranked 172nd out of 193 countries, according to the United Nations Development Programme (UNDP, 2024). Faced with poverty, several groups of vulnerable people can be identified, such as people living with disabilities, street children, etc. Women in general, but especially single mothers, female-headed households, etc. can also be included in this list. Several resilience activities are being considered by women to address poverty, and this research focuses on studying agricultural entrepreneurship practiced by women. Entrepreneurship is designated as one of the means to combat poverty (Halaissi, 2018), even if the income generated is low, it has been proven that it contributes significantly to improving well-being (Fall, 2012).

This concept of "women agripreneur households" is widely discussed in our work and constitutes our study population. We considered women agripreneur households to be households whose primary income comes from women who engage in agripreneurship; they may or may not be heads of household.

Our objective was to determine the characteristic profiles of women agricultural entrepreneurs. That is, to identify the variables that influence the poverty and resilience of these households, establish a resilience prediction equation, and identify the characteristic profiles of poor and non-poor households, resilient, highly resilient, and non-resilient households.

It is important to study agricultural entrepreneurship in the DRC because it represents a lever to support development, hence the interest in studying the situation of these households. The eradication of poverty through agricultural development remains an important issue for the DRC because the agricultural sector in its various links of value chains employs a large workforce of the population.

II. Setting, Materials, and Method

2.1.Setting

The following figure shows the city of Kisangani, which is our study environment.

