Measuring returns to education and decomposition of rural-urban inequality: evidence from Senegal

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Abstract

This study provides a Bayesian estimation method for unconditional quantile regression based on the recentered influence function (RIF). The method consists of estimating a non-linear RIF-regression model using a Gibbs-within-Metropolis-Hastings sampler to perform better in the presence of heavy-tailed distributions. These techniques are used to evaluate the impact of changes in the distribution of covariates on the conditional quantiles of the marginal distribution of the dependent variable. Applied to a nationally representative household survey, the Senegal Poverty Monitoring Report (2005), the results show that the change in the rate of returns to education across quantiles is substantially lower at the primary level of education compared with secondary, and tertiary levels of education. The results also demonstrate that the high rural-urban inequality in Senegal is attributed in particular to the difference in returns to various covariates, even for lower quantiles.

Keywords: hybrid MCMC sampler, quantile regression, influence function, inequality, education.
JEL: C11, C14, C52.

1. Introduction

Modern theories of human capital investment recognize knowledge and skills as the greatest source of long term poverty reduction and of stability in modern democracies. The international community, during the "World Education Forum" held in Dakar in April 2000 collectively agreed to place education at the heart of the development priorities for eradicating extreme poverty. The last two decades have seen a large increase in the enrollment rate of primary education in most developing countries responding also to the second priority of the Millennium Development Goals (MDGs), "primary education for all". Psacharopoulos and Patrinos (2002) underline that "primary education continues to be the number one investment priority in developing countries". While education is increasingly acknowledged as an important dimension of poverty reduction, there remain some challenges in measuring its return, for example on household's welfare. Studies emphasizing the role of education on poverty reduction have recently exploded and regression analysis relying on both household surveys and cross-country data have been widely used in this literature. These regressions, using reduced-form equations, generally provide a simple but partial framework for examining the marginal effect of education on household's income[1]. Since the distribution of income

[1]The consumption expenditure is considered as an indicator of household's income.

is generally skewed to the left, the mean regression models do not provide complete and meaningful information, and then, the analysis of each point of the distribution is of particular interest to assess changes at these different points. Introduced by Koenker and Bassett (1978), quantile regression models have been increasingly used in empirical labour market studies[2] to parsimoniously describe the entire distribution of an outcome variable. To overcome some limitations[3] of conditional quantile regression models, Firpo et al. (2009) propose the Re-centered Influence Function (RIF)-regression. This regression evaluate the impact of changes in the distribution of covariates on the conditional quantiles of the marginal distribution of the dependent variable. Running the two-steps estimation of the RIF-regression remains a challenging problem. A "classical" approach consists of estimating independently the RIF and the regression coefficients (see Firpo et al. (2009)). This approach does not take into account the uncertainty related to the first step of estimation. Lubrano and Ndoye (2013) develop a Bayesian estimation of the RIF-regression where they consider simultaneously the two-steps of estimation by estimating the density function of the outcome variable by a mixture of log-normals. While being consistent[4] in the presence of heavy tails, their approach makes the underlying restrictive hypothesis of linearity. This study extends this approach by considering the dichotomous structure of the RIF to implement a Bayesian estimation method for the RIF-regression in a non-linear case. The method consists of estimating first the RIF by Gibbs sampling and then running it in a probit-regression (logistic-regression) where coefficients are estimated by Metropolis Hastings sampler using Gibbs output.

These approaches are employed in the empirical analysis to address the two following questions:

1. What is the extent to which the private rate of the marginal effect of primary education on household's income changes across quantiles compared with those of higher education ?

2. What determines the gap in consumption expenditures across quantiles between rural and urban households ? (return effects versus covariate effects).

The investment in primary education devotes the largest budget allocation in developing countries to achieve development priorities (Psacharopoulos 1994, Psacharopoulos and Patrinos 2002). In Senegal, the enrollment rate in primary school has climbed from 54 percent in 1994 to 70 percent in 2001 and 82.5 percent in 2005, accompanied by an increase in female enrollment rate and rural sectors enrollment rate[5]. However, the IMF 2007's report reveals that 78.51% of Senegalese youth aged 15-19 dropped out before finishing lower secondary school in the country.

Senegal like many developing countries is also facing the problem of urban biased. Modern infrastructures are directed toward urban sectors, thereby creating a widening gap between the urban and rural economies.

The empirical analysis of this paper uses the data from a nationally representative survey: the Senegal Poverty Monitoring Report (ESPS, 2005) conducted by the National Agency of Statistics and Demography (ANSD)[6]. This survey is largely used by empirical studies, government monitoring

[2]Buchinsky 1994, Chamberlain 1994, Machado and Mata 2001.

[3]unlike conditional means, conditional quantiles do not average up to their unconditional population counterparts

[4]Mixture models provide flexible extensions of parametric models and the Bayesian approach takes into account the uncertainty related to the first step of the estimation.

[5]Source: published reports and papers, see for instance IMF 2007, Delaunay 2012. These ratios correspond to the number of students formally registered in primary school.

[6]ESPS, "Enquête Suivie de la Pauvreté au Sénégal", 2005-2006; ANSD, "Agence National de la Statistique et de la Démographie".

reports, institutional strategic documents and in a poverty reduction strategies papers (PRSPs) in Senegal[7].

This study applies the RIF-regression method in a Mincer[8] equation type, to primarily investigate the changes in the return to education across quantiles. Second, it uses the Oaxaca-Blinder decomposition[9] approach to examine the rural-urban inequality in consumption expenditures.

The empirical results primarily demonstrate evidence from heterogeneous pattern of changes in the rate of return to education across quantiles. The rate of change in the return to primary education does not vary much between the lower and the upper quantiles (0.50, 0.75, 0.90) compared with those to secondary and tertiary education. This result supports findings showing that in countries that rapidly expand access to primary education, the returns to primary education fall, while returns to higher education rise (Psacharopoulos 1994, Psacharopoulos and Patrinos 2002). The results also provide evidence of dissimilarities in the pattern of change in the returns to education between urban and rural sectors. The primary education does not significantly affect lower quantiles in rural sectors. Second, the detailed decomposition result show that the high rural-urban inequality in consumption expenditure across quantiles is attributed in particular to the difference in returns to various covariates. In contrast, we find a weak contribution of the difference in covariates even for low quantiles. These findings demonstrate the need for the rural industrialization to create appropriate higher level jobs leading to reducing the strong rural exodus and to attract rural migration and immigration. The China's Township and Village Enterprises (TVEs) provide an excellent model of how a rural industrialization has remarkably contributed to rural development in China.

