Original Research Article

Is Living in Mwanza Region More Economically better and Happier than Living in Kagera Region? Finite Mixture (FIMIX) Approach

Abstract

The study aimed to uncover the unobserved heterogeneity of the population in Mwanza and Kagera regions. The study examined if living in Mwanza region is more economically better and happier than living in Kagera region. The cross-sectional survey research used with the cross-sectional data from 211 individuals sampled randomly from 4 districts, Nyamagana and Misungwi from Mwanza region, and Bukoba and Muleba from Kagera region. The FIMIX-PLS used to analyse the data. The study found that the population of Mwanza and Kagera regions can be grouped into two mains classes which are class one with a lower annualised income below 1.5 TZS millions per capita and a lower mean score of fundamental psychological factors for happiness (FPFH) in comparing to the class two. The class two is characterised with a higher annualised income about 2.45 TZS millions per capita and a higher mean score of FPFH in comparing to class one. The study evidenced that respondents of Mwanza region have a higher annualised income and FPFH scores than respondents of Kagera region in each class. Therefore, the study concluded that living in Mwanza region is more economically better and happier than living in Kagera region. The study recommended the immigration to seek the economic opportunity and happiness, for example immigration from Kagera region to Mwanza region or nation to nation is encouraged. Moreover, further study recommended by using a panel data to attest the posed facts because this study limited to the cross-sectional data.

Key words: FIMIX-PLS, immigration, Economic growth, Factors of Happiness (FPFH), hand individual income

JEL: A12; A 13; A14

1.1: Introduction

Kagera and Mwanza are the two regions in the Lake Victoria zone that are 370.02 kilometres apart by road metric (URT, 2012). The two regions have a historical strong inter-regional trade relationship (URT, 2019c). Unfortunately, they acutely differ in economic performance. Kagera performs worse than Mwanza region (URT, 2019a; 2019b). Despite the endless effort of Kagera region on improving the economic performance across the region, its economic growth reported to grow at -0.3 percent in 2018 (URT, 2019a). The economic performance inequality (EPI) is still increases across the lake zone. Unfortunately, no relevant diagnostic of this economic problem has been successfully attempted to rescue or address this situation. The Kagera investment guide (2019) provides a lot of economic promises with less probability of achievement. That it, is still unknown which are unobserved heterogeneity that cause the inequality of economic performance in Mwanza and Kagera regions. Clearly, it is still unknown why Mwanza is economically well-off than Kagera region.

In addition, it is not yet confirmed that the economic growth in Mwanza is associated with happiness of the producers as the debate on it is not ended. Researchers reached diametrically opposed conclusions. For example, Easterlin (1973; 2017) empirically evidenced the paradox effects on income and happiness (subjective well-being). Moreover, some recent studies, such as Roka (2020), Semeijn, van der Heijden and de Beuckelaer (2020), Meyer and Hamilton (2020), Li and Shi (2019) and Stevenson and Wolfers (2008; 2013) evident the significant positive effects of subjective well-being (happiness) on the economic growth, while Stoop, Leibbrandt and Zizzamia (2019) confirmed negative effects of subjective well-being (happiness) on the economic growth. These findings create a contradictory evidence gap that this study worked on it. Until now there is no consensus have been reached on the ongoing debate and adversely it increases a policy dilemma for decision makers. Hence, the main objective of this study was to examine if living in Mwanza region is more economically better and happier than living in Kagera region. That is, to examine if the happiness is associated with the economic growth. The specific objectives were uncovering the hidden subpopulations (classes) of the population of Mwanza and Kagera regions by classification of their unobserved characteristics or behaviour in the aspects of demographic characteristics environmental factors, human behavioural factors and economic factors as suggested as the fundamental psychological factors for happiness (FPFH) (Bundala (2020).

Logically, because Mwanza region has a higher economic growth than Kagera region, then it implies that the Mwanza region residents are happier than that of Kagera region. To test this general hypothetical statement a researcher used finite mixture partial least squares (FIMIX-PLS) and finite mixture models (FMM). Both FIMIX-PLS and FMM are method to uncover unobserved heterogeneity in the inner (structural) model (Hair, Sarstedt, Mattews and Ringle, 2016). They capture heterogeneity by estimating the probabilities of class memberships for each population (observation) and simultaneously estimate the path coefficients for all classes (Hair et al. 2016). And, then the determination of characteristics of the producers each class was done.

1.2 Conceptual and data analytics framework

The basic concept of this study was to uncover or examine the unobserved heterogeneity of the producers in Mwanza and Kagera regions. At the first examination the structural linear relationship was established by using PLS-SEM. In this stage the beta coefficients of the linear relationship between the FPFH and economic growth was established by using the basic or normal application of PLS. Therefore, the study examined the unobserved heterogeneity of the PLS path influence of FPFH on economic growth. The study used the methods of modelling the unobserved heterogeneity of the linear relations suggested by Hahn, Johnson, Herrmann and Huber (2002). In this analytics the inner structural model was considered. PLS-SEM has two types of measurement models, the outer measurement models which involve the reflective and formative indicators relations and the inner measurement or structural models that involve the relationship among the latent variable (endogenous and exogenous variables). For the purpose of this study the inner measurement or structural model was considered, because the study aimed to uncover the unobserved heterogeneity of the relationship between the endogenous and exogenous latent variables. Therefore, according to Hahn et al. (2002), the inner measurement model can be expressed as:

$$B\eta_i + \Gamma\xi_i = \zeta_i \dots\dots\dots\dots\dots\dots\dots\dots\dots.\dots\dots\dots\dots(1)$$

Where η_i and ξ_i is the vector of the endogenous and exogenous variables of the inner model for item (observation) *i*, respectively.
B (Q x Q) and Γ(Q x P) are path coefficient matrices with Q = number of endogenous variables, P = number of exogenous variables, and ζ_i is a random vector of residuals (Hahn et al. 2002).
As the study aimed to uncover the unobserved heterogeneity subpopulations (classes) with their probability of membership, then the study assumes endogenous and exogenous variable (η_i) is specifically distributed as a finite mixture of the conditional multivariate normal densities, $f_{i|k}(.)$, as follow:

$$\eta_i \sim \sum_{k=1}^{K} \rho_k f_{i|k}\left(\eta_i|\xi_i, B_k, \Gamma_k, \Psi_k\right) \dots\dots\dots\dots\dots.(2)$$

Which it can be expressed as,

$$\eta_i \sim \sum_{k=1}^{K} \rho_k \left[\frac{|B_k|}{\sqrt[M]{2\pi\sqrt{|\Psi_k|}}} \exp\left(-\frac{1}{2}(B_k\eta_i + \Gamma_k\xi_i)'\Psi_k^{-1}(B_k\eta_i + \Gamma_k\xi_i)\right)\right] \dots..(3)$$

Where, *k* is number of latent classes or subpopulation in a sample population K (classes); M is the number of endogenous variables, and Ψ_k is the (Q x Q) matrix of K subpopulations or classes with the variances for each regression of the inner measurement model on the diagonal and zero else, and ρ_k is a vector of the K mixing proportions of the finite mixture.

