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Determinants of Poverty of Households in Rwanda: An Application of Quantile Regression

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ABSTRACT Eradication of poverty is the main objective of most societies and policy makers, but developing a perfect or accurate poverty assessment tool to target poor households, in most cases, is a challenge for applied policy research. In this paper, the principal component analysis was first used to create an asset index for each household and thereafter the quantile regression model was used to identify the determinants of poverty of households in Rwanda. The characteristics of households as well as household heads were considered. Data from the Rwanda Demographic and Health Survey (2010) was used as application. The findings showed that education level, gender and age of household head, province, size of the household and place of residence were significant predictors of poverty of households in Rwanda. The quantile regression model allowed the researchers to study the impact of predictors on different desired quantiles of the asset index, and thus to get a complete picture of the relationship between the asset index and predictor variables.

INTRODUCTION

Eradication of poverty is an important objective of many societies and policy makers, but developing a perfect or accurate poverty assessment to target poor households, in most cases, is a challenge for applied policy research. The measurement and analysis of poverty have classically been done based on income and consumption or expenditure in developing countries. However, collecting data on income and expenditure can be time consuming and expensive (Vyas and Kumaranayake 2006). Furthermore, in low-income countries, measurement of consumption and expenditure is fraught with difficulties such as problems of recall and reluctance to divulge information. Moreover, prices are likely to differ substantially across times and areas, necessitating complex adjustments of the expenditure figures to reflect these price differences (Deaton and Zaidi 1999). Sahn and Stifel (2003) studied the theoretical framework underpinning household income or expenditure as a tool for classifying socio-economic status (SES) in developing countries. Various researchers (Filmer and Pritchett 1998, 2001; Montgomery et al.2000; Lokosang et al. 2014) used Principal Component Analysis (PCA) to create an asset index using the demographic health survey variables such as durable goods, source of drinking water, toilet facilities and housing quality to describe the household welfare, instead of using a household's income or expenditure.

There are many other methods in literature used to compute the weights of an asset index other than PCA. For instance, multiple correspondence analysis (MCA), multivariate regression, factor analysis and inverse of the proportion of households that own a particular asset. MCA is analogous to PCA, but is used for discrete data (Galbraith et al. 2002). Whilst this method does not remove the complexity and unfamiliarity of PCA, nor the problem of first dimension explaining the small proportion of the total variance, it is appropriate for the analysis of the categorical data commonly collected on most assets. Booysen et al. (2008) used MCA to construct wealth indices for seven sub-Saharan African countries and found that the index was very highly correlated with one constructed using PCA. They also showed that the weights assigned to index items by the two methods were generally similar. With multivariate regression, dimensionality reduction is accomplished by simply choosing which variables to leave out, at the expense of ignoring some dimensions of the data. Factor analysis was used by Sahn and Stifel (2003) and has a similar aim to PCA, in terms of expressing a set of variables into a smaller num-

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ber of indices or factors. The only difference between PCA and factor analysis is that while there are no assumptions associated with PCA, the factors derived from factor analysis are assumed to represent the underlying processes that result in the correlation between the variables. The main problem of the factor analysis method is that not all the assets show a linear relationship with living standards. PCA is the most frequently used method because it is computationally easier, it can use the type of data that can be easily collected in household surveys (Vyas and Kumaranayake 2006), and use all of the variables in reducing the dimensionality of the data (Jobson 1992). However, it is not explicit when interpreting the asset index as a poverty measure since its effectiveness depends on the choice of asset used. PCA, as in the case of other statistical methods, has both advantages and disadvantages. The main challenge of PCA based indices is to ensure that the range of asset variables used is broad enough to avoid problems of clumping and truncation. Once these specific problems are identified, one of the solutions is to include additional variables that capture inequalities between households (McKenzie 2005). The World Bank, in its series on socioeconomic differences in health, nutrition and population, has also constructed PCA based asset indices using Demographic and Health Survey (DHS) data.

Many studies have been done on the determinants of poverty, but most of them used consumption and expenditure and logistic regression as their primary analysis (Mok et al.2007; Rodriguez and Smith 1994; Achia et al.2010; Habyarimana et al. 2015). Others used consumption and expenditure and censored quantile regression (Jalan and Ravallion 2000; Muller 2002). Muller (2007) studied the determinants of poverty of households in Rwanda using consumption and expenditure to create the poverty index from a sample of 270 rural households. Muller's study used the data collected before the 1994 genocide in Rwanda. Accordingly Muller's findings may be irrelevantin post genocide Rwanda. For this reason, it is imperative to carry out a large scale survey with sound and advanced statistical analyses. The current paperfocused on application of PCA to compute the asset index of households in Rwanda and thereafter used the quantile regression model to identify the key determinants of poverty of households in Rwanda. There is no study in literature using the asset index from Rwanda Demographic and Health Survey (RDHS) data and quantile regression as primary tools of analysis. The findings of this paper will endeavour to contribute to identifying the key factors of poverty of households in Rwanda and hence contribute to the Economic Development and Poverty Reduction Strategy of Rwanda.