The paper is organized as follows: Section 2 presents the RIF-regression and the different estimation methods employed. It implements a Bayesian RIF-probit estimation by a Gibbs-Metropolis Hastings sampler. Section 3 describes the data. Section 4 discusses the empirical results. Section 5 concludes and discusses on some policy implications. An appendix gives a sensitivity analysis with classical regression.

2. RIF-regression models

We consider the following quantile regression model

$$y_i = x_i^{'}\beta_\tau + \epsilon_i, \tag{1}$$

where (y_i, x_i), $i = 1, 2, \ldots, n$ are independent observations, y_i being the single-response variable and $x_i^{'} = (1, x_{i1}, \cdots, x_{ik})$ being the $(k+1)$ known covariates. $\beta_\tau^{'} = (\beta_{\tau 0}, \cdots, \beta_{\tau k})$ represents the $(k+1)$ unknown regression parameters and ϵ_i, $i = 1, \ldots, n$ are the error terms which are supposed to be independent and identically distributed. The τ^{th} quantile of ϵ_i is assumed equal to zero, $q_\tau(\epsilon_i|X) = 0$.

[7]Among the recent studies using the ESPS datasets, we can cite Azam et al., 2007, Boccanfuso et al. 2008, Boccanfuso et al. 2009, Bussolo et al. 2009, Ndoye et al. 2009, Mesplé-Somps and Robilliard 2010, Boccanfuso and Savard 2011, Diawara 2011, Diawara 2012, among others and the national and institutional reports: DSRP 2005, IMF and IDA 2006, IMF 2007, ANSD 2007, SNDES 2009, DSRP-II 2010.

[8]The standard Mincer 1974 earnings equation linearly regress the log of wage on the year of education and the quadratic function of labor market experience.

[9]The decomposition method based on the RIF-regression can provide a better and more detailed decomposition in the spirit of the traditional Oaxaca-Blinder decomposition (see for instance Firpo et al. 2011).

Firpo et al. (2009) developed an Unconditional quantile regression method based on the Re-centered Influence Function (RIF) to evaluate the marginal impact of changes in the distribution of the explanatory variables on the quantiles of the marginal distribution of the dependent variable.

The Influence Function (IF) studies how a changing in the distribution of covariates affects a distributional statistics $\nu(F)$, where F is a class of distribution functions. It is defined as

$$IF(y,\nu,F) = \lim_{\epsilon\to 0}\frac{\nu(F_{\epsilon,\Delta_y}) - \nu(F)}{\epsilon} = \frac{\partial\nu(F_{\epsilon,\Delta_y})}{\partial\epsilon}|_{\epsilon=0}, \tag{2}$$

where Δ_y is a perturbation distribution which puts a mass 1 at any point y and $F_{\epsilon,\Delta_y} = (1-\epsilon)F + \epsilon\Delta_y$ is a mixture model. Firpo et al. (2009) consider the τ^{th} quantile, q_τ as the distributional statistics $\nu(F)$ and show that the IF can be expressed as

$$IF(y_i, q_\tau) = \frac{\tau - 1\!\!1(y_i \leq q_\tau)}{f_Y(q_\tau)},$$

where $f_Y(.)$ is the density of the variable of interest, Y. A convenient property of IF is that $\mathrm{E}_Y(IF(Y,\nu,F)) = 0$. Firpo et al. (2009) define the Re-centered Influence Function (RIF) as $RIF(y_i,\nu,F) = IF(y_i,\nu,F) + \nu(F)$. For quantiles, the RIF can be expressed in the following convenient way

$$\begin{aligned} RIF(y_i, q_\tau) &= q_\tau + IF(y_i, q_\tau) \\ &= q_\tau + \frac{1\!\!1(y_i > q_\tau)}{f_Y(q_\tau)} - \frac{1-\tau}{f_Y(q_\tau)} \\ &= c_{1,\tau}1\!\!1(y_i > q_\tau) + c_{2,\tau}, \end{aligned} \tag{3}$$

where $c_{1\tau} = 1/f_Y(q_\tau)$ and $c_{2\tau} = q_\tau - (1-\tau)c_{1\tau}$.

The RIF-regression model consists of regressing the function RIF given in (3) on a set of covariates X. The conditional expectation of the RIF is expressed as

$$\begin{aligned} E(RIF(Y,q_\tau)|X=x) &= c_{1,\tau}E[1\!\!1(Y > q_\tau)|X=x] + c_{2,\tau} \\ &= c_{1,\tau}Pr[1\!\!1(Y > q_\tau)|X=x] + c_{2,\tau}. \end{aligned} \tag{4}$$

Since $E(RIF(Y,q_\tau)|X=x)$ in (4) is linear on $Pr[1\!\!1(y > q_\tau)|X=x]$, the average marginal effect of covariates, $\hat{\beta}_\tau$ can be consistently estimated using a simple OLS regression in a Linear Probability Model (LPM), or using Probit or Logit regressions (RIF-Logit) in a more general case.

2.1. Bayesian estimation of the RIF-regression in a LPM

We consider a Linear Probability Model (LPM), $1\!\!1(y_i > q_\tau) = x_i^{'}\alpha_\tau + \epsilon_i$, where $E(\epsilon_i|X) = 0$ under the LPM assumption. The RIF-regression given in (3) can be expressed as

$$RIF(y_i, q_\tau, F) = c_{2,\tau} + x_i^{'}\beta_\tau + \epsilon_i,$$

where $\beta_\tau = c_{1,\tau}\alpha_\tau$. The estimation makes use of the methodology developed in Lubrano and Ndoye (2013). The two sequential steps proposed method is a Gibbs sampler within a linear regression. The first step models the distribution of the observed consumption expenditure by a mixture of log-normal densities $f(y|\theta)$ as given in (1). The parameter $\theta = (\theta_j)_{j=1,\ldots,K}$, where $\theta_j = \left(\mu_j, \sigma_j^2, p_k\right)$, and (μ_j, σ_j^2) are the component specific mean and variance. Conditionally on each draw of the parameter $\theta_j^{(t)}$, we have an analytical expression for the RIF-regression. The conditional posterior density of β_τ in the RIF-regression is Student

$$\varphi(\beta_\tau|\theta, y, X) = f_t(\beta_\tau|\beta_*(\theta), s_*(\theta), M_*, n). \tag{5}$$

If we suppose a non-informative prior for β_τ and σ_τ^2, the hyper-parameters in (5) are given by:

$$\begin{aligned} M_* &= X'X, \\ \beta_*(\theta) &= M_*^{-1}X'RIF(y, q_\tau, F|\theta), \\ s_*(\theta) &= RIF(y, q_\tau, F|\theta)'(I_N - X(X'X)^{-1}X')RIF(y, q_\tau, F|\theta). \end{aligned} \tag{6}$$

Where $RIF(y, q_\tau, F|\theta)$ is a vector formed by the n observations $RIF(y_i, q_\tau, F|\theta)$. Marginal moments are obtained by integrating out θ.