Now, for maximization of the vector of latent endogenous variable (η_i), the objective function is the likelihood function for η_iN vectors. The likelihood function (L) is given by:-

$$L = \prod_{i=1}^{N}\left[\sum_{k=1}^{K} \rho_k \left[\frac{|B_k|}{\sqrt[M]{2\pi\sqrt{|\Psi_k|}}} \exp\left(-\frac{1}{2}(B_k\eta_i + \Gamma_k\xi_i)'\Psi_k^{-1}(B_k\eta_i + \Gamma_k\xi_i)\right)\right]\right] \dots\dots(4)$$

The mixing proportion ρ signified as prior probabilities of any item belonging to K subpopulations (latent classes). Therefore, posterior probability membership for item *i*in subpopulation k ($\hat{P}_{ik}$) is computed by using Bayes' theorem under the conditioned estimates of class-specific parameters$\hat{\rho}_{k1}$, $\hat{B}_{k1}$, $\hat{\Gamma}_{k1}$ and $\hat{\Psi}_k$[13]. That is,

$$\hat{P}_{k1} = \frac{\hat{\rho}_k f_{i|k}\left(\eta_i|\xi_{i1}\hat{B}_{k1}\hat{\Gamma}_{k1}\hat{\Psi}_k\right)}{\sum_{k=1}^{k}\hat{\rho}_k f_{i|k}\left(\eta_i|\xi_i\,\hat{B}_k\,\hat{\Gamma}_k\hat{\Psi}_k\right)} \dots\dots\dots\dots.\dots\dots\dots..\dots\dots\dots\dots\dots.\dots\dots.(5)$$

To ensure the maximum likelihood and convergence of the inner model, the EM-formulation of FIMIX-PLS algorithm is used. This process involves two stages of estimations, the calculation of expectation of endogenous and exogenous variables (E-step). The second step is the maximization part (M-step). In a formulation of the EM-algorithm, the non-observed data represented by indicator function,

$$\mathrm{Z_{ik}} = \begin{cases} 1 & \text{if item } i \text{ belongs to subpopulation k} \\ 0 & \text{Otherwise} \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

Then, the non-observed data in the vector $\mathrm{Z_{ik}}$ are independently and identically multinomial distributed probabilities ρ_k, therefore, a complete joint likelihood of η_i and Z_i is represented by:-

$$L = \prod_i \prod_k [\eta_i | \xi_i, B_k, \Gamma_k, \Psi_k]^z \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

The objective function of the maximization of the log-likelihood (lnL) of the vector endogenous (η_i) is achieved by using the EM-Algorithm. That is,

$$\mathrm{lnL} = \sum_{\mathrm{i}} \sum_{\mathrm{k}} \mathrm{Z_{ik}} \ln\big(\mathrm{f}\,(\eta_i | \xi_i, B_k, \Gamma_k, \Psi_k)\big) + \sum_{\mathrm{i}} \sum_{\mathrm{k}} \mathrm{Z_{ik}} \ln(\rho_k) \ldots\ldots (8)$$

The EM-algorithm starts with an E-step, where the expectation of lnL is evaluated over the conditional distribution of the non-observed data Z given the predicted values of η_i and ξ_i of the observed data, and the provisional estimates (B^*, Γ^*, Ψ^* and ρ^*) of the parametersB, Γ, Ψ *and* ρ respectively. These estimates are calculated from a random sample of membership probabilities of $P_{i|k}$.

The expectation of the log- likelihood function is,

$$E(\ln; \xi_i, \rho = \rho^*, B = B^*, \Gamma = \Gamma^*, \Psi = \Psi^*) \ldots\ldots\ldots\ldots\ldots (9)$$

Which it can be expanded to:

$$= \sum_{\mathrm{i}} \sum_{\mathrm{k}} E(Z_{ik}; \xi_i, B^*, \Gamma^*, \Psi^*, \rho^* | \eta_i) \ln\big(f(\eta_i | \xi_i, \rho_k^*, B_k^*, \Gamma_k^*, \Psi_k^*)\big) + \sum_{\mathrm{i}} \sum_{\mathrm{k}} E(\xi_i, B^*, \Gamma^*, \Psi^*, \rho^* | \eta_i) \ln\rho_k^* \ldots\ldots\ldots\ldots\ldots (10)$$

The conditional expectation of Z_{ik} can be calculated by

$$E(Z_{ik};\ \xi, \rho = \rho^*, B = B^*, \Gamma = \Gamma^*, \Psi = \Psi^*) \ldots\ldots\ldots\ldots\ldots\ldots (11)$$

Which it can be expanded to

$$= \frac{\rho_k^* f(\eta_i | \xi_i, B_k^*, \Gamma_k^*, \Psi_k^*)}{\sum_k \rho_k^* f(\eta_i | \xi_i, \rho_k^*, B_k^*, \Gamma_k^*, \Psi_k^*)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

Therefore, the conditional expectation of Z_{ik} is equal to the posterior membership probability $\widehat{P}_{ik}$ for i item and class k.

The number of classes is unknown and requires a statistical solution. Bozdogan and Sclove(1984) proposed the use of Akaike's Information Criterion (AIC) to determine the number of classes in a mixture model.

$$\mathrm{AIC_K} = -2\ln L + c\mathrm{N_K} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (13)$$

Where c = 2 and $\mathrm{N_K}$ is the number of free parameters which is defined as:

$$\mathrm{N_K} = (K-1) + KR + KQ \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (14)$$

Where K = number of classes or subpopulations, R = number of predictor variables in all regressions of the inner model and Q = number of endogenous variables in the model. Moreover, the separation of the classes, the entropy statistic was used to measure the degree of separation in the estimated individual class probabilities, that is;

$$\mathrm{EN_K} = 1 - \frac{\sum_i \sum_k -P_{ik} \ln P_{ik}}{I \ln K} \dots\dots\dots\dots\dots\dots\dots (15)$$

According to Hair et al. (2019) the entropy criterion above 0.50 is recommended for optimal separation.