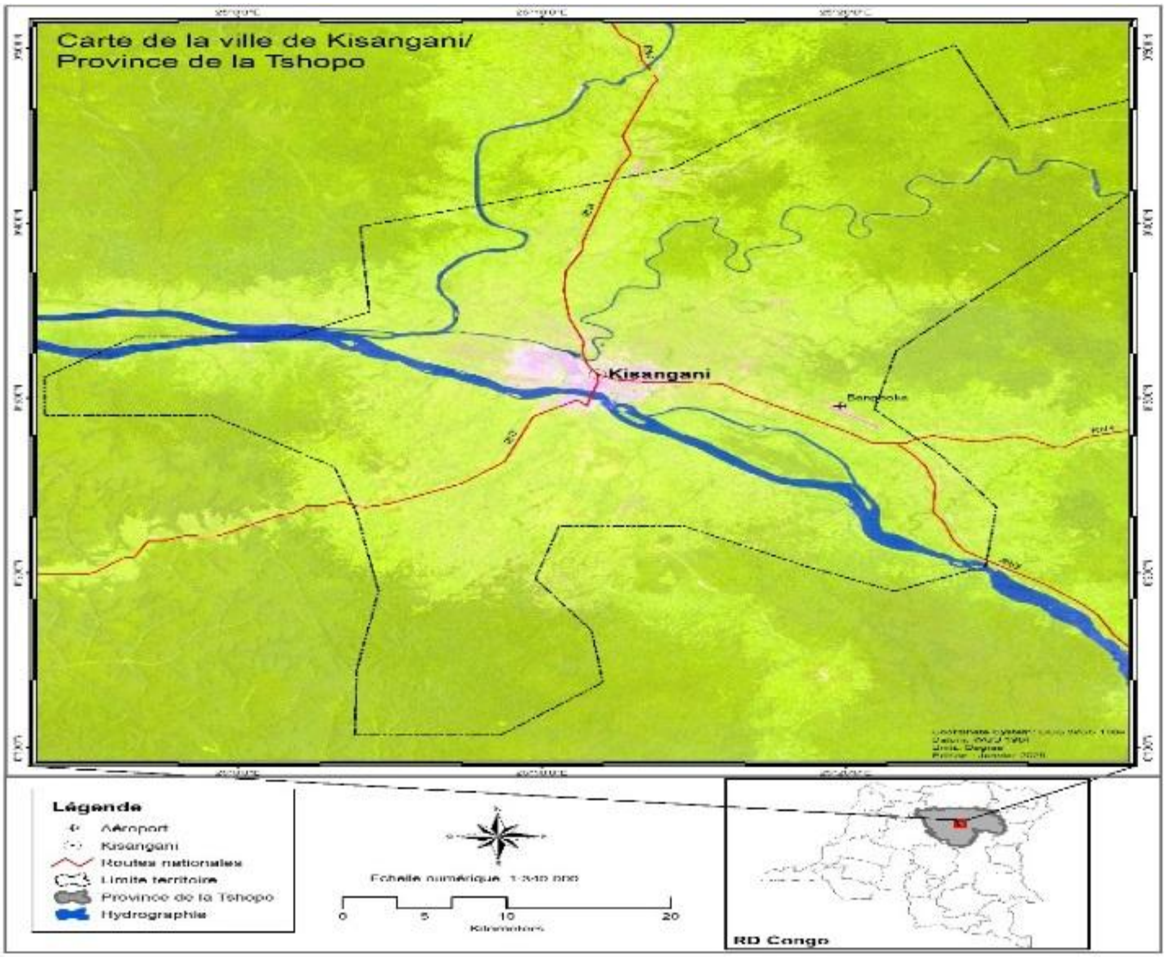


Figure 1: Map of the City of Kisangani

2.2. Materials

This research will require the following materials:

- A motorcycle: as a means of transportation to reach our respondents;
- A tablet: this will help us conduct mobile data collection;
- A computer equipped with specialized software for data processing and analysis;

2.3. Method

We used a survey approach to conduct the research, coupled with a questionnaire technique to collect data from our study units, which consisted of a sample of 107 women agripreneur households.

The analyses focused on identifying the variables that influence poverty and resilience, and then constructing an equation to predict poverty and resilience for these households, taking into account the variables that influence it.

2.3.1. Study Variables

The household elements converted into variables are as follows:

a. Income: Our study unit was also characterized by two types of income, including income from the household's agripreneurial activities and income outside of agripreneurship.

b. Household size: This is the total number of people who make up a household. A household is generally defined as an individual or a group of people who occupy the same dwelling and who do not have a usual residence elsewhere.

c. Education level of the female agripreneur: This refers to the intellectual abilities of the female agripreneur, making her capable and flexible in certain aspects (reading, writing, calculating, bargaining, etc.) of her activity. We grouped this variable into three categories:

Low level: for women who have not attended school and those who have attended primary school but have not obtained a primary school certificate. Middle level: Includes women agripreneurs who have obtained the primary school certificate up to those who have completed the second year of the orientation cycle (2nd C.O) currently called 8th year.

Higher education: For agripreneurs who began their studies in the humanities and advanced to a state diploma, and for some, to university.

As a qualitative variable, to facilitate analysis, we assigned numbers to these different categories: Low education (0); Medium education (1); Higher education (2).

d. Source of income: The household could have multiple sources of income or not. This variable had two categories: (0) for households with only agripreneurship as a source of income and (1) for households with multiple sources of income.

2.3.2. Analysis of Economic Resilience (ERS) Using Multinomial Logistic Regression

In addition to the poverty analysis, a multinomial logistic regression was conducted to study household economic resilience. The dependent variable (ERS) was categorized into three levels:

0 = Not resilient; 1 = Resilient; 2 = Highly resilient

This model allowed us to examine the impact of explanatory factors (RVT, SDR, NEA, and TDM) on the probability of achieving a high level of resilience. The objective was to better understand the dynamics that promote households' ability to cope with the adverse situation of poverty and adapt to life's fluctuations.

2.3.3. Mixed Data Factor Analysis (MDFA)

MDFA was particularly useful for identifying the underlying structures of the data and highlighting the complex interactions between factors influencing poverty and resilience in the households studied. It allowed us to explore the relationships between the variables studied, thus providing a comprehensive view of socioeconomic determinants.