However, linearity in the RIF regression is a strong assumption which does not hold in applications. Given the structure of the dependent variable in (3), a non-linear RIF-regression can be estimated using a Probit or a Logit regression estimation procedure. However, there is hardly any difference between Probit and Logit regression estimation procedure. We use the pro bit regression method as a basis of comparison with the RIF-Probit estimation suggested by Firpo et al. (2009). We implement a Bayesian RIF-Probit regression using a Gibbs-within-Metropolis algorithm.

2.2. Bayesian estimation of the RIF-Probit regression

In the model given in (4), the average marginal effect from a pro bit model will be consistent only if $Pr(Y > q_\tau|X = x) = \Lambda(x_i^{'}\beta_\tau)$, where $\Lambda(x_i^{'}\beta_\tau)$ is the cumulative distribution function (cdf) of a logistic distribution and β_τ is a vector of coefficients,

$$\Lambda(x_i^{'}\beta_\tau) = \Phi(x_i^{'}\beta_\tau)^{y_i}\left(1 - \Phi(x_i^{'}\beta_\tau)\right)^{1-y_i}, \tag{7}$$

where $\Phi(.)$ is the cdf of the standard Gaussian distribution.

The Likelihood of the probit distribution is given by

$$L(\beta_\tau|y, X) \propto \prod_{i=1}^{n} \Phi(x_i^{'}\beta_\tau)^{y_i}\left(1 - \Phi(x_i^{'}\beta_\tau)\right)^{1-y_i}.$$

The Gibbs sampler is difficult to implement since conjugate priors do not exist because the likelihood function does not belong to the exponential family. We may have recourse to the Metropolis-Hastings sampler which can be tuned only with the likelihood function under a flat prior on β. The Metropolis-Hastings random walk sampler works well for binary regression problems with a small number of predictors (see for example Marin and Robert 2007). We propose the Metropolis-Hastings sampler algorithm for the RIF-probit estimation. The first stage in the estimation procedure of the RIF-probit regression consists of estimating the density function of y, $\hat{f}(y)$. Both parametric as well as non-parametric estimation approaches may poorly smooth the approximating tails. Thanks to their semi-parametric framework, mixture models provide very flexible extension of simple parametric models. Bayesian and classical methods of inference have been developed in recent litterature (see for instance McLachlan and Peel 2000, Marin et al. 2005, Frühwirth-Schnatter 2006, Marin and Robert 2007). We particularly interest on Bayesian inference method, and, we consider lognormal distribution thanks to its particular convenience on modeling income distribution. A straightforward MCMC method when using data augmentation is the Gibbs sampler. Therefore, the extended approach developed is a *RIF-Probit Gibbs within Metropolis-Hastings Sampler algorithm* as it first requires the use of Gibbs sampler to estimate the mixture of lognormal densities for $\hat{c}_\tau = 1/\hat{f}(\hat{q_\tau})$.

Gibbs-within-Metropolis-Hastings Sampler algorithm

- Estimate the density function of y by Gibbs sampling to obtain $\hat{c}_{1\tau} = 1/\widehat{f(q_\tau())}$
- Initialization: Set $\beta_\tau^{(0)} = \hat{\beta}_\tau$, compute $\hat{\Sigma}$, where $\hat{\beta}_\tau$ and $\hat{\Sigma}$ are gibbs output drawn respectively from (5) and (6).
- Iteration: for $t = 1, \cdots, m$
  1. Generate $\tilde{\beta}_\tau \sim N(\beta_\tau^{(t-1)}, \hat{\Sigma})$
  2. Compute the acceptance probability $\rho(\beta_\tau^{(t-1)}, \tilde{\beta}_\tau) = \min\left(1, \frac{\pi(\tilde{\beta}_\tau|y)}{\pi(\beta_\tau^{(t-1)}|y)}\right)$
  3. Set $\beta_\tau^{(t)} = \tilde{\beta}_\tau$ with probability $\rho(\beta_\tau^{(t-1)}, \tilde{\beta}_\tau)$ otherwise set $\beta_\tau^{(t)} = \beta_\tau^{(t-1)}$
  4. Compute $\hat{\beta}_\tau^{(t)} = \hat{c}_{1\tau} * \beta_\tau^{(t)}$
- Average $\hat{\beta}_\tau^{(t)}$ to obtain the estimates of RIF-regression coefficents, $\hat{\beta}_\tau$.

For a given prior $\pi(\beta)$, the posterior distribution $\pi(\beta_\tau|y, X)$ is

$$\pi(\beta_\tau|y, X) \propto \pi(\beta) \times \prod_{i=1}^{n} \Phi\left(x_i^{'}\beta_\tau\right)^{y_i} \left(1 - \Phi(x_i^{'}\beta_\tau)\right)^{1-y_i}. \tag{8}$$

Without any prior information, the flat prior on β can be considered.

$$\pi(\beta_\tau) \propto 1.$$

For comparison purposes, we will consider the Zellner's non-informative G-prior:

$$\pi(\beta_\tau) \propto det\left((X^{'}X)^{1/2}\right)\Gamma\left[(2k-1)/4\right]\left(\beta^{'}(X^{'}X)\beta\right)^{-(2k-1)/4}\pi^{-k/2}.$$

The corresponding posterior distribution $\pi(\beta_\tau|y, X)$ is

$$\pi(\beta_\tau|y, X) \propto \pi(\beta_\tau) \times \prod_{i=1}^{n} \Phi\left(x_i^{'}\beta_\tau\right)^{y_i} \left(1 - \Phi(x_i^{'}\beta_\tau)\right)^{1-y_i}. \tag{9}$$

The RIF-OLS as well as the RIF-Probit estimation approaches make assumptions on functional forms of the density of y and on $P(Y > q_\tau|X = x)$ in (4). Firpo et al. (2009) suggest the nonparametric-RIF (NP-RIF) regression method based on polynomial series approximations and show that RIF-Probit regression yield estimates very close to the fully nonparametric estimator. However, the choice of the nonparametric estimator is not crucial in large samples as discussed by Newey (1994), if the domain is unbounded polynomial series would also approximate badly the tails. An appendix will provide the classical RIF-OLS regression for comparison with the Bayesian RIF regression and for making sensitivity analysis with the classical OLS.