Source of Data

The RDHS (2010) was completed in two stages. In the first stage, 492 villages (known as clusters or enumeration areas) were considered with 12540 households, of which 2009 and 10531 were urban and rural, respectively. Secondly, systematic sampling was used to select households in the selected villages. All women and men aged between15-49 and 15-59 years respectively, were eligible to be interviewed. The survey included various types of questionnaires such as for households, men and women. The researchers used only the household data to identify the factors determining the poverty among households in Rwanda. The questionnaire topics included households' ownership of durable goods, school attendance, source of drinking water, sanitation facilities, washing places and housing characteristics such as building material.

METHODOLOGY

Principal Component Analysis and Computation of Poverty Index

PCA is a multivariate statistical technique that linearly transforms an original data set of variables into a substantially smaller set of uncorrelated variables that represent most of the information in the original set of variables (Jackson 1991; Lewis-Beck 1994; Joliffe 2002; Manly 2004). Let consider $X_1,X_2,...,X_k$,as poverty indicators measured in *m* households, the main objective of the PCA is to take these *k* poverty indicator variables and find their combination to produce indices $Z_1,Z_2,...,Z_k$, that are not correlated and whose variances decrease from first to last (Chatfield and Collins 1981); the Z_k indices produced are then the principal components given by

$$Z_k=b_{k1}X_1+b_{k2}X_2+...+b_{kk}X_k=b^t_k X \quad (1)$$

where $b^t_k = [b_{1k},...,b_{kk}]$ are vectors of the scoring factors or weights. The coefficients of principal components are chosen such that the first component Z_1 accounts for as much of the variation in the original data as possible, subjected to the constraint that the sum of the squares of the scoring factors (or weights) is equal to 1. The second component is completely uncorrelated with the first component, and explains additional but less variation than the first component, subject to the same constraint of the sum of the squares of the scoring factors equal to 1. The subsequent components are uncorrelated with the previous components; therefore each component captures an additional dimension in the data, while explaining smaller and smaller proportions of the variation of original variables in the data. The remaining components are computed in a similar fashion. The cutoff point for the number of principal components is based on the magnitude of the variances of the principal components. The graphical method, called a scree diagram, uses the steepness of the graph change as a cutoff point.

The first principal component is used as the household's wealth index (Filmer and Pritchett 1998; Manly 2004). The scoring factors for each indicator from this first principal component are used to generate a household score. The assets that are more unequally distributed across the sample will have a higher weight in the first principal component. Asset indices derived from DHS data can be subjected to a number of tests (Filmer and Pritchett 1998). For instance, a good index has to be internally coherent, which means that it has to consistently produce a clear separation across poor, middle and rich households for each asset included in the index. This means that each of the variables included in the index can be compared across households that fall into the poor 40 percent, middle 40 percent and richest 20 percent of the population, based on the asset index. It also has to be robust; that means to produce similar classifications of households or individuals across constructions of asset index based on different subsets of variables (Filmer and Pritchett 2001; Booysen 2002).

Test for Reliability of Asset Index

For Rwanda household questionnaire data, which has 53 variables, PCA analysis scree plot (Fig. 1) shows the cut-off points of two principal components. The internal coherence test is