The integration of MDFA into our methodological approach was an essential complement to regression models. By providing an intuitive graphical representation of the relationships between household groups and variables, it facilitates the interpretation of results and allows us to identify specific profiles within the study population, thus characterizing the sub-segments of our study units. This approach thus improves the robustness of the conclusions by capturing dynamics that could be masked by purely traditional statistical analyses.

Using this mixed data factor analysis test, we characterized and profiled the households of women agripreneurs in the city of Kisangani. The results of this analysis are: the profile of poor and non-poor households, and the profile of non-resilient, resilient, and highly resilient households.

III. Search Results

3.1. Poverty Modeling (PVT) by Binary Logistic Regression

The table 3 presents the results of poverty modeling using binary logistic regression.

	coeff	*s.e.*	*Wald*	*p-value*	*exp(b)*
Intercept	44,80	12,20	13,4919408	**0,0002*****	2,8474E+19
RVT	-12,79	3,38	14,2875761	**0,0002*****	2,784E-06
SDR	-17,48	7307,09	5,7198E-06	0,9981	2,5727E-08
NEA	1,54	0,80	3,77317899	0,0521	4,68679206
TDM	1,26	0,32	15,1973461	**0,0001*****	3,50901621

Table 3. Relationship between poverty and other household variables
Legend: PVT = Poverty; RTV = Total income; SDR = Source of income; NEA = Education level of the agripreneur woman; TDM = Household size; RHA = Income outside agripreneurship; RDA = Income from agripreneurship; coeff = Coefficient; s.e. = Standard error; Wald = Wald statistic; p-value = P-value; exp(b) = Exponential of the coefficient (Odds Ratio).

Analysis of the binary logistic regression results highlights the factors influencing the probability of being in poverty. First, the coefficient for total income (RVT) is negative (-12.79) and statistically significant with a p-value of 0.0002*, indicating a strong inverse association between total income and the probability of being poor. As total income increases, the probability of being in poverty decreases.

In contrast, the source of income (SDR) has a negative coefficient (-17.48) but an extremely high p-value (0.9981), meaning that this variable is not significant in explaining poverty.

The agripreneur's education level (NEA) has a positive coefficient (1.54) and a p-value of 0.0521, indicating an influence close to the significance threshold. This result suggests that education may play a role in poverty reduction, but that its effect is not sufficiently strong in the sample studied. Quality education could improve financial management and entrepreneurship skills, thus enabling access to more profitable economic opportunities.

Household size (HS), for its part, is significantly associated with poverty, with a positive coefficient (1.26) and a very low p-value (0.0001***). This result indicates that the larger the household size, the higher the probability of being in poverty. This is explained by the fact that a larger household implies a heavier financial burden, thus reducing per capita income and increasing the risk of poverty.

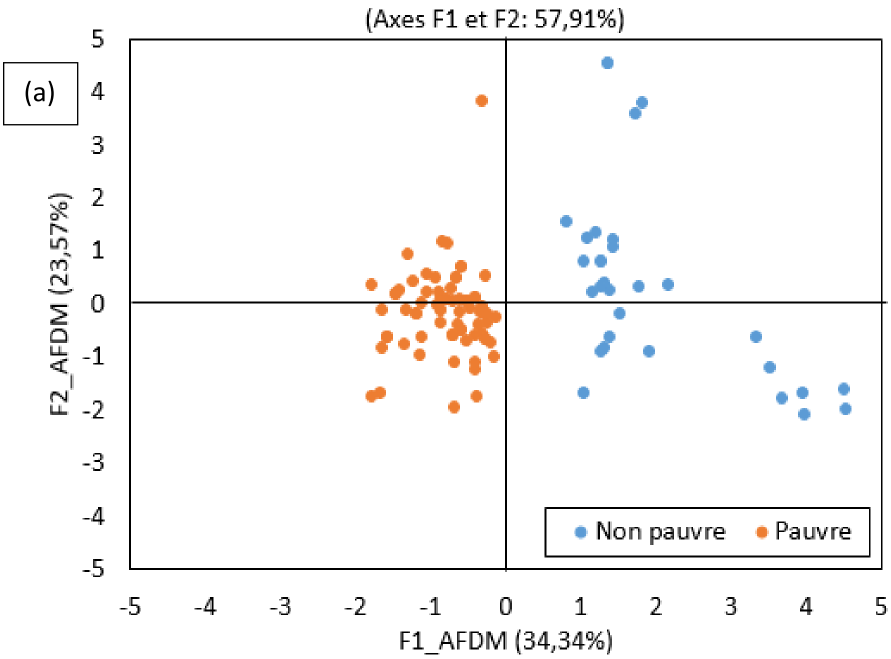
The model can thus be represented by equation (1). In this model, the significant variables explaining poverty are total income (TRI) and household size (HS):