3. Empirical analysis

3.1. Labour market in Senegal

Senegal like many developing countries is facing the problem of urbanization, modern infrastructures are directed toward urban sectors. The urban labour market is more skilled and offers higher earnings than the rural labour market. Consequently, more educated people in rural areas are more likely to migrate towards urban areas.

The rural labour market in Senegal is predominantly agricultural involving roughly three-quarters of the country's workforce. Agriculture in Senegal is mainly seasonal. The rainy season only lasts less than four months, from June to November. These climate constraints require a long period of inactivity for the majority of the rural population, leading to a poor performance of the agricultural sector[10] and to a strong migration of the youth towards urban cities. This is evidenced by the rapid growth in urban populations, especially in the "bidonvilles" of Dakar leading to an increase of urban unemployment and to a deterioration of living standards.

In recent years, interesting background programs and innovative policies in the agricultural sector have been implemented in Senegal[11]. Among them, the Return to Agriculture ("le plan REVA", 2006) aiming at creating opportunities for lucrative and gainful employment in rural areas. It is also expected to promote modern and sustainable models of Integrated Agricultural Farms and to significantly contribute to the growth of agricultural exports. The program Great Push Forward for Agriculture, Food, and Abundance ("le plan GOANA", 2008) has the objective of achieving food self-sufficiency and at the same time of developing the agricultural sector and farming. While being far from being reached, such programs are strongly encouraged, in addition to the rural industrialization program.

3.2. Data and descriptive statistics

The Senegal Poverty Monitoring Report (ESPS, 2005) is a nationally representative surveys conducted by the National Agency of Statistics and Demography. The survey is constructed to provide information related to the evaluation of poverty and to the assessment of the impact of public policies. The ESPS sample covers 13500 of households of all social classes and from all geographical areas of residence.

Table 1 reports descriptive statistics concerning the characteristics of households and information on the head of the household. It reveals evidence of differences in characteristics between urban and rural sectors.

Table 1 shows that more than half of the population live in rural areas and households are predominantly male-headed. Two-thirds of household-heads are illiterate, around 13 percent have reached primary education, 9 percent a secondary education level, and less than 5 percent a tertiary level and equivalent. The urban modern-sector bias in government expenditures which is at the core of urban-rural inequalities in infrastructure can explain the rural-urban gap in educational attainment. More than 85 percent of household-heads in rural areas are illiterate compared with less than 55 percent in urban areas. Around 17 percent of household-heads in urban areas have reached primary education in contrast to less than 8 percent in rural areas. These inequalities are even more pronounced on higher levels of education. The urban sector recorded more than 17.0 percent

[10]Senegal is one of the most food import-dependent country in West Africa (see Stads and Sène (2011) for more details).

[11]A list of these programs and their evaluation are provided by Stads and Sène (2011).

Table 1: Characteristics of households and heads

Characteristics of households				Characteristics of heads			
	Urban	Rural	National		Urban	Rural	National
Residence				**Education**			
Proportion	46.44	53.55		Illiterate	58.47	87.38	71.22
Size				Primary	17.20	7.80	12.63
Mean	8.59	9.75	9.01	Secondary	18.45	4.16	11.58
1-4	23.54	14.21	20.13	Tertiary	5.87	0.65	4.57
5-9	48.65	50.28	49.25	**Age**			
10-14	17.02	20.60	18.33	Mean	50.57	50.70	50.62
15, +	10.79	14.91	12.29	less 40	22.87	23.74	21.97
Basic services				40-65	58.88	56.25	57.92
Electricity	69.71	13.90	47.71	65 and plus	18.25	20.01	30.11
Safe water	82.59	39.34	69.22	**Gender**			
Land ownership				Female	27.3	11.532	22.55
Refrigerator	31.37	1.98	17.96	**Marital status**			
TV	51.36	8.61	26.18	Monogamy	56.56	55.72	57.03
Car	9.52	1.78	5.29	Polygamy	21.72	35.97	25.39
				Single	4.54	1.51	3.40
				Widower	14.44	6.00	11.71
				Divorced	2.69	0.92	2.39
				Other	0.05	0.08	0.07
				Occupation			
				Employed	66.90	75.41	70.6

Computations are based on ESPS 2005-2006 after dropped household without any information on educational attainment of the head or on the total consumption expenditures. Calculations were done with DAD software using the weight of the survey.

in the secondary level and more than 6 percent in tertiary level and equivalent, while the rural sectors registered less than 4 percent in secondary and less than 1 percent in tertiary level and equivalent. To preserve the cultural and religious values, Koranic schools are more favored than official schools in rural areas. Traditional cultures are also more entrenched in rural areas explaining some differences in household's characteristics.

Senegalese families are often extended, 9 persons per household on average. Families are larger in rural areas than in urban areas. The average age of household-heads is estimated at about 50 years. More than half are between 40 and 65 years old. The household-heads are older in rural on average. About 80 percent of household-heads are employed (self-employed or salaried). The rural sector recorded more employed household heads, about 75 percent on average compared to 66 percent in urban areas. Retired and housewives are more prevalent in the urban sector.

More details on the descriptive statistics of these data are given in the summary reports of the two surveys published by the National Agency of Demography (ANSD 2007).

The estimation of a given equivalence scale relies on a particular consumption model which is rather restrictive, and therefore may lead to identification problems. The usual practice consists of using the per capita income, dividing the household income by the household size. That is what we use in this study referring to Deaton and Muellbauer (1980), Deaton (1997) and empirical work by the Word Bank with Ravillon (2001).

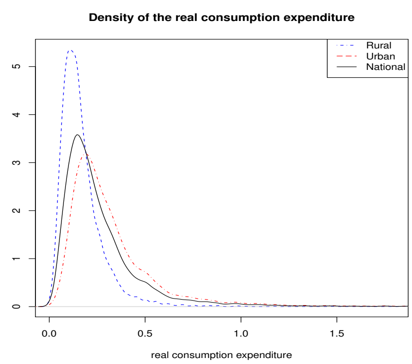
3.3. Real consumption expenditure per capita distribution

We consider the annual real consumption expenditure as an indicator of permanent income. The consumption expenditures are expressed in CFA francs.[12] The WAEMU[13] Harmonized Consumer Prices Index(HCPI) are respectively 10.94 in 2001 and 11.3 in 2005 revealing a small inflation rate of 0.036 points. The total consumption expenditures in the survey are already deflated by sectors using the national Consumer Prices Index (CPI). The differences in weight in CPI between urban and rural sectors nicely reflect the consumption expenditure structure. In fact, foods are typically less expensive in rural sector, and urban households are more likely to consume higher quality goods, which increases their consumption expenditures. The total consumption expenditure in the sample is the sum of food and non-food expenditures, added self-consumption.