2. Methodology of the study

The study used an exploratory research design with a cross-sectional data. The sample size was 211 individuals, estimated by using Tabachnick and Fidell (2019) approach that used when the actual numbers of the respondents are unknown. The randomly sampling procedures were used in four districts Nyamagana and Misungwi from Mwanza region and Bukoba and Muleba districts from Kagera. The study used self-administered survey to collect data and self-reporting checklist questionnaires to collect data. Both the method and tool for collection data were suggested to be suitable and strong to capture the psychological attribute or data from the targeted population (Ghauri, Grønhaug and Strange, 2020; Kothari, 2009; Saunders, Lewis and Thornhill, 2009). The reliability and validity of the data collection tools were examined by using PLS-SEM. The data was analysed by using FIMIX-PLS and FMM enabled by Smartpls 3 and stata software respectively.

The dependent variable of this study is economic growth measured by the annualised income per capita. That is, averaged GPD per capita (AGDP) = monthly income of individual *i* x 12 (number of month in a year). The monthly income is assumed to be constant over the year, due to nature of economic activities is similar and has almost a constant monthly return. On the other hand, the independent variables are psychological limiting factors (PSY) which measured by psychological human behavioural index (*Hube*), psychological economic index (*Ecofa*), psychological environmental index (*Envi*), and psychological demographic characteristics index (*Demo*); all indices are based on the 5-points Likert scale. The general construct of the psychological limiting factors index is given by,

$$\mathbf{PSY}_i = \frac{\sum_{i=1}^{n} \sum_{i=1}^{m} Q_i \, xLS_i}{\sum_{i-1}^{n} Q_i \, xLS_{max}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (\mathbf{16})$$

Where, n is the number of variables measured in a psychological factor, m *is* the number of questions that measures or proxy for variable, $\boldsymbol{Q_i}$ question posed for variable i, $\boldsymbol{LS_i}$ the score of individual question on the Likert scale, and $\boldsymbol{LS_{max}}$ is the maximum score of individual question on the Likert scale.

Hube latent variable was measured by observed variables which are lifestyle, metacognition and motivation of individual. The *Demo* latent variable was measured by observed variables which are age, marital status, income, education, and number of family members. *Ecofa* latent variable was measured by observed variables which are prices of commodities, fashion of products, and weather conditions. Moreover, *Envi* latent variable was measured by observed variables which are environmental sustainability, social awareness on environmental issues, policies and regulations.

3. Findings

3.1: Sample information

The study considered the demographic information of the sample such as gender, education, marital status, and ages to profile the nature of the respondents in relation to their information provided. The female education level measured in college level composed by 36.84 percent; primary level composed by 33.05 percent and 39.19 percent in secondary. On the other hand, the male educated in college or university level were about 63.16 percent, primary level composed by 66.95 percent, and about 60.81 percent were educated in secondary levels. In general, the female who at least has a primary education level were about 55.15 percent. Moreover, it evidenced that a sample composed by 52.61 percent of respondents with ages of 18-30 years, about 21.80 percent of ages of 31-40 years, about 16.11 percent of ages 41-50 years, about 7.11 percent of ages of 51-60 years, and 2.4 percent were respondents of ages of 61-70 years. On the other hand, about 33.18 percent and 62.56 percent of respondents were single and married respectively, and the rest were divorced and separated which composed 3.3 percent. The lesson learned through this demographic information of respondents is that a study involved the relevant respondents as composes a broad range of education, ages and marital statuses.

3.2 Evaluation of data quality measures

The internal consistency reliability was measured by using rho-A coefficient as suggested by Dijkstra and Henseler (2015) that is more precise measures of internal consistency reliability than others. This study evidenced that questionnaires have the higher internal consistency reliability since its rho-A coefficients were above 0.90 which indicate a tool was reliable (Table 1). Furthermore, the study examined the convergent validity of each construct measure. The convergent validity was measured by using average variance extracted (AVE) for all items on each construct. An acceptable AVE is at least 50 percent, which indicates that at least 50 percent of the variance of its items (Hair, Risher, Sarstedt and Ringle, 2019). The AVE of this study ranges from 0.863 to 0.925 (Table 1).

Table1: Construct Reliability and Validity

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Demo	0.946	0.929	0.974	0.882
Ecofa	0.956	0.948	0.971	0.919
Envi	0.933	0.955	0.980	0.925
Hube	0.920	0.932	0.950	0.863

Source: Analysed field data (2021).

The table 1 shows the construct reliability and validity for latent constructs. The internal consistency reliability was measured by using Cronbach's alpha, rho-A and composite reliability. Specifically, the convergent validity was measured by using average variance extracted (AVE).

Furthermore, the discriminant validity of latent constructs was examined by using Heterotrait-Monotrait (HTMT) as recommended by Henseler, Ringle and Sinkovics (2009).The recommended cut-off is 90 percent for the conceptually similar items and 85 percent for non-conceptually similar items (Hair et al. 2019). The HTMT ratio of this study ranges from 0.277 to 0.674 which indicate the absence the discriminant validity problems (Table 2).

Table 2: The Heterotrait-Monotrait Ratio (HTMT) for latent constructs

	AGDP	Demo	Ecofa	Envi
Demo	0.674			
Ecofa	0.544	0.394		
Envi	0.277	0.429	0.298	
Hube	0.390	0.311	0.338	0.438

Source: Analysed field data (2021).

The table 2 shows the Heterotrait-Monotrait (HTMT) ratio of the latent constructs. The table evidenced the absence of the discriminant validity problems as all HTMT ratios are less that 0.85 or 0.90 as recommended by (Hair et al. 2019).

3.3 Descriptive statistics

The descriptive statistics for exogenous and endogenous variables were provided. The mean, standard deviation and minimum and maximum were explained (Table 3).