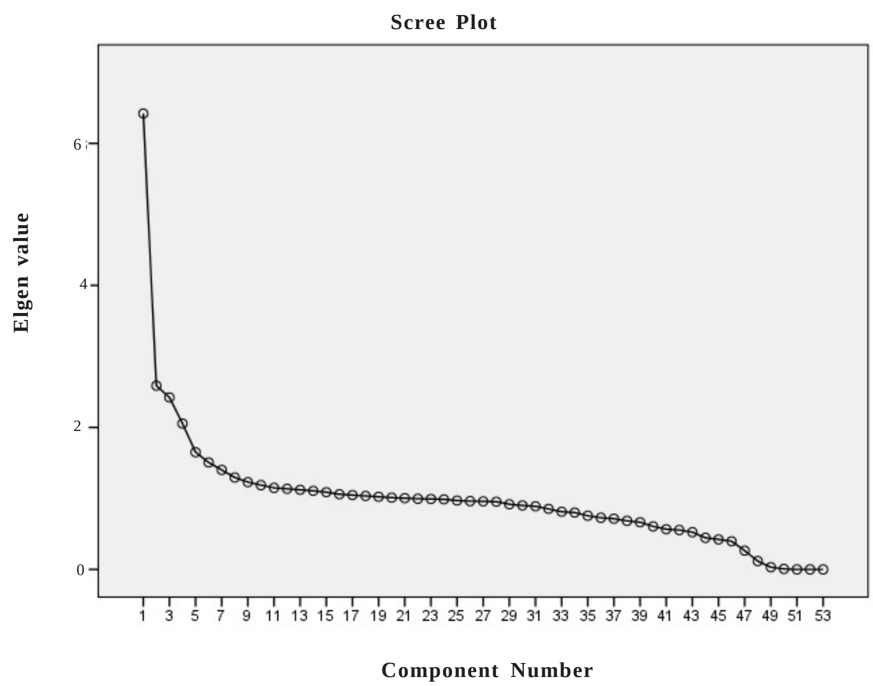

Fig. 1. Scree plot

shown inTable 1, where the last three columns compare the average ownership of each asset across the poor, middle and richest households. The robustness is tested in Table 2 and can be found by comparing the differences between the ranking of the poor 40 percent of the households of the original asset index and their ranking based on the indices constructed using some subsets of different variables. The researchers used 12 variable indicators of durable goods and six variable indicators of housing infrastructure (toilet facilities, wall material, floor material, roof material, source of drinking water and source of cooking fuel). The asset index produced a similar classification when different subsets of variables were used (Table 2). Therefore, this asset index is robust. Table 1 reports the scoring factors of 53 variables and their corresponding percentage in the wealth quintile. Generally, a variable with a positive factor score or weight contributes to higher SES, and conversely a variable with a negative factor score weighs towards lower SES. Usually, the richest households (20% or fifth quintile) have assets with higher factor scores. For instance, 8.1 percent of the richest households have flush toilets whereas 0.0 percent of the poorest or middle households fall into this category; 85.2 percent of the richest households have a cement floor against 0.0 percent of the poorest households and 1.7 percent of middle households; 81.0 percent of richest households have a metal roof against 53.2 percent of middle households and 34.4 percent of poor households. A total of 53.5 percent of fifth quintile households own electricity against 0.8 percent of third and fourth quintile and 0.0 percent of first and second quintile; 86.6 percent of richest households own a mobile phone against 56.6 percent of middle and 3.3 percent of poor households. A total of 9.5 percent of the richest households own a personal computer against 0.0 percent of middle and 0.0 percent of poor households (see Table 1). The higher percentage of poor households (40% or first and second quintile), would have assets with lower scores. For instance, 98.9 percent of poor households own a latrine toilet against 87.3 percent of the richest households. All, or 100 percent, of poor households have earth/sand floors against 94.3 percent of middle households and 10.0 percent of the richest households; 7.7 percent of poor households have a thatch roof against 0.0 percent of the richest households. A majority, 82.1 percent, of poor households use wood as cooking fuel whereas only 44.6 percent of the richest households use wood for cooking; 97.7 percent of poor households own land usable for agriculture against 53.3 percent of fifth quintile (Table 1).

QuantileRegression Model

While both linear and logistic regression estimate how the predictor variables are related to the mean value of the dependent variable, quantile regression allows for studying the impact of predictors on different quantiles of the response distribution, and thus provides a complete picture of the relationship between the response variable and predictor variables. The quantile regression method is robust to extreme points in the response space (outlier) but not to extreme points in the covariate space (leverage points);quantile regression is also a robust method in the sense that it makes no assumption about the distribution of error term in the model. This ability of quantile regression, as introduced by Koenker and Bassett (1978), to characterize the impact of variables on the whole distribution of the outcome of interest motivated the use of quantile regression when assessing the determinants of poverty of households in Rwanda.

Model Formulations

For a random response variable Y with probability distribution function $F(y) = Pr(Y \leq y)$, the θ^{th} quantile of Y is defined as the inverse function $0(\theta)=\inf\{y:F(y)\geq\theta\}$, where $0<\theta<1$(Chen 2005; Koenker and Bassett 1978). Let $X=(x_1,...,x_m)$ be a vector of length m containing household characteristics, environmental (spatial) characteristics and household head characteristics, and let $Y=(y_1,...y_m)$ denote the m observed responses variables. The model for linear quantile regression is given by Hao and Naiman(2007) andKoenker and Bassett (1978) as $v_i,=x,b_0+\varepsilon_i$, with $i=1,2,3,...m;$ where $\beta_\theta=(\beta_{1\theta},...,\beta_{k\theta})$ is the unknown k-dimensional vector of parameters and $\varepsilon_i = (\varepsilon_1,..., \varepsilon_m)$ is the m dimensional vector of unknown errors. The β_θ can be found as the solution of the following minimization problem:

$$\min_{\beta_w \varepsilon R^k} \left[\Sigma_{i\,\varepsilon\{i:yi\geq xi\beta\theta|} y_i - x_i\,\beta_\theta| + \Sigma_i \varepsilon(i:\ y_i<x_i\beta_\theta\,(1-\theta)\ |y_i -\ x_i\beta_w|\right] \tag{2}$$