Table 2 presents the distribution of the real annual consumption expenditure per capita in both national and urban-rural sectors. It clearly provides the evidence of dissimilarities in consumption between urban and rural sectors, at any points of the distribution. The consumption expenditures and inequality are higher in urban sectors.

Table 2: Real annual consumption expenditure per capita

	Urban	Rural	National
$q_{0.10}$	12.51	6.53	8.89
$q_{0.25}$	17.55	9.59	13.54
Median	25.76	14.25	20.71
Mean	33.05	16.83	27.11
$q_{0.75}$	38.61	20.67	32.40
$q_{0.90}$	58.46	29.76	50.07
N	7138	6189	13326
Gini	0.363	0.330	0.388



The sample reveals that the largest part of the Senegalese household's consumption expenditure is on food (45.6%) and housing (20%), the remainder of the budget is mostly used to cover the clothing expenditure, health and items expenditure.

Since the distribution of consumption expenditure is often skewed to the left, we impose a restriction on the form of the distribution. We estimate the density function by a mixture of lognormals using a Gibbs sampler. A Gibbs sampler approach for inference in lognormal densities proceed in the same way as inference for a mixture of normals (see forMarin and Robert (2007), **?**).

4. Empirical application

In the RIF-regression models, we consider a Mincer type model where the logarithm[14] of the consumption expenditure per capita is the dependent variable. We estimate returns to education at

[12] CFA [Communauté Financière Africaine (African Financial Community)]. CFA franc has a fixed exchange rate with Euro (1 euro = 656 CFA) in 2013.

[13] West African Economic and Monetary Union.

[14] We take the logarithm for convenience of the interpretation of the Oaxaca-Blinder decomposition

different levels by converting the continuous years of schooling variable into three dummy variables referring to the completion of the main schooling cycles[15]. This return to education refers to the marginal effect of the level of education on the household's consumption expenditure per capita. We consider the following set of covariates: *primary*, *secondary* and *tertiary* as dummies which refer to the level of education of the head of household; *age* and its square age^2 refer to the age of the heads of household, the dummy *female* refers to a female headed-household; the dummy *married* refers to a married household's head, the dummy *rural* is the rural geographical area of residence. We restrict the estimations to five quantiles (0.10, 0.25, 0.50, 0.75, 0.90).

In this case, the RIF-regression allows us to evaluate the marginal effect of the changes in the distribution of X on the quantiles of the marginal distribution of Y.

We first estimate the RIF-regression model in the whole sample using both estimation methods developed in this paper. Second, we consider the linear probability model to disentangle the analysis in rural and urban areas. The estimated unconditional expectations of the RIF for both sectors are used to examine the rural-urban inequality in consumption expenditures by using the Oaxaca-Blinder decomposition method described above.

4.1. Measuring returns to education

Table 3 and 10 report the RIF-regression estimates. They show the marginal effects of different covariates on the household's expenditure consumption per capita and their changes across the five quantiles. The regression coefficients are estimated by the two Bayesian RIF estimation methods presented in this paper. The density function of the dependent variable (log of the expenditure consumption per capita) is estimated by a mixture of normal distributions.

Table 3: Bayesian RIF estimates on the log-income

	Lowest	Lower middle	Median	Upper middle	Highest
	.10	0.25	.50	.75	.90
			Linear Probability Model		
Intercept	11.926	12.389	12.801	13.296	13.882
	(0.104)	(0.072)	(0.064)	(0.073)	(0.106)
primary	**0.038**	0.075	0.113	0.122	0.110
	(0.030)	(0.021)	(0.019)	(0.021)	(0.031)
secondary	0.064	0.177	0.285	0.454	0.669
	(0.032)	(0.022)	(0.019)	(0.022)	(0.032)
tertiary	0.132	0.276	0.548	0.971	1.827
	(0.053)	(0.037)	(0.033)	(0.037)	(0.054)
age	−0.842	−1.052	−1.148	−1.212	−1.645
	(0.391)	(0.271)	(0.241)	(0.272)	(0.399)
age^2	0.814	0.940	1.109	1.121	1.429
	(0.359)	(0.248)	(0.221)	(0.250)	(0.365)
size	−0.021	−0.025	−0.030	−0.037	−0.048
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
female	0.090	0.127	0.125	0.104	0.060
	(0.029)	(0.020)	(0.018)	(0.020)	(0.030)
rural	−0.686	−0.599	−0.524	−0.397	−0.302
	(0.022)	(0.015)	(0.014)	(0.016)	(0.023)
married	0.084	0.093	0.089	0.044	**0.046**
	(0.032)	(0.022)	(0.020)	(0.022)	(0.033)

The age variable was divided by 100. Standard errors are indicated in parentheses. Bold figures correspond to posterior means for which 0 is contained in a 95% HPD interval

[15] primary education corresponds to 6 years or less, secondary is between 7 and 13 years and tertiary more than 13 years.

Table 4: Bayesian RIF estimates on the log-income using without prior β

	Lowest	Lower middle	Median	Upper middle	Highest
	.10	0.25	.50	.75	.90
RIF-probit regression using flat prior					
Intercept	18.321 (1.669)	6.497 (0.571)	2.992 (0.378)	1.250 (0.521)	−4.175 (1.421)
primary	**0.482** (0.449)	0.465 (0.145)	0.541 (0.093)	0.829 (0.133)	2.175 (0.405)
secondary	1.421 (0.555)	1.564 (0.182)	1.391 (0.103)	2.322 (0.129)	6.060 (0.346)
tertiary	5.905 (1.651)	4.145 (0.554)	3.653 (0.271)	4.712 (0.238)	11.332 (0.490)
age	−0.697 (0.290)	−0.412 (0.099)	−0.308 (0.067)	−0.256 (0.095)	**0.089** (0.273)
age^2	0.030 (0.012)	0.017 (0.004)	0.014 (0.003)	0.013 (0.004)	**0.001** (0.012)
size	−0.222 (0.020)	−0.148 (0.008)	−0.167 (0.007)	−0.376 (0.013)	−1.468 (0.053)
female	1.460 (0.469)	0.927 (0.152)	0.609 (0.093)	0.735 (0.126)	1.641 (0.347)
rural	−8.137 (0.318)	−3.251 (0.098)	−2.412 (0.071)	−3.128 (0.130)	−6.341 (0.473)
married	1.222 (0.503)	0.688 (0.165)	0.465 (0.103)	0.504 (0.139)	2.183 (0.378)