Table 3: The mean, standard deviation and minimum and maximum

```
. sum AGDP Demo Envi Hube Ecofa

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
        AGDP |        211    1.627217    .7928693      .2832      4.992
        Demo |        211    .6264498    .1853113       .185       .985
        Envi |        211    .6727057     .203334       .211          1
        Hube |        211    .7198768    .1525275       .201          1
       Ecofa |        211    .7047915    .1760979       .201          1
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Source: Analysed field data (2021).

The table 3 shows descriptive statistics for exogenous and endogenous variables for the sampled data from Mwanza and Kagera regions. The average GDP per capita was 1.6272 TZS millions, with a minimum and maximum of 0.2832 TZS millions to 4.992 TZS millions respectively. The sample has a minimum variation multiplier factor (MIVMF) of the economic growth of 17.63 times or a maximum variation multiplier factor (MAVMF) of 0.0567 times. The MAVMF is defined as a ratio of the maximum value (numerator) and minimum value (denominator) of variables. The MAVMF is the reciprocal of MIVMF (That is, MAVMF = 1/ MIVMF or min/max). It measures the distance-frequency of values of variable from the lowest earners to the highest earners. This is very important in decision making as indicates inequality distance among the sample or population. The value higher than one is an undesirable for MIVMF, and the value nearest to one for MAVMF is desirable. Clearly, MIVMF provides information that how many times or numbers of frequency of the current value or level of the variable to meet the maximum values. Therefore, it measures a forward distance frequency. On the other hand, MAVMF provides information that how many times or number of frequency of the current value or level of variables to meet the minimum value. Therefore, it measures a backward distance – frequency. Strictly, MAVMF ranges from 0 to 1(min/max), and MIVMF ranges from 1 to infinite (max/min).

Moreover, the mean score of Demo was 0.6264, with minimum and maximum values of 0.185 and 0.985 respectively. The MIVMF of the sample was 5.3243 times, indicating that the current Demo score of the lowest scorer requires 5.3243 frequencies to reach a maximum score. On the other hand, MAVMF of 0.1878 times indicates that 18.78 percent of maximums scores represent the minimum scores. Hence, a sample population has a high variation of Demo. The mean score of Envi was 0.6727, with minimum and maximum values of 0.2110 and 1.00 respectively. Therefore, the MAVMF and MIVMF were 0.2110 times and 4.7393 times respectively. This also indicates the higher variation of the Envi score as about 21.10 percent of the maximum value of Envi represents the minimum values of Envi in the sample population. Moreover, Hube has a mean score of 0.7199 with minimum and maximum values of 0.2010 and 1.00 respectively. Similarly, Ecofa has a mean score of 0.7048, with minimum and maximum values of 0.2010 and 1.00 respectively. Both Hube and Ecofa have the same maximum and minimum values, therefore they have also the same MIVMF and MAVMF values. The MIVMF and MAVMF of Hube and Ecofa were 4.9751 times and 0.2010 times respectively. The same facts evidenced that Hube and Ecofa varied significant in the sample population as about 20.10 percent of the maximum values represent the minimum values in the sample.

3.4 Finite Mixture (FIMIX) Models

Traditionally, most of researchers assume that data are sampled from the uniform population that share a lot of similarities. But in reality, most of the samples are drawn from the heterogeneous population; there are subpopulations within the population that may affect the generalisation of the findings. Individuals from the same population may be highly differ in marital status, lifestyle and status, education level, income level or economic status and social or psychological aspects. To understand this, FIMIX models which are proposed by Hahn et al. (2002) were applied to reveal unobserved heterogeneity in the sampled population in Mwanza and Kagera regions. For examining the characteristics of classes of Mwanza and Kagera regions population the linear relationship between the average economic growths per capita (AGDP) and latent variables Demo, Envi, Hube and Ecofa was established. The finite mixture models (FMM) and FIMIX-PLS established two classes or subpopulations. In a class one of the sample population, the economic growth was significantly positively influenced by only Demo and Hube (Table 4).

Table4: The finite mixture regression model for class one in Mwanza and Kagera regions

Class : 1
Response : AGDP
Model : regress

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
AGDP						
Demo	1.597675	.2738457	5.83	0.000	1.060948	2.134403
Envi	.0607458	.2271347	0.27	0.789	-.38443	.5059217
Hube	.9595088	.2856851	3.36	0.001	.3995763	1.519441
Ecofa	.1083678	.2602061	0.42	0.677	-.4016268	.6183625
_cons	-.3318422	.2305561	-1.44	0.150	-.7837238	.1200394
var(e.AGDP)	.2036201	.0289071			.1541626	.2689442

Source: Analysed field data (2021).