$\log(\frac{PVT}{1-PVT})$ =44,80−12,79×RVT+1,26×TDM (1)

Where PVT is the probability of being in a situation of poverty.

3.2. Profiling Women Agripreneur Households Based on Poverty

The figures presented in this section illustrate how certain variables influence households' positions on the factor axes



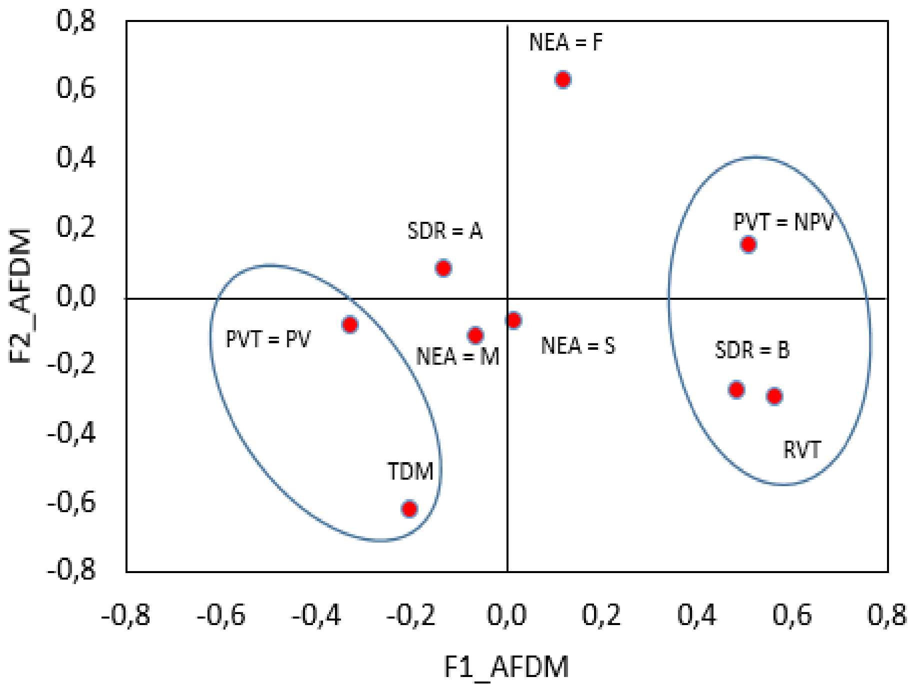


Figure 1: (a) Projection of households by poverty status and (b) correlation of variables with poverty on the F1 and F2 axes (Mixed Data Factor Analysis: MDF).

Mixed data factor analysis (MDF) highlights a clear distinction between poor and non-poor households when considering the first two factor axes (F1 = 34.34% and F2 = 23.57%).

Figure (a) shows that households in poverty (orange dots) are mainly clustered on the left side, while non-poor households (blue dots) are predominantly located on the right. This differentiation is consistent with binary logistic regression, which showed that total income (TDI) has a strong negative influence on the probability of being poor.