The age variable was divided by 100. Standard errors are indicated in parentheses. Bold figures correspond to posterior means for which 0 is contained in a 95% HPD interval

Table 5: Bayesian RIF estimates on the log-income

	Lowest	Lower middle	Median	Upper middle	Highest
	.10	0.25	.50	.75	.90
RIF-probit regression using Zellner's non-informative prior					
Intercept	18.272 (1.669)	6.492 (0.571)	3.001 (0.378)	1.204 (0.521)	−4.075 (1.421)
primary	**0.487** (0.449)	0.470 (0.145)	0.534 (0.093)	0.842 (0.133)	2.117 (0.405)
secondary	1.391 (0.555)	1.558 (0.182)	1.392 (0.103)	2.317 (0.129)	6.013 (0.346)
tertiary	5.984 (1.651)	4.065 (0.554)	3.621 (0.271)	4.686 (0.238)	11.266 (0.490)
age	−0.701 (0.290)	−0.414 (0.099)	−0.309 (0.067)	−0.251 (0.095)	**0.066** (0.273)
age^2	0.030 (0.012)	0.017 (0.004)	0.014 (0.003)	0.013 (0.004)	**0.002** (0.012)
size	−0.220 (0.020)	−0.148 (0.008)	−0.167 (0.007)	−0.372 (0.013)	−1.455 (0.053)
female	1.444 (0.469)	0.915 (0.152)	0.613 (0.093)	0.735 (0.126)	1.606 (0.347)
rural	−8.127 (0.318)	−3.245 (0.098)	−2.409 (0.071)	−3.104 (0.130)	−6.341 (0.473)
married	1.239 (0.503)	0.680 (0.165)	0.476 (0.103)	0.494 (0.139)	2.174 (0.378)

The age variable was divided by 100. Standard errors are indicated in parentheses. Bold figures correspond to posterior means for which 0 is contained in a 95% HPD interval

Returns to education: For both estimations, the marginal effect of education monotonically increases with the level of education and with quantiles. The rate of change in the returns to education across quantiles provides evidence of significant differences between the bottom and the top of the distribution. For all educational attainment levels, the marginal effects and their rate of change are significantly larger for upper quantiles (0.5, 0.75, 0.90), especially the secondary and the tertiary levels. The marginal effects of the secondary and tertiary education largely dominate the upper part of the distribution. The primary education is significant for all quantiles except the

lowest 10 percent, its return increases from the first quartile to the third quartile and then slightly decreases for the highest quantiles. The rate of change in the return to primary education is small and much lower than those to secondary and tertiary educations.
The marginal effects of the household's size monotonically decrease and their rate of change across quantiles are higher for upper quantiles. Living in rural areas has a negative and significant effect on the consumption expenditures for all quantiles. Senegal's rural economy is largely agricultural which is seasonal. The marginal effects of living in rural are comparatively higher than the other effects of covariates for poor households. Indeed, the urban labour force is more skilled and earns higher wages than the rural labour force.

These results are perfectly in line with those found above showing that poverty in Senegal is more predominant and more severe in rural areas and in illiterate-headed households.

4.2. Rural-urban inequality decomposition

In this section, we consider the Linear Probability Model (LPM) to disentangle the analysis in rural and urban areas. The estimated unconditional expectations of the RIF for both sectors are used to examine the rural-urban inequality in consumption expenditures by using the Oaxaca-Blinder decomposition.

4.2.1. Oaxaca-Blinder decomposition and RIF-regression

The Oaxaca-Blinder decomposition (Oaxaca 1973; Blinder 1973) approach is generally used to decompose changes in the mean of an outcome variable between two groups. In a classical linear mean regression model, the conditional expectation of the dependent variable Y on X is $\mathrm{E}_Y(Y|X) = X'\hat{\beta}$ leading to $\mathrm{E}(Y) = \mathrm{E}_X(\mathrm{E}(Y|X)) = \mathrm{E}(X)\hat{\beta}$. This property is not valid for quantile regression models as $q_\tau(Y) \neq \mathrm{E}[q_\tau(Y|X)] = \mathrm{E}(X)\beta_\tau$. Then, for quantile regression, the difference in unconditional quantiles is not equal to the difference between conditional quantiles. Several re-sampling methods are developed in the literature[16], but none of these methods can be used to decompose quantiles in the same spirit as means can be decomposed when using the conventional Oaxaca-Blinder method. Firpo et al. (2011) show that the method based on the estimation of RIF-regressions is more consistent for estimating the detailed components of both the wage structure and the composition effects.

To analyse the difference in consumption expenditure between rural and urban sector, we first estimate the RIF-regression for each sector s ($s = U, R$). The total difference in consumption expenditures across quantiles between the rural and urban sector is expressed as

$$\underbrace{\mathrm{E}\left(RIF(Y_U, q_\tau|X_U)\right) - \mathrm{E}\left(RIF(Y_R, q_\tau|X_R)\right)}_{\Delta_{\tau,O}} = \underbrace{(\bar{X}_U - \bar{X}_R)\beta_{\tau,R}}_{\Delta_{\tau,X}} + \underbrace{(\beta_{\tau,U} - \beta_{\tau,R})\bar{X}_R}_{\Delta_{\tau,\beta}}. \tag{10}$$

The first right hand component, $\Delta_{\tau,X}$ is attributed to the explained part, it is associated with the difference in characteristics between rural and urban households given the structure of returns in urban sector ("covariate effect"). The second right hand term, $\Delta_{\tau,\beta}$ is the "unexplained" part, it is interpreted as the difference in returns to covariates given individual characteristics in rural sectors ("return effect").