The table 4 shows the finite mixture regression model for class one in the Mwanza and Kagera regions. The linear regression model evidenced that Ecofa and Envi have a non significant positive impact on economic growth. The key lesson to draw in this class is that the economic growth is the most sensitive on Demo and Hube. In this group, the maximization of the individual's psychological well-being and demographic characteristics improve the economic growth. On the other hand, the psychological environmental and economic factors are not important factors in this class. In the class two, only Demo and Ecofa have a significant positive impact on economic growth (Table 5).

Table 5: The finite mixture regression model for class two in Mwanza and Kagera regions

Class : 2
Response : AGDP
Model : regress

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
AGDP						
Demo	2.61613	.5718064	4.58	0.000	1.49541	3.73685
Envi	-.7899568	.5863799	-1.35	0.178	-1.93924	.3593267
Hube	1.183294	.871284	1.36	0.174	-.5243911	2.89098
Ecofa	2.863355	.8723924	3.28	0.001	1.153497	4.573213
_cons	-1.703381	.6579131	-2.59	0.010	-2.992867	-.4138952
var(e.AGDP)	.1973082	.0814934			.0878166	.4433162

Source: Analysed field data (2021).

The table 5 shows the finite mixture regression model for the class two in Mwanza and Kagera regions. The model in class two indicates that Hube has a non-significant positive impact on economic growth and Envi has a non-significant negative impact on economic growth. It has a negative coefficient of -0.7899, z-score of -1.35, p-value of 0.178. Therefore, it statistically accepted that Envi has no significant impact on economic growth. Hube has non-significant positive coefficient of 1.1833, z-score of 1.36, with p-value 0.174. Therefore, it accepted that Hube has no significant positive impact on economic growth. The lesson drawn from this class, that is, the economic growth does not influenced by the psychological well-being (Hube) and Envi. For more clarity, the proportion of the individuals in each class was established by examining the latent class marginal probabilities (Table 6).

Table 6: Latent class marginal probabilities (LCMP) for finite mixture regression model

Latent class marginal probabilities Number of obs = 211

	Margin	Delta-method Std. Err.	[95% Conf.	Interval]
Class				
1	.8287787	.0598184	.6793517	.9170709
2	.1712213	.0598184	.0829291	.3206483

Source: Analysed field data (2021).

The table 6 shows the LCMP of finite mixture regression models. The class one composes about 82.88 percent of individuals in sample populations. The class two has a proportion of individuals about 17.12 percent of the sample population. To understand which group or class belong to the higher or lower economic growth, the latent class margin means (LCMM) was established. The LCMM estimates the means of margins of the latent class on the economic growth (Table 7).

Table7: Latent Class Marginal Means of the finite mixture regression model

Latent class marginal means Number of obs = 211

	Margin	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
AGDP	1.47699	.0481147	30.70	0.000	1.382687	1.571293
2						
AGDP	2.273979	.1752024	12.98	0.000	1.930588	2.617369

Source: Analysed filed data (2021).

The table 7 shows the latent class margins means of finite mixture regression models on the economic growth. The class one has an average margin of 1.477 TZS millions which ranges 1.3827 TZS millions to 1.5713 TZS millions. The class two has an average margin mean value of 2.274 TZS millions, which ranges from 1.9306 TZS millions to 2.6174 TZS millions. The LCMM evidenced that the class two has a higher margin mean than a class one. This means that, it is about 17.12 percent of the population that have about 2.27 TZS millions per capita in Mwanza and Kagera regions.

The model selection was done by using the Bayesian information criterion (BIC). The BIC analysis evident that the class one has a BIC value of 411.5946 and the class two has a BIC value of 412.2069. The values enable the selection of both models as their values were almost equal (Table 8).

Table 8: The Bayesian information Criterion of the finite mixture regression model

Bayesian information criterion

Model	N	Type	ll(model)	df	BIC
fmm1	211	user-specified	-189.7417	6	411.5946
fmm2	211	user-specified	-171.3164	13	412.2069

Source: Analysed field data (2021).

The table 8 shows BIC values for class one and class two. The two classes or subpopulations were selected as BIC values of both classes were almost equal. Therefore, both classes were relevant and kept for further analysis (ex post analysis). The fit indices for the FIMIX –PLS structural model was established to particularly to describe the entropy statistics (Table 9).

Table 9: Fit indices of the FIMIX-PLS structural model

AIC (Akaike's Information Criterion)	4728.721
AIC3 (Modified AIC with Factor 3)	4757.721
AIC4 (Modified AIC with Factor 4)	4786.721
BIC (Bayesian Information Criteria)	4825.925
CAIC (Consistent AIC)	4854.925
HQ (Hannan Quinn Criterion)	4768.012
MDL5 (Minimum Description Length with Factor 5)	5446.740
LnL (LogLikelihood)	-2335.360
EN (Entropy Statistic (Normed))	0.681
NFI (Non-Fuzzy Index)	0.736
NEC (Normalized Entropy Criterion)	67.315

Source: Analysed field data (2021).