Table 1: Component scores and classification into wealth quintile

Variable	*Category*	*Mean*	*Standard deviation*	*Components score*	*Poorest 40%*	*Middle 40%*	*Richest 20%*
Toilet Facilities	Flush toilet	.0162	.12628	.465	0.0	0.0	8.1
	Latrine	.9398	.2378	-.262	98.9	92.3	87.3
	Ventilated	.0187	.1355	.075	0.0	2.9	3.7
	Other	.0118	.1080	-.027	0.6	2.0	0.6
Floor Material	Earth/Sand	.7975	.4019	-.736	100	94.3	10.0
	Dung	.0072	.0847	-.004	0.0	1.5	0.6
	Ceramic tiles	.0053	.0726	.339	0.0	0.0	2.6
	Cement	.1770	.3817	.710	0.0	1.7	85.2
	Other	0.130	.1133	.005	0.0	2.5	1.6
Roof Material	Palm leaves	.0458	.2091	-.132	7.7	3.7	0.0
	Rustic/Plastic	.0067	.0813	-.038	0.8	0.9	0.1
	Metal	.5121	.4999	.434	34.4	53.2	81.0
	Ceramic tiles	.4232	.4941	-.383	55.7	41.2	17.6
	Cement	.0016	.1024	.001	1.4	0.9	0.7
	Other						
Wall Material	Dirt	.0449	.2070	-.084	5.6	5.1	1.0
	Bamboo/ stone/ trunks	.3480	.4764	-.235	43.6	37.0	12.7
	Uncovered adobe	.0825	.2751	-.113	9.7	10.3	1.3
	Reused	.2038	.1523	-.039	2.9	2.3	1.6
	Cement	.0016	.0400	.072	0.1	0.1	0.6
	Covered adobe	.3963	.4892	.124	33.2	38.4	54.9
	Other	.0106	.1024	.001	1.4	0.9	0.7
Cooking Fuel	Biogas	.0002	.0127	.016	0.0	0.0	0.1
	Kerosene	.0011	.0335	.078	0.0	0.0	0.6
	Charcoal	.1116	.3149	.763	0.7	3.7	47.0
	Wood	.7512	.4323	-.12	82.1	83.3	44.6
	Straw	.1188	.3236	-.107	16.7	11.4	3.3
	Other	.0035	.0586	.079	0.0	0.5	1.0
Source of Drinking Water	Piped into dwelling	.0510	.2199	.285	0.0	0.0	1.7
	Piped to yard	.2586	.4379	.647	0.0	0.6	24.3
	Public tap water	.0234	.1513	.147	12.6	33.2	37.7
	Borehole	.0249	.1558	-.027	1.7	3.2	2.0
	Protected well	.0187	.1355	-.032	2.4	2.7	2.2
	Unprotected well	.3770	.4846	-.054	2.3	1.9	0.9
	Protected spring	.1409	.3479	-.288	2.4	32.3	19.1
	Unprotected spring	.0835	.2767	-.157	18.3	14.4	5.0
	River/dam/lake	.0039	.0619	-.085	9.6	9.7	3.1
	Rain water	.0014	.0380	-.009	0.3	0.5	0.3
	Bottled	.0133	.1146	.139	0.0	0.0	0.7
	Other	.0039	.0626	.55	0.3	1.6	2.9
Ownership	Has electricity	.1100	.3130	.804	0.0	0.8	53.5
	Has radio	.6300	.4830	.287	38.7	75.2	87.4
	Has television	.0600	.2410	.760	0.0	0.1	30.8
	Has bicycle	.1500	.3550	.065	4.8	21.8	20.9
	Has motorcycle	.2300	.4220	.194	0.0	0.2	5.1
	Has watch	.0100	.1050	.293	6.8	30.9	40.6
	Has refrigerator	.0200	.1250	.569	0.0	0.0	7.9
	Has car/truck	.0100	.1030	.471	0.0	0.0	5.4
	Has mobile phone	.4100	.4920	.503	3.3	56.6	86.6
	Land for agriculture	5700	.4950	-.463	97.7	77.3	53.3
	Livestock	.8100	.3950	-.196	60.4	59.6	43.7
	Has compute	.0200	.1360	.562	0.0	0.0	9.5

Table 2: Difference in the classification of the households on the original index two assets indexes constructed from different sets of variables

	Index with 12 asset ownership variables		
Full asset index	*Bottom 40%*	*Middle 40%*	*Richest 20%*
Bottom 40%	83.5	16.5	0.0
Middle 40%	11.5	74.7	13.5
Richest 20%	4.5	25.5	70.5
Index with 6 housing infrastructure variables			
Full asset index	*Bottom 40%*	*Middle 40%*	*Richest 20%*
Bottom 40%	83.5	16.5	0.0
Middle 40%	11.5	74.7	13.5
Richest 20%	4.5	25.5	70.5

In particular, when θ=0.5 the quantile regression reduces to the median regression.