[16]Juhn et al. 1993, DiNardo et al. 1996, Machado and Mata 2005 or Melly 2005

We can estimate each component by replacing $\beta_{\tau,s}$ in 10 by its estimate $\hat{\beta}_{\tau,s}$. The estimates of both components can be evaluated as:

$$\widehat{\mathrm{E}(\Delta_{\tau,X})} = (\bar{X}_U - \bar{X}_R)\hat{\beta}_{\tau,R}, \quad \widehat{\mathrm{E}(\Delta_{\tau,\beta})} = \bar{X}_R\left(\hat{\beta}_{\tau,U} - \hat{\beta}_{\tau,R}\right).$$

The variances of the decomposition components are obtained as

$$\begin{aligned}\widehat{\mathrm{V}(\Delta_{\tau,X})} &= (\bar{X}_U - \bar{X}_R)'\mathrm{V}(\hat{\beta}_{\tau,R})(\bar{X}_U - \bar{X}_R),\\ \widehat{\mathrm{V}(\Delta_{\tau,\beta})} &= \bar{X}_R'\left(\mathrm{V}(\hat{\beta}_{\tau,U}) + \mathrm{V}(\hat{\beta}_{\tau,R})\right)\bar{X}_R,\end{aligned}$$

provided $\hat{\beta}_{\tau,U}$ and $\hat{\beta}_{\tau,R}$ are independent.

4.2.2. Returns to covariates by sectors

Table 6 presents the marginal effects of covariates in urban and rural sectors.

Table 6: Bayesian RIF estimates by sectors using a LPM.

	Lowest .10	Lower middle .25	Median .50	Upper middle .75	Highest .90
			rural		
Intercept	11.275 (0.174)	11.762 (0.123)	12.292 (0.107)	12.708 (0.115)	13.119 (0.153)
primary	**-0.013** (0.061)	**-0.013** (0.043)	**0.032** (0.037)	0.085 (0.040)	0.108 (0.053)
secondary	**0.069** (0.082)	**-0.041** (0.057)	0.103 (0.050)	0.212 (0.054)	0.343 (0.072)
tertiary	**0.371** (0.201)	**0.160** (0.141)	0.436 (0.124)	0.566 (0.133)	0.834 (0.177)
age	−0.715 (0.640)	−0.819 (0.450)	−1.059 (0.395)	−1.463 (0.425)	−1.399 (0.563)
age^2	0.620 (0.594)	0.773 (0.418)	0.870 (0.366)	1.367 (0.394)	1.244 (0.522)
size	−0.016 (0.003)	−0.024 (0.002)	−0.026 (0.001)	−0.026 (0.002)	−0.031 (0.002)
female	0.116 (0.059)	0.160 (0.041)	0.190 (0.036)	0.215 (0.039)	0.200 (0.052)
married	0.159 (0.068)	0.142 (0.048)	0.100 (0.042)	0.118 (0.045)	0.110 (0.060)
			urban		
Intercept	12.022 (0.106)	12.247 (0.080)	12.842 (0.075)	13.380 (0.0869)	13.886 (0.129)
primary	0.099 (0.029)	0.133 (0.021)	0.138 (0.020)	0.143 (0.0235)	0.142 (0.035)
secondary	0.232 (0.028)	0.272 (0.021)	0.350 (0.020)	0.437 (0.0232)	0.572 (0.034)
tertiary	0.334 (0.046)	0.430 (0.034)	0.605 (0.032)	0.959 (0.0374)	1.577 (0.056)
age	−0.927 (0.404)	−0.577 (0.305)	−1.152 (0.287)	−1.409 (0.3286)	−1.627 (0.491)
age^2	0.851 (0.367)	0.620 (0.277)	1.093 (0.261)	1.312 (0.2988)	1.440 (0.446)
size	−0.023 (0.001)	−0.028 (0.001)	−0.034 (0.001)	−0.043 (0.0016)	−0.049 (0.002)
female	0.079 (0.028)	0.113 (0.021)	0.097 (0.019)	0.053 (0.0227)	0.064 (0.034)
married	0.066 (0.030)	0.087 (0.022)	0.057 (0.021)	**0.036** (0.0246)	**0.005** (0.036)

Standard errors are indicated in parentheses: Bold figures correspond to posterior means for which 0 is contained in a 95% HPD interval

Returns to education: In rural sector, the return to education is only significant for high quantiles. For both sectors, the rate of change in the returns differs across quantiles and across the educational attainment level. The return to education monotonically increases with quantiles and are comparatively higher in the upper part of the distribution. However, the rate of change in return to primary education is comparatively lower than those to higher educations. For each level of education, the returns to education are higher in urban sector support that education is more beneficial in urban sectors.

In rural sectors as well as in urban sectors, the household's size effect is negative and significant for all quantiles with different pattern of changes across quantiles. In both sectors, the marginal effects monotonically increase and are larger in the upper part of the distribution. These marginal effects are higher in urban sectors for upper quantiles. This is explained by the urban cost of living to which can be added the cost of inactive adults.

In both areas, the effect of age of the head of households is significant and negative for high quantiles. Its marginal effect is higher in urban sector. Being female-headed has a positive and significant effect on the consumption expenditure with a small rate of change across quantiles. However, its marginal effect is comparatively higher for high quantiles.

These findings provide the evidence of difference in the marginal effects of covariates between the urban and the rural sectors, especially in the upper part of the distribution.

4.2.3. Return effect versus covariate effect

Table 7 reports the results from the Oaxaca-Blinder decomposition of the urban-rural inequality across quantiles in the logarithm of household's consumption expenditure per capita.

As described above, the RIF-regression provides a detailed decomposition of the rural-urban inequality into two subcomponents: the **covariate effect** wich measures the difference in the average characteristics themselves and the **return effect** which indicates the difference in returns to covariates. Table 8 provides the contribution of each covariate in each component to the total rural-urban inequality.

Total effect: Results indicate a positive and significant difference in mean consumption expenditure per capita between urban and rural sectors with different pattern of changes. The total difference increases monotonically across quintiles.

Covariate effect: The total covariate effect is significant for all quantiles. The total difference in characteristics increases monotonically across quintiles and is comparatively higher in the upper part of the distribution. However, the contribution of the difference in characteristics into the overall rural-urban gap is weak. It represents less than 20% on average at each quantile.

The difference in educational attainment is not significant for lower quantiles. Table 8 shows that the contribution of primary education to the covariate effect is small and comparatively much lower than the contribution of the secondary and tertiary education. The latter provides the largest contribution in the upper part of the distribution.

Some other covariates such as households size, female-headed household and married-headed household have largely contributed to the total difference in covariates in the lower part of the distribution. While the difference in education is only significant in the upper part of the distribution.

Return effect: The differences in return to various covariates are significant except the two extreme quantiles (0.10 and 0.90). The total return effect provide the largest contribution in the total rural-urban inequality in consumption expenditure as shown in Table 8. In the lower part, except the intercept, only the difference in returns to education is significant. The differences in return to age and to being married are not significant at any quantiles.