The table 9 shows the fit indices of the finite mixture models in PLS –SEM. The fit indices established by PLS-SEM indicate that the only two classes as the separation statistic – the entropy statistics which is 0.681 is above the recommended value of 0.50 (Hair et al. 2015). Moreover, the loglikelihood (LnL) of -2335.360 is maximum at the two classes, and Aikaike's Information Criterion (AIC), modified AIC with factor 3 and 4 (AIC3 and AIC4) are optimal at two classes. More important, the non-fuzzy index (NFI) is 0.736 which is greater than a recommended threshold of 0.50. This means that the separation of two classes does permit unambiguous classification (Hair et al. 2016).

3.5 Ex Post analysis of FIMIX models

The ex post examination was done to reveal more uncovered heterogeneity in classes or subpopulations identified. The membership –probability sorting (MPS) method was used to identify the nature of heterogeneity of the population sample. The probability of the final partition was sorted relatively to variables. This method helped to understand the actual numbers of members of each class and it facilitated a researcher to examine the specific features or behaviour of each class. Consequently, the size of each class in terms of number of members composed was established in each region (Table 10).

Table 10: The mean scores of exogenous and endogenous variables of classes of population

	Class 1 (Low Economic Growth)			Class 2 (High Economic Growth)		
	Kagera	Mwanza	Total	Kagera	Mwanza	Total
Size	57 (40.4%)	84(59.6%)	141	43 (61.4%)	27(38.5%)	70
AGDP	0.8632	1.6298	1.5081	1.789	2.9739	2.4465
Demo	0.5340	0.5564	0.5474	0.7562	0.8328	0.7858
Envi	0.5884	0.6445	0.6218	0.7584	0.8020	0.7752
Hube	0.6520	0.7408	0.7049	0.7477	0.7536	0.750
Ecofa	0.661	0.6530	0.6563	0.8009	0.8052	0.8026

Source: Analysed Field data (2021).

The table 10 shows mean scores of exogenous and endogenous variables in FIMIX-PLS. The class one is a group of respondents that are characterised with a low economic growth and low psychological resources. The within group analysis or in-class analysis in class one, Mwanza respondents have the higher economic growth and higher FPFH scores, which indicates that they are more economically better and happier than Kagera respondents within their class status. The same facts was traced or evidenced in the group or class two where the averaged economic growth in Mwanza region was greater than that of Kagera region. In connection to that, the mean scores of FPFH were higher than that of Kagera region; this also evident that the residents or respondents of Mwanza region are economically better and happier than the residents of Kagera region.

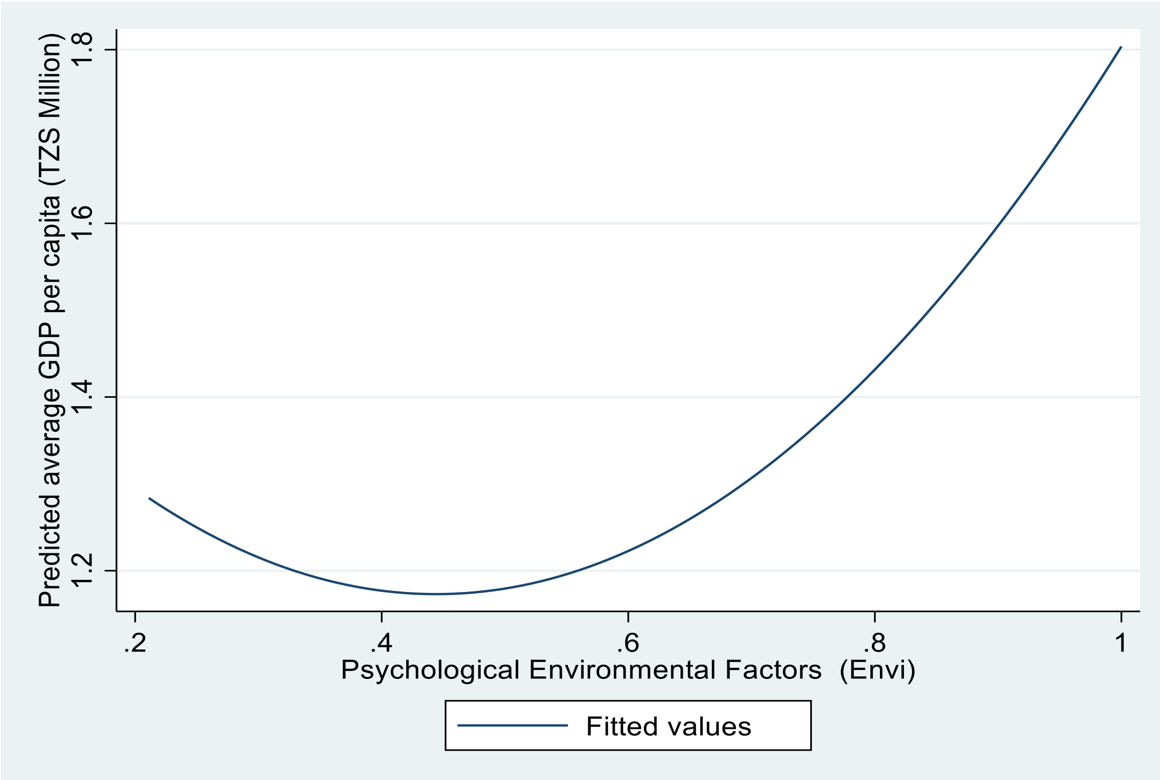
In the class one, which is characterised by a low economic growth and a low mean score of the FPFH, Kagera residents composed by 40.4 percent of the sample population. The class has an annualised income of 0.8632 TZS millions per capita which is below the annualised class mean income of 1.5081 TZS millions per capita. Moreover, Mwanza residents composed by 59.6 percent of the sample population; it has annualised income of 1.6298 TZS millions per capita which is above the annualised class mean income of 1.5081 TZS millions per capita. This can be interpreted that, the class one is dominated by the residents of Mwanza region by 59.6 percent. In the class two which is composed by 33.18 percent of total respondents, about 61.4 percent of respondents were sampled from Kagera region and have the annualised mean income of 1.789 TZS millions per capita which is less than annualised class mean income of 2.4465 TZS millions per capita. On the other hand, the Mwanza region composed by 38.5 percent has the annualised mean income of 2.9739 TZS millions per capita which is above the annualised class mean income of 2.4465 TZS millions per capita.

In general, it is observed that there are two main classes of the sample population. More evidenced that the class one is the class that composed by respondents from Mwanza region which are about 59.6 percent. The class has a higher annualised income than the annualised class mean income. This class is classified as the class with a low annualised income of 1.50 TZS millions per capita. In connection to that, the class is characterised with lower factors of happiness scores than in the class two. On the hand, the class two is characterised with a higher economic growth above the annualised mean income of 1.50 TZS millions per capita. This class composed by 61 percent of Kagera region, but it has the less annualised mean income than the annualised class mean income. In this class, the residents were earning more than 1.50 TZS millions in average. The within –class analysis revealed that Mwanza region has the higher economic growth and mean score of FPFH in each class. Therefore, it confirmed that living in Mwanza region is economically better and happier than living in Kagera region. This statement can be stated as far as an individual living in Mwanza region would have a high economic opportunity and happiness than living in Kagera region.

4. Discussion of the results