Figure (b) confirms this relationship by associating the non-poor (PVT = NPV) with a high total income (RVT) and a B source of income (SDR = B), while poor households (PVT = PV) are correlated with household size (TDM). This supports the interpretation that larger household size increases the probability of poverty, as revealed by logistic regression. Finally, the dispersion of education levels (NEA) and sources of income (SDR) around the central axis indicates that they play a moderate but not systematically significant role in explaining poverty.

The following table presents an overview of the poverty profiling of women agripreneur households.

Table 4: Profile of poor and non-poor households

Variables	Poor households	Non-poor households
Household size	High	Low
Total income	Low	High
Diversity of income sources	No	Yes

From this summary table of results on poverty modeling and AFDM characterization, we see that:

a) The profile of poor households is: Large household size, low total income, and no diversification of income sources

b) The profile of non-poor households is: Small household size, high total income, and diversification of income sources.

3.3. Analysis of individual resilience (RSE) using multinomial logistic regression

The following table presentsfactors influencing the resilience of highly resilient individuals

Table 2: Factors influencing the resilience of highly resilient individuals

	coeff	*s.e.*	*Wald*	*p-value*	*exp(b)*
Intercept	-6,642	2,259	8,647	**0,003****	0,001
RVT	1,203	0,518	5,395	**0,02***	3,331
SDR	-1,422	0,993	2,051	0,152	0,241
NEA	1,122	0,409	7,543	**0,006****	3,071
TDM	0,071	0,077	0,844	0,358	1,073

Source: Results of processing our survey database

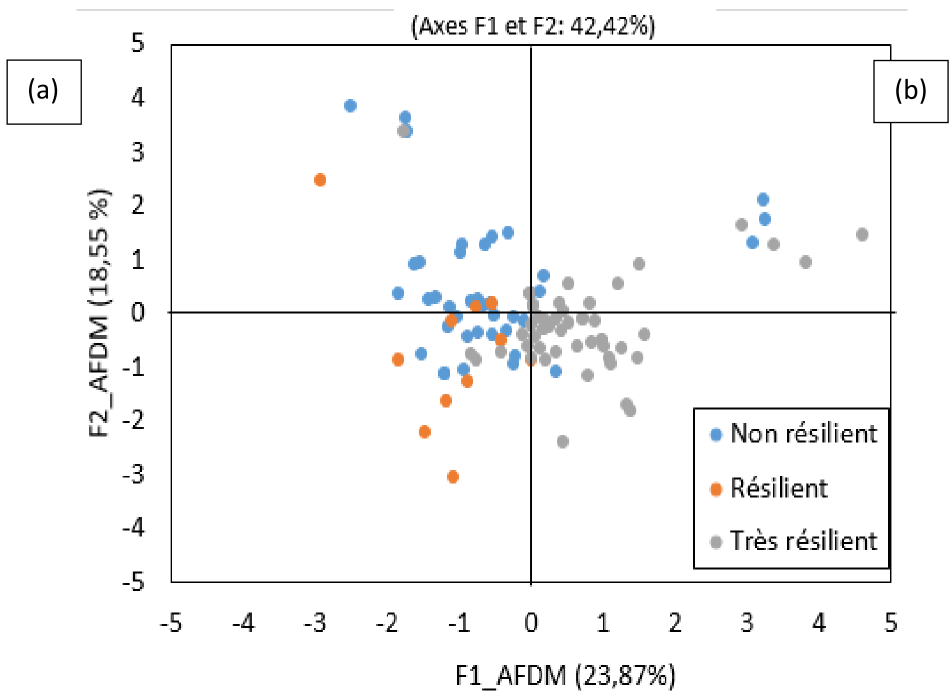
The results show that total income (RVT) has a positive coefficient (1.203) with a p-value of 0.02*, indicating that higher income significantly increases the likelihood of being highly resilient. In other words, individuals with higher income have more resources to cope with economic shocks and adapt to market fluctuations.
Educational level (NEA) is also significant with a positive coefficient (1.122) and a p-value of 0.006. This indicates that the education of the female entrepreneur in the household promotes resilience by providing the household with skills that allow them to diversify their income sources and better manage economic risks. In contrast, source of income (SDR) and household size (TDM) are not significant (p-values of 0.152 and 0.358, respectively), suggesting that they do not have a direct impact on the probability of being highly resilient.
Equation (2) of the model for highly resilient individuals only retains significant variables:

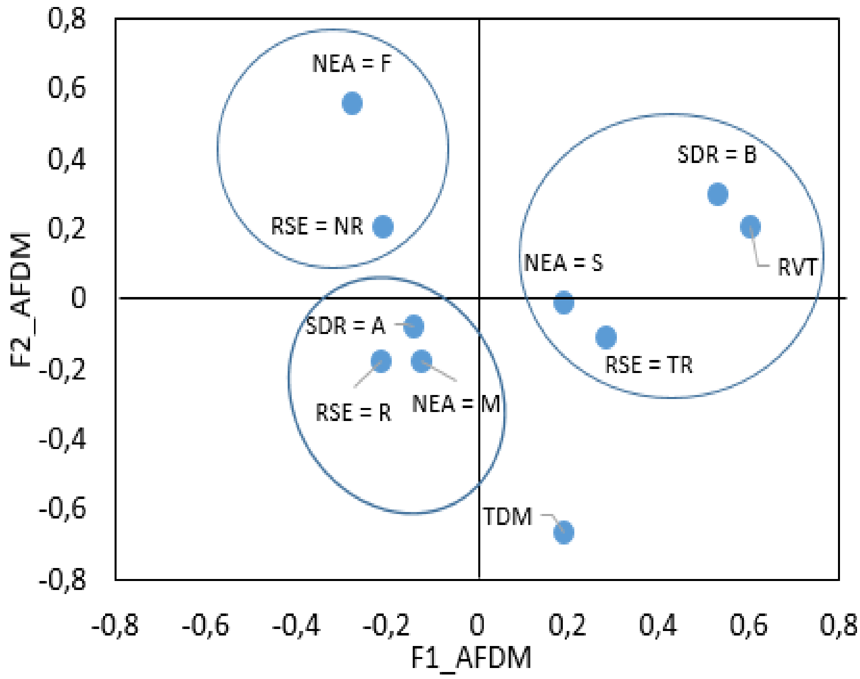
$$\log\left(\frac{P(RSE=2)}{P(RSE=0)}\right) = -6{,}642 + 1{,}203 \times RVT + 1{,}122 \times NEA \quad (2)$$

Where RSE=2 represents highly resilient individuals and RSE=0 represents non-resilient individuals.

3.4. Profiling of women agripreneur households based on resilience

The profile of women agripreneur households shows the characteristics of each household group in relation to the variables, depending on whether the household is resilient, highly resilient, or non-resilient.
Figure 13: (a) Projection of households according to their resilience level and (b) correlation of the variables with poverty on the F1 and F2 axes (Mixed Data Factor Analysis: MDF).





Mixed data factor analysis (MDFA) highlights the structure of households according to their level of resilience. Figure (a) illustrates the distribution of households in the factor space according to three categories: non-resilient, resilient, and highly resilient. We observe that highly resilient households (gray) are located mainly on the right side of the graph, in relation to total income (RVT) and source of income B (SDR = B) in figure (b). This confirms the results of the multinomial logistic regression, where higher income significantly increases the probability of being highly resilient. Furthermore, education level (NEA = S) is also correlated with this category, corroborating the fact that a higher level of education promotes resilience.

Resilient households (red) are characterized by the variable sources of income A (SDR=A); that is, having only one source of income which is agripreneurship, the level of education (NEA = M). On the other hand, the non-resilient (blue) are associated with a low level of education (NEA = F) and are mainly located on the left of the graph.