If the weights are specified as w_i, $i = 1,2,...,m$, therefore the weighted quantile regression of equation(2) can be written as

$$\min_{b_w \varepsilon R^k} \Big[\Sigma_{i\,\varepsilon\{i:yi>xi\beta w} \; w_i\,\theta|y_i - x_i\,\beta_\theta| \qquad (3)$$
$$+ \; \Sigma_i\varepsilon(y_i<x_i\beta_w \; w_i\,(1\text{-}\theta)\;|y_i - x_i\beta_w|\Big]$$

Model Fitting

As the RDHS data was collected using multistage sampling, the researchers included sampling weights in the analysis to account for complex sampling design. PROC QUANTREG in SAS 9.3 was used to compute parameter estimates, statistical inferences as well as to plot quantile plots. As the data set is large enough 12540> 5000, the researchers used a resampling method to compute the confidence intervals (Koenker and Machado 1999) and the interior algorithm was used to compute the quantile regression estimates in SAS. The non-linearity between age of household head, size of household head and the asset index was assessed by including the quadratic term for age and size in the analysis and their significance was then examined. The goodness-of-fit and the equality of slopes are tested as in Koenker and Machado (1999). Various researchers (Habyarimana et al. 2015; Filmer and Pritchett 1998; Booysen 2002; Lokosang et al. 2014), created asset index, where households were classified into five quintiles as follows; first quintile (20%) as poorest, second quintile (20%) as poor, third quintile as middle (20%), fourth quintile (20%) as rich and the fifth quintile (20%) as richest (highest). Based on this classification and the results from Table 1, the researchers used 10^{th} (lowest), 20^{th}, 40^{th}, 50^{th} and 80^{th} percentiles and Ordinary Least Square (OLS) was reported for comparison purposes.

RESULTS

The Wald test was used to test the hypothesis of pure location shift that all the slopes coefficients of the quantile regression model fitted to the household data are the same across the five quantiles. The joint test for equality slopes coefficients of household data for the following quantiles 0.10, 0.20, 0.40, 0.50 and 0.80 was significant (p-value<.0001); which means that the effects of explanatory variables on the household data are not the same across the five quantiles. The goodness-of-fit of the quantile regression to the household data at each of the five quantiles was assessed using pseudo R-square by Koenker and Machao (1999). The values of pseudo R-square at 10^{th}, 20^{th}, 40^{th}, 50^{th} and 80^{th}quantiles, together with the value of the measure of goodness-of-fit for the OLS (R-square), are shown in the last row of Table 3; where the value of pseudo R-square increases with the quantile being increased by almost the same amount.

In the interpretation that follows any variable that is positively associated with household asset index decreases the poverty of the household, and conversely any variable that is negatively associated with the household asset index increases the poverty of the household. The level of education of the household head is highly significant at all five quantiles of the distribution. In addition, the coefficient increases with increasing the quantiles in all levels of education, where it is the highest at the upper quantile.The asset index is lower at the lower end (10th percentile) and higher in the upper end (80th percentile) in all levels of education. The household headed by anindividual with primary, secondary or tertiary education level is found to increase the asset index, as compared to a household headed by a person with no formal education from 0.135 to 6.973, 0.185 to 7.779, 0.322 to 10.13, 0.407 to 11.21 and 0.695 to 15.54 for 0.10, 0.20, 0.40 and 0.50 and 0.80 quantiles respectively.

From Table 3, the researchers observe that a household headed by a female is negatively associated with the asset index, as compared to a household headed by a male. It is interesting to note that it decreases with increases from 10th to 50th percentiles. The size of the household is also negatively associated with asset index, but is only significant at the upper quantile (80th percentile) and at the conditional mean from OLS. The place of residence of household is highly associated with household asset index (Table 3). From this table, it can be observed that an urban household is positively associated with household asset index in all five quantiles as compared to a rural household, where it increases from 0.424 (p-value<.0001) of 10th percentile to 3.361 (p-value<.0001) of 80th percentile.

From Table 3, it can be observed that the province is highly associated with the household asset index, a household from Kigali increases the asset index from lower tail to upper tail as compared to a household from Eastern province, whilst a household from Southern, Western or Northern province decreases the asset index, as compared with a household from Eastern province in all percentiles. It is interesting to note that in all provinces except Kigali, the asset index is higher at the lower quantile and lower at the upper quantile when compared to Eastern province; where Southern province most negatively affects the household asset index. This means that Southern province is the poorest, compared to other provinces.

The quadratic term of household size is statistically significant in all quantiles as well as in OLS. The researchers were also interested to include the quadratic term of age of household head but it was neither significant at any of the considered quantiles nor at OLS. The researchers examined the possible interaction effects and found only one significant interaction between gender of household head and the age of household head. From Figure 5 it can be observed that the asset index increases with increasing percentiles, but the effect is not significant at 80th percentile. Figures 2-5 present a summary of quantile regression results that show quantile