The paper aimed to uncover the unobserved heterogeneity of the sample population from Mwanza and Kagera regions. The general question asked by a researcher is if living in Mwanza region is more economically better and happier than living in Kagera region. The finite mixture model (FMM) and FIMIX-PLS models were used. The study revealed that the population of Mwanza and Kagera regions have two major classes or subpopulations which are class one composed by individuals who their annual earnings are less or equal to 1.50 TZS millions. This class or subpopulation characterised with the lower happiness in comparing to the class two. The economic growth in this class is activating by Demo and Hube. Envi and Ecofa have an insignificant positive impact on economic growth. The latent class margin probabilities (LCMP) of the class one is 82.88 percent of the sample population.

The class one evidenced to be economically efficient on Demo and Hube but not on Ecofa and Envi because Demo and Hube are more significant in a linear relationship with economic growth than in non-linear relationship which it is vice versa for Envi and Ecofa. Envi and Ecofa have more significant impact on a non-linear relationship (quadratic or higher degree polynomial function) than in the linear relationship with economic growth (Fig. 1 &2).

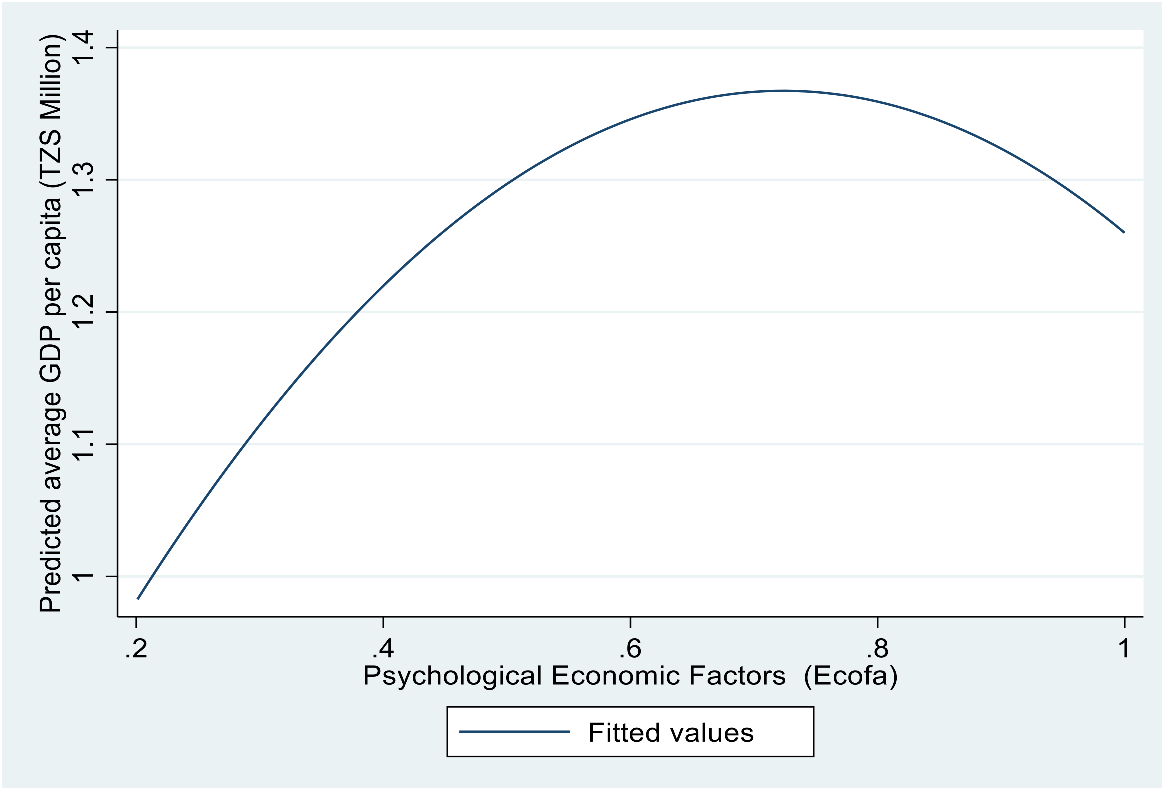


Source: Analysed field data (2021).

Fig.1: The non-linear relationship between economic growth and Envi in class one

The figure 1 shows the relationship between economic growth and Envi. The figure indicates the U-shaped relationship. The implication of the U-shaped relationship of variables is that, at the low level of psychological awareness of the individual on environmental issues, the economic activities tend to be negatively related to psychological environmental factors. At the Envi scores between 0.4 and 0.6 an individual starts to get a substantial psychological awareness on environmental issues and the economic activities starts to grow with the increase of the Envi score, but it is not significant at this level. The class one population is characterised with low Envi about 0.6218, which is between the “take off –point”, the score from 0.40 to 0.60. That is why the Envi has a positive impact on economic growth in class one but it is not significant. From this fact, the Envi above the cut-off value of 0.60 has a significant positive impact on economic growth.

On the other hand, the nature of the relationship between economic growth and psychological economic growth (Ecofa) is represented by inverted U-shaped relationship in the class 1 population (Fig. 2).

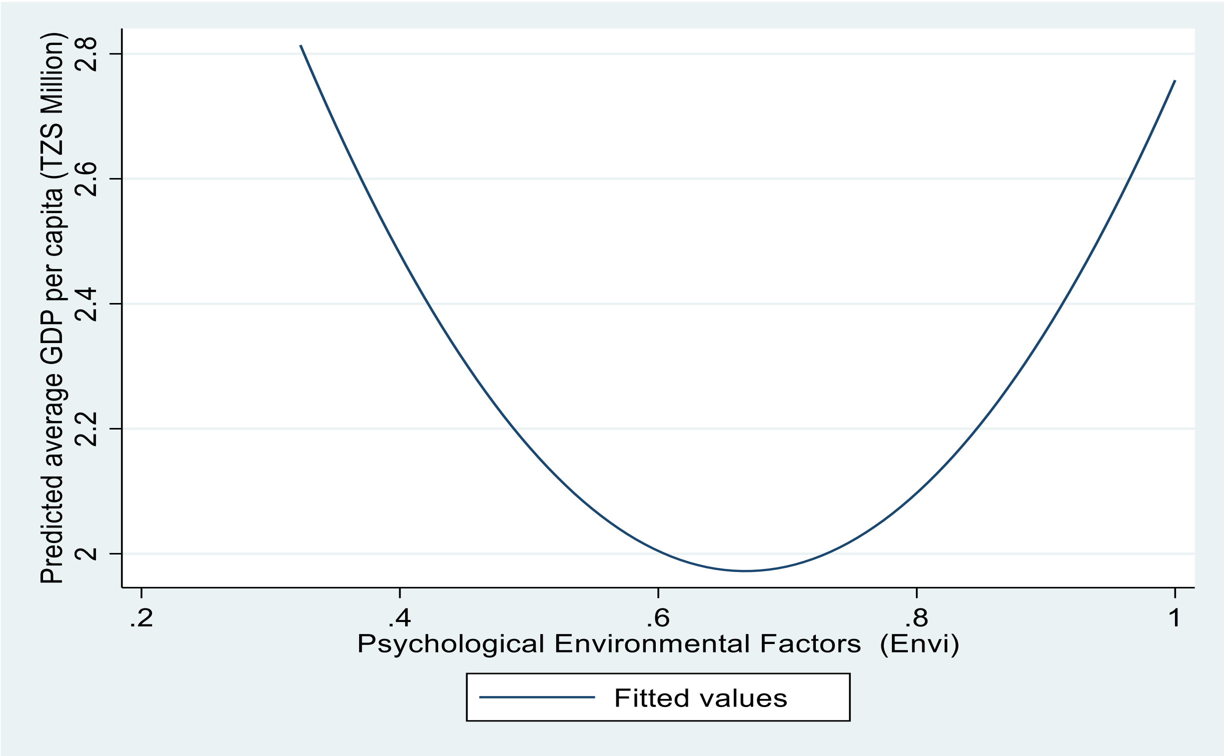


Source: Analysed field data (2021)

Fig. 2: The non-linear relationship between economic growth and Ecofa in class 1 population

The figure 2 shows the invested U-shaped relationship between the economic growth and psychological economic factors (Ecofa). The inverted U-shape signifies the concavity function of economic growth and psychological economic factors. The concavity function has its optimality value of its inputs. In clear interpretation of the concavity function follows three stages of growth which characterised with a positive slope (profit) at the first stage (early and positive accelerated growth), zero slope at the second stage(maturity growth, no acceleration growth), this stage is a breakeven point. The last stage is declined stage that is characterised by a negative slope (loss or deceleration growth). Therefore, the inputting of variable (Ecofa) above the maturity cut-off value (0.60) will result to either a zero slope or a negative slope (loss). At class one population, the average value of Ecofa is 0.6563 which is above the maturity value of 0.60. Therefore, at this value of 0.6563 of Ecofa the growth is just starting to decelerated, i.e., the impact is positive but is very minimal and accelerating to negative impact. Logically, the level of Ecofa is determining the degrees of risk aversion in economic decisions, therefore should be kept minimal less than 0.60 for individual to have entrepreneurial attributes. For example, the positive psychological affect of prices of commodities should be limited to avoid the misused of the resources in both micro and macro-economic planning. This finding confirmed the Schoemaker (1980) who explained the nature of production function that describes the concavity nature of the cardinal utility function.

On the other hand, the class two or subpopulation two in the sample population in Mwanza and Kagera regions composed by 17.12 percent of individuals in the sample population. In this class, the economic growth is activated by Demo and Ecofa. Hube and Envi have no significant impact on economic growth. This class has a latent class margin means (LCMM) of 2.45 TZS millions. Envi and Hube have an insignificant linear impact on economic growth but they have significant non-linear impact on economic growth (Fig. 3 &4).

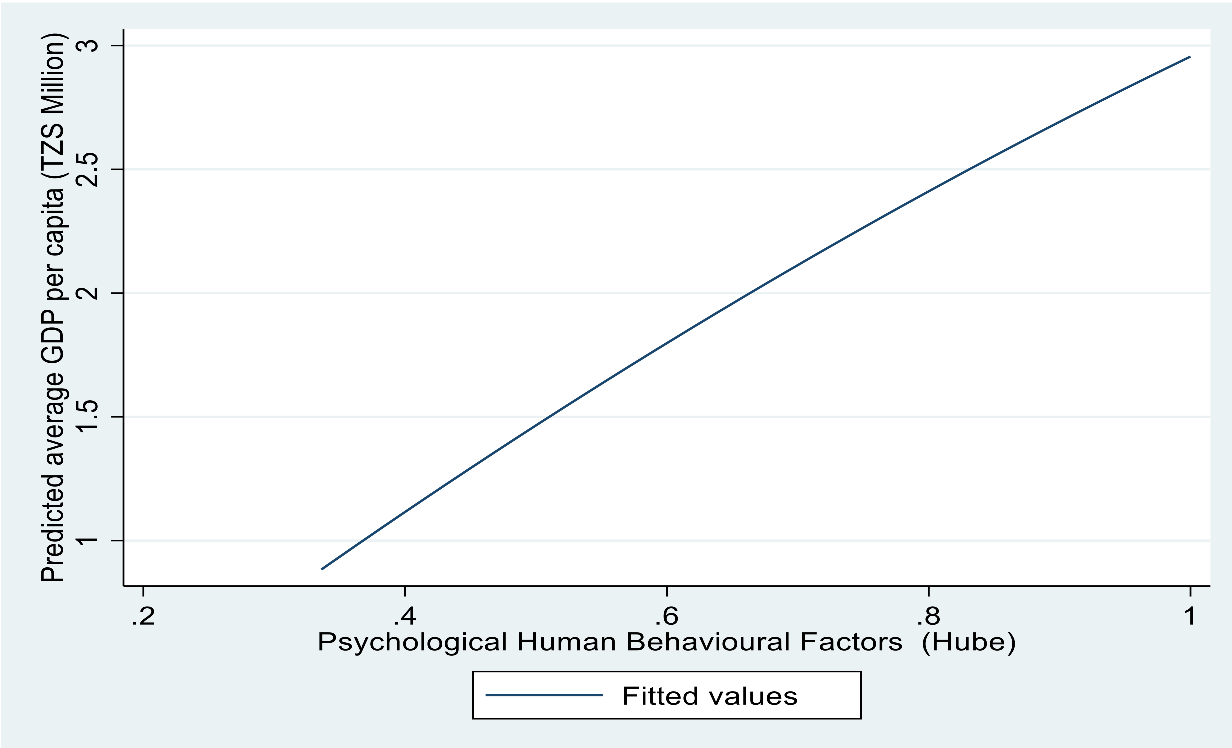


Source: Analysed field data (2021).

Fig. 3: The non-linear relationship between economic growth and Envi in class two

The figure 3 shows the U-shaped relationship between economic growth and psychological environmental factors (Envi). The same implications of the U-shape or convexity behaviour of the psychological environmental factors (Envi) on economic growth as the same as explained in the class 1. Specifically, in this class, the average value of Envi is 0.7752 which is at the negative impact on the economic growth. From this evidence, the value of Envi equal or more than 0.80 has a significant positive impact on economic growth in the population with a high economic growth (class two).This finding supported by Everelt, Ishwaran, Ansaloni and Rubin (2010) who evidenced the negative relationship between economic growth and environmental policy in short –run. Moreover, the study contradicted to Kuznets (1955) and Malcolm and Nicholas (2015) who evidenced the inverted U-shaped relationship between economic growth and environmental quality management.