Thus, we can say that agripreneurship is a resilience activity, but the female agripreneur's education level must be average (having obtained a primary school certificate). If the household has a second source of income and the female agripreneur has a higher level of education, the household will be highly resilient in the face of poverty.

Household size (HS), although displayed in graph (b), appears to have little influence, which is consistent with the lack of significance in the logistic regression. These results thus highlight the importance of economic resources and education in household resilience.

Table 3: Profile of non-resilient, resilient, and highly resilient households

Variables	Non-resilient households	Resilient households	Highly resilient households
Education level of female agripreneurs	Low	Middle	High
Diversity of income sources	No	No	Yes
Total income	Low		High

Source : Results of processing our survey database

This summary table of the results of resilience modeling and household characterization using mixed data factor analysis shows that:

a) The profile of highly resilient households is: higher education level of female agripreneurs, diversification of income sources, and high total income;

b) The profile of resilient households is: average education level of female agripreneurs and no diversification of income sources;

c) The profile of non-resilient households is: low education level of female agripreneurs

IV. Discussion

Relationship between poverty, income, and household size

(Lachaud, 1997) conducted his study on poverty, household size, and gender in Burkina Faso and found that the size elasticity of poverty was 0.58%. This means that if household size increased by 1%, poverty increased by 0.58%. In our case, the results of the binary logistic regression showed that when the household size of an agricultural household increased by 1%, the probability of that household being poor increased by 1.26%.

These results also confirm those of (Moummi, 2010), who, after analyzing poverty profiling in the DRC, stated that regarding the household size factor, his results showed that large households tended to be poorer than small households. Thus, the poverty rate was around 44% for households consisting of three individuals, but approached 80% when the number of individuals exceeded five. This shows that household size is an aggravating factor of poverty in the DRC.

The depth of poverty and its intensity by household size followed the upward trend according to the number of individuals per household. Thus, the depth of poverty recorded a rate of 16% when the household size was less than three people, compared to a rate of 36% when it exceeded five members. This reflects the gap between these groups of households based on the number of individuals they comprise.

In this same vein, he also linked education level and poverty, which attested to the idea that education improves household living standards. Thus, the results showed that households with a low level of education are the most exposed to poverty, with 76% compared to only 34% for households with a university or postgraduate level of education.

(Fambon, 2010) had proven through his research that in Cameroon, poverty is likely to decrease more rapidly than the growth rate of living standards, provided that the latter does not generate an increase in inequality. His results showed that at the country level as a whole, the absolute value of expenditure elasticities was significantly greater than unity for all poverty measures. Thus, a 1 percent increase in expenditure leads to a reduction in the depth of poverty (P1) of 1.53 percent, all other things being equal.

Also, the expenditure elasticity for the depth of poverty (P1) was -1.52 when the poverty line was considered, but rose to -2.219 when the ultra-poverty line was taken into account.

Such results also indicate that if economic growth is negative, poverty is highly likely to increase.

Relationship between resilience and household parameters

Our results confirm the research of (Dubois & Rabemalanto, 2010), who found that household resilience is measured based on living conditions and household resources. It also relates to social and economic opportunities that broaden people's choices of action.

Our results also confirm the World Bank studies which place the low level of education as one of the obstacles to female entrepreneurship in Congo alongside other obstacles such as difficulties in accessing financing, the lack of support services, inadequate regulations, social prejudices, and heavy family responsibilities (Banque Modiale, 2017)

V. Conclusion

This study consisted of characterizing typical household profiles based on resilience and poverty. The results allow us to conclude that poverty interacts with household size and household income, while resilience depends on total household income, the education level of the women agripreneurs, and the diversity of income sources available to a household. Thus, any government action aimed at strengthening the resilience of women agripreneurs' households in the face of poverty in the city of Kisangani must conduct activities aimed at encouraging these women agripreneurs to develop intellectual skills that will enable them to expand their activities and increase their total income, which will subsequently have an impact on household health, basic needs subsidization, leisure, and savings.

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