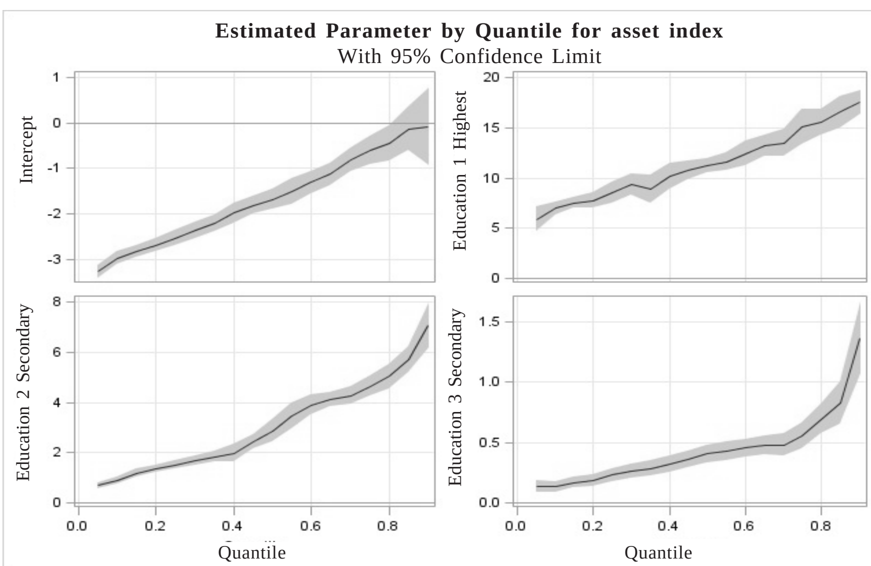

Fig. 2. Quantile processes with 95% confidence bands for the intercept and education

Table 3: Quantile regression parameter estimates and OLS

	QRegression										*OLS*	
	Q.10		*Q.20*		*Q.40*		*Q.50*		*Q.80*			
Indicator	*β*	*P-value*	*β*	*P-value*	*β*	*P-value*	*â*	*P-value*	*â*	*P-value*	*â*	*P-value*
Intercept	-2.97	<.0001	-2.68	<.0001	-1.98	<.0001	-1.68	<.0001	-0.45	0.023	-1.86	<.0001
Education Level of the Household Head (No Education=Reference)												
Secondary	0.889	<.0001	1.355	<.0001	1.99	<.0001	2.873	<.0001	5.032	<.0001	3.859	<.0001
Higher education	6.973	<.0001	7.779	<.0001	10.1	<.0001	11.21	<.0001	15.54	<.0001	11.52	<.0001
Province (Eastern=Reference)												
Kigali	1.185	<.0001	1.606	<.0001	3.97	<.0001	4.488	<.0001	6.052	<.0001	4.175	<.0001
Southern	-0.32	<.0001	-0.36	<.0001	-0.55	<.0001	-0.63	<.0001	-0.74	<.0001	-0.63	<.0001
Western	-0.19	<.0001	-0.25	<.0001	-0.34	<.0001	-0.41	<.0001	-0.50	<.0001	-0.27	<.0001
Northern	-0.21	<.0001	-0.29	<.0001	-0.38	<.0001	-0.44	<.0001	-0.64	<.0001	-0.53	<.0001
Gender of Household Head (Male=Reference)												
Female	-0.26	<.0001	-0.30	<.0001	-0.48	<.0001	-0.51	<.0001	-0.37	0.049	-0.58	0.0001
Size of household	0.004	0.872	0.01	0.816	-0.05	0.189	-0.06	0.075	-0.26	0.0001	-0.09	0.025
Age of household head	-0.00	0.124	-0.00	0.088	-0.00	0.003	-0.00	0.003	-0.00	0.205	-0.00	0.980
Place of Residence (Rural=Reference)												
Urban	0.424	<.0001	0.583	0.0001	1.04	<.0001	1.107	<.0001	3.361	<.0001	2.137	<.0001
Size*size	0.007	0.008	0.008	0.005	0.02	<.0001	0.018	<.0001	0.048	<.0001	0.030	<.0001
Age by gender of the household	0.003	0.012	0.003	0.474	0.01	0.004	0.006	0.003	0.005	0.169	0.009	0.012
R1/i and	0.107		0.145		0.22		0.267		0.446		0.540	

regression estimates for the entire distribution and their confidence band.

DISCUSSION

From Table 3 it can benoted that the results from OLS and quantile regression at 50th percentile are almost the same in magnitude as well the direction. However, the quantile regression model allows for the study of the impact of predictors on different desired quantiles of the response distribution, and thus to get a complete picture of the relationship between the response variable and predictor variables. This is one of the advantages of quantile regression which is evident from this paper. Another advantage of quantile regression over OLS and logistic regression is the robustness to extreme points in the response space (outlier).

From Table 3 and Figure 2, the researchers observed thatthe coefficient increases with increasing the quantiles in all levels, where it is the highest at the higher level of education and in the upper quantile. This means that education has a stronger effect on asset index in richer households. In other words, education is the key to overcoming poverty. Such progress or development could only occur when government educational policies are geared towards a functional education that can lead to job creation and also self-reliance. Entrepreneurship education is a means through which government could attain such development in society (Mberu et al. 2014; Mahadea 2011).