Moreover, the significant positive linear relationship between economic growth and Hube in the class one population was confirmed. The class is characterised with low Hube scores. On the other hand, in the class two where Hube scores are higher than that of class one, the significant positive linear relationship between economic growth and Hube is not evidenced. Therefore, the non-linear relationship was examined. The non-linear relation between economic growth and Hube is evidenced by a positive sloping-half concavity curve (Fig. 4).



Source: Analysed field data (2021)

Fig. 4: The non-linear relationship between economic growth and Hube in class two

The figure 4 shows non-linear relationship between economic growth and psychological human behavioural factors (Hube) in class two populations. The implication of this nature is as far the Hube score increases, its slope (impact) decreases, hence become not significant, the slope increment is becoming lesser and lesser as the Hube score increases. The mean score of the Hube in the class two populations is 0.750 which is above the cut-off value of 0.60.

On the other hand, the ex post analysis revealed that about 59.6 percent of individuals in class one population have annualised income higher than the annualised class mean income of 1.5 TZS millions and their factors for happiness are higher than that of Kagera region. This can be interpreted that in the class one population, the individual who resides in Mwanza region are more economically well-off and happier than who lives in Kagera region. Moreover, in the class two populations, the Mwanza region residents have an annualised income above the annualised class mean income of 2.45 TZS millions per capita, and their factors for happiness are higher than that of Kagera region. This also, implicates that Mwanza region residents are more economically well-off and happier than who live in Kagera region. Therefore, it is empirically evidenced that the place or country that has a higher income they experiences higher degrees of happiness. This study confirmed the study by Stevenson and Wolfer (2008; 2013), Roka (2020) and others. Notably, both classes evidenced that residents of Mwanza region have a higher annualised income and experience a higher degree of happiness than the residents of Kagera region.

5. Conclusion and policy implication

In conclusion this study found that the population of Mwanza and Kagera region can be grouped into two mains subpopulation or classes. The class one is characterised with the lower annualised income below 1.50 TZS millions per capita and have the lower score of FPFH in comparing to the class two; it composed by 82.88 percent of the sample population. In this class the individual sampled from Mwanza region found to have a higher income and are happier than the individuals sampled from Kagera region. In the class two, which composed by 17.12 percent of the sample population is characterised with higher annualised income of 2.45 TZS millions per capita. This class has a higher score of FPFH in comparing to that of class one. It is evidenced that, the class two, the individuals sampled from Mwanza region have a higher annualised income and happiness than that of sampled from Kagera region. Therefore, the study concluded that living in Mwanza region is more economically better and happier than living in Kagera region. Moreover, the countries with a higher level of "hand" or close individual incomes are experience a high degree of happiness than those countries with a lesser level of hand or close individual incomes. A hand or close individual income is the income that earned direct or indirect by an individual at the family level from legal sources. Notably, the individual income if is measured by the GDP per capital will result to the Easterlin paradox (Easterlin, 1973; 2017; Li and Shi, 2019; Stevenson and Wolfer, 2013).

The study implicated the economic policy in two ways. First, the study recommended the regional or internal immigration that would increases the economic opportunity and reduces the economic performance inequality in a country. Specifically, the immigration from Kagera region to Mwanza region or nation to nation is encourage because would increase the probability of getting a higher income and happiness, instead of living in Kagera region or in a nation with a lesser individual hand incomes as evidenced by this study. Second, the study recommended the increases of environmental awareness on economic issues by establishment the legalised national days for planting and cleanliness because the study evidenced the low score of Envi in Tanzania which severely hurts the economic growth in a country. Moreover, further study is recommended by using a panel data to attest the posed facts as this study limited to cross-sectional data.

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