A household from Kigali was found to increase the asset index, as compared to a household from Eastern province (Table 3 and Fig.3), however, a household from Southern, Western or Northern provinces was found to decrease the asset index, compared to a household from Eastern province. This means that a household from Kigali is less likely to be poor as a household from Eastern province. From Table 3, a household from Southern province is seen to most negatively affect the asset index, this shows that this province is the most poor compared to other provinces. These findings are in line with NISR et al. (2012) and Habyarimana et al. (2015). When 50th percentile is considered, the results found in this paper are in line with Habyarimana et al.(2015), NISR et al. (2012) and Achia et al. (2010).

The results from Figure 4 show that urban households' wealth index is higher than that of

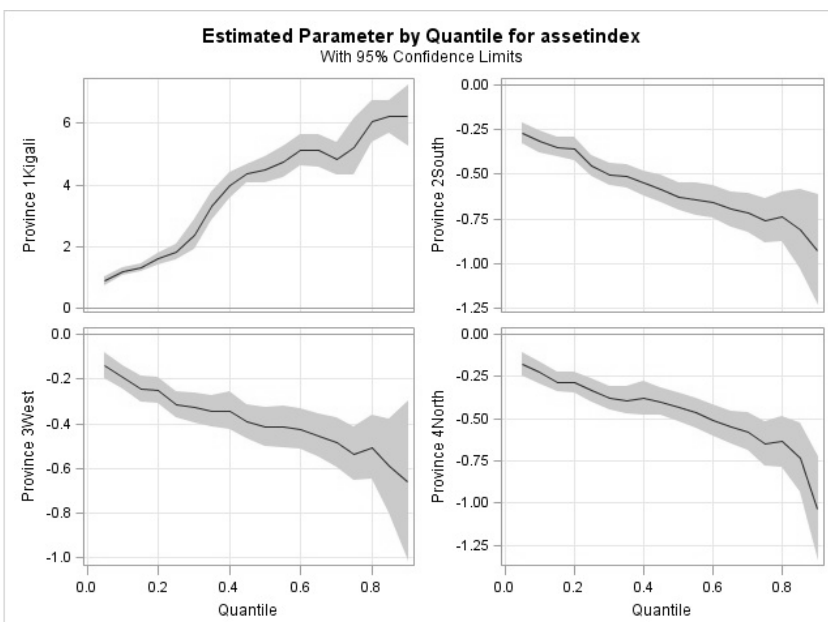

Fig. 3. Quantile processes with 95% confidence bands by province

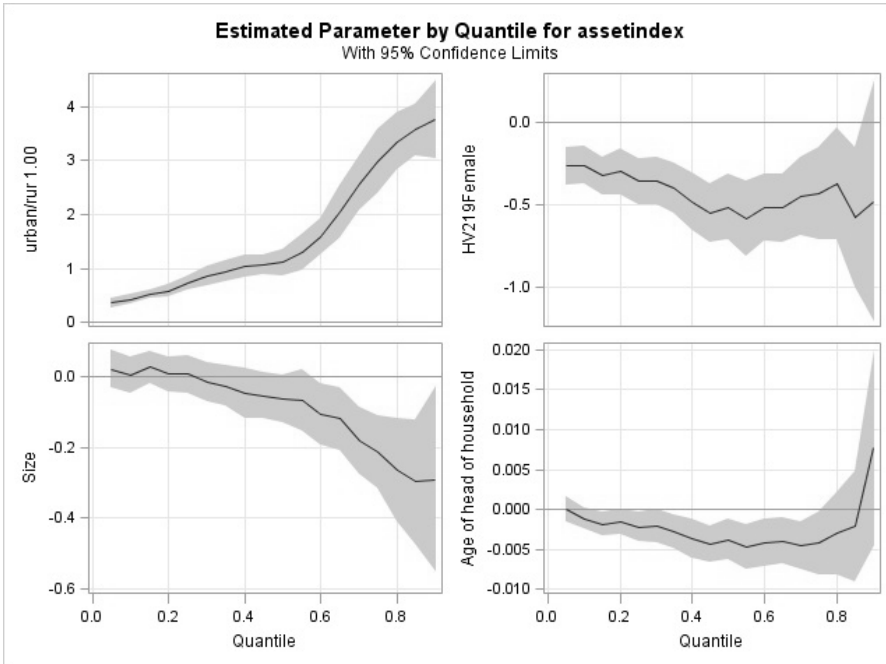

Fig. 4. Quantile processes with 95% confidence bands for gender, family size, age and rural-urban

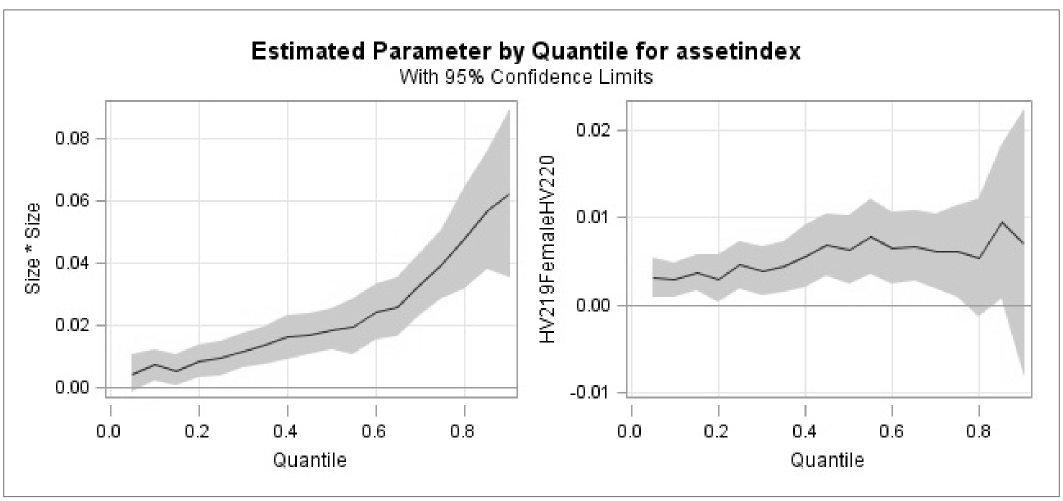

Fig. 5. Quantile processes with 95% confidence bands for quadratic family size and gender

rural households in the lower tail of the distribution, in the middle and higher quantiles. This is perhaps why growth and development in economies is often restructured away from agriculture into manufacturing and services (Christensen and Todo 2014). Urbanization sees a shift toward more remunerative non-farm activities. In fact rural-to-urban migration is a necessary component of the economic development process, as the migration of labor out of agriculture has been a feature of the growth path of every country that has developed (de Brauw et al. 2014).

The second plot from Figure 4 shows that female household head wealth is less than that of male household head for any chosen quantile; this difference is smaller in the lowerquantiles of the distribution. Achieving gender equality in African countries is still critical and continues to be a major challenge in Africa. Some of the inequities are embedded in the deep-rooted cultural norms and beliefs of the African societies (Manda and Mwakubo 2014).

The linear and quadratic effects for the household size are shown in Figure 4 and Figure 5, respectively. The effect of the household size is clearly negative as the quantiles increase. At the higher quantiles, the quadratic effect of the household size is more concave. The effect of family size amongst the lower quantiles is negligible. This is perhaps because households have some economic support from children. This is one of the rationales for parents to increase the number of children so that they will have a high probability of being supported financially (Anyanwu 2014). The relationship between the age of household head and household wealth index shows a flat u shaped relationship (Fig. 4). Among the lower quantiles, the poorest households, the effect of the age of the household head is negative but not significant. Among higher quantiles, the richest households, age has apositive effect. In the move from the lower –to middle quantiles the negative effects become more pronounced. However, in the move from the middle to higher quantiles the negative effect of age diminishes. The result is in agreement with Mberu et al. (2014) conclusion that the propensity to move out of poverty consistently increases as the age of heads of households increases.

CONCLUSION

Based on the asset index and quantile regression, this paper identified the determinants of poverty of household in Rwanda. The results showed that the level of education of household head, gender of household head, age of household head, size of household, place of residence (urban or rural) and province are the determinants of poverty of households in Rwanda. Poverty is not uniformly distributed across geographic allocations in Rwanda. The paper shows that economic growth occurs in urban than in rural Rwanda.It seems that a move from rural agricultural economy to urban based manufacturing and services isa way forward for poverty reduction. Education, family size and the age of the household head are significant predictors of moving into or out of poverty. This shows that anti-poverty policy options should allow for provision of improving educational levels and include family size reduction programs.

RECOMMENDATIONS

The findings of this paper suggest that all Rwandese households in urban areas are relatively wealthier than rural households. This finding supports the existing policy of grouped settlements where people are advised to build their houses in townships known as *Imidugudu*.

Education vitally increases labour productivity and wages and ultimately reduces poverty. The Rwandan government's effort to improve the existing access to higher education is recommendable to speed up the eradication of the poverty of households.

Though gender inequality is a long standing cultural issue, to some extent, the inequalities can partly be addressed by formulating and enforcing laws that promote women's economic empowerment. Thus, more comprehensive research work is still required to highlight challenges associated with gender inequality and what needs to be done to move towards reducing gender inequality.

Finally, since poverty levels are different by province it is important to understand poverty from a provincial perspective. More importantly, the future directions of research include creating a detailed spatial distribution of poverty in Rwanda.

LIMITATIONS

This paper contributes to the understanding of the determinants of household wealth among Rwandese. However, it has the limitation of being not exhaustive, in terms of all the factors. For instance the effects of policy changes and program interventions are not included. This would require longitudinal study instead of the cross-section study which is reported in this paper. The unavailability of longitudinal data has also limited understanding of the poverty trends in Rwanda.

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