Moreover, our findings contrast those of Binh et al. (2007) for Vietnam and to those of Mattita and Chirwa (2009) for Malawi. Binh et al. (2007) show that the rural-urban inequality in Vietnam

Table 7: Bayesian RIF estimates for rural-urban inequality decomposition
ESPS, 2005-2006

	Lowest .10	Lower middle .25	Median .50	Upper middle .75	Highest .90
Differences	0.651	0.604	0.592	0.625	0.675
	(0.019)	(0.014)	(0.012)	(0.014)	(0.019)
return effect					
total	**0.606**	0.569	0.505	0.509	**0.520**
	(0.468)	(0.241)	(0.194)	(0.306)	(0.615)
Intercept	0.746	0.485	0.550	0.672	0.766
	(0.267)	(0.192)	(0.172)	(0.222)	(0.315)
primary	0.019	0.025	0.018	0.010	0.007
	(0.011)	(0.007)	(0.006)	(0.011)	(0.015)
secondary	0.030	0.057	0.045	0.041	0.042
	(0.014)	(0.010)	(0.009)	(0.016)	(0.023)
tertiary	−0.002	0.015	0.010	0.023	0.043
	(0.012)	(0.008)	(0.007)	(0.013)	(0.019)
age	**-0.107**	**0.122**	**-0.047**	**0.027**	**-0.115**
	(0.563)	(0.404)	(0.362)	(0.450)	(0.637)
age^2	**0.064**	**-0.042**	**0.062**	**-0.015**	**0.054**
	(0.259)	(0.186)	(0.167)	(0.213)	(0.302)
size	**-0.061**	**-0.038**	−0.075	−0.142	−0.158
	(0.090)	(0.065)	(0.059)	(0.067)	(0.094)
female	**-0.010**	**-0.012**	−0.025	−0.044	−0.037
	(0.016)	(0.011)	(0.010)	(0.017)	(0.024)
married	**-0.072**	**-0.043**	**-0.033**	**-0.064**	**-0.082**
	(0.063)	(0.045)	(0.040)	(0.062)	(0.089)
covariate effect					
total	0.0444	0.0352	0.0870	0.1160	0.1551
	(0.0216)	(0.0152)	(0.0133)	(0.0143)	(0.0143)
primary	**-0.001**	**-0.001**	**0.003**	0.008	0.010
	(0.0057)	(0.0040)	(0.0035)	(0.0038)	(0.0050)
secondary	**0.010**	**-0.006**	0.015	0.030	0.049
	(0.0117)	(0.0082)	(0.0072)	(0.0077)	(0.0103)
tertiary	**0.019**	**0.008**	0.023	0.029	0.043
	(0.0105)	(0.0074)	(0.0064)	(0.0069)	(0.0092)
age	0.001	0.001	0.001	0.002	0.002
	(0.0008)	(0.0006)	(0.0005)	(0.0005)	(0.0007)
age^2	−0.001	−0.002	−0.002	−0.004	−0.003
	(0.0015)	(0.0011)	(0.0009)	(0.0010)	(0.0014)
size	0.019	0.028	0.030	0.031	0.036
	(0.0035)	(0.0024)	(0.0021)	(0.0023)	(0.0031)
female	0.018	0.025	0.030	0.034	0.031
	(0.0093)	(0.0065)	(0.0057)	(0.0061)	(0.0082)
married	−0.021	−0.019	−0.013	−0.015	−0.014
	(0.0090)	(0.0063)	(0.0055)	(0.0060)	(0.0079)

Standard errors are indicated in parentheses: Bold figures correspond to posterior means for which 0 is contained in a 90% HPD interval.

between poor households is mainly due to the difference in characteristics, while the gap between the richest households are attributable to the difference in returns. Following Binh et al. (2007)'s methodological approach, Mattita and Chirwa (2009) show that 59% of the rural-urban gap in Malawi is due to the difference in characteristics. In contrast, our results show that the difference in characteristics weakly contributes to the rural-urban inequality in Senegal. It represents less than 20% for each point of the distribution. The rural-urban inequality is largely attributed to the difference in returns to covariates for all quantiles, especially in the upper part of the distribution. However, in the lower part of the distribution only returns to education reveal a significant impact through the return effects, while other factors show a significant impact through covariate effects. The large contribution of the difference in returns to the total rural-urban inequality in Senegal is not surprising. It is mainly explained by the structure of the labour market in Senegal.

Table 8: Contributions in % of covariates to the total
rural-urban inequality

	0.10	0.25	0.50	0.75	0.90
return effect					
total	*92.73*	93.97	85.95	81.21	*78.14*
primary	3.36	3.99	2.85	*1.60*	*0.90*
secondary	5.22	9.84	7.41	6.20	6.27
tertiary	-0.46	2.74	1.99	3.59	6.00
age	*-27.9*	*12.12*	*-19.62*	*-8.70*	*-27.38*
size	*-9.74*	*-5.72*	-13.71	-22.79	-24.62
female	*-1.95*	*-2.24*	-3.44	-6.64	-5.65
married	*-12.4*	*-7.63*	*-4.69*	*-9.88*	*-11.37*
covariate effect					
total	**7.26**	**6.02**	**14.05**	**18.78**	**21.85**
primary	*-0.23*	*-0.20*	*0.42*	1.30	1.63
secondary	*1.75*	*-1.02*	2.16	4.55	7.45
tertiary	*3.28*	*1.45*	3.59	4.59	6.13
age	0.27	0.36	0.50	0.70	0.58
size	3.46	4.54	4.33	5.08	5.89
female	3.29	4.32	4.41	5.10	4.80
married	-3.56	-3.29	-2.11	-2.46	-2.06

Italics corresponds to differences which are not significant

5. Conclusion and policy implications

In this study, we have investigated both changes in the returns to education across quantiles and rural-urban inequality decomposition in consumption expenditure. We have employed the RIF-regression method developed by Firpo et al. (2009), to better performs a detailed quantile decomposition in the spirit of the traditional Oaxaca-Blinder decomposition for the mean (Firpo et al. 2011). We have also extended the Bayesian approach for the linear RIF-regression developed by Lubrano and Ndoye (2013) using the dichotomous structure of the RIF to sample a logistic-regression with a Metropolis Hastings sampler. The approaches are applied to a nationally representative survey, the Senegal Poverty Monitoring Report (2005).

Our findings primarily show evidence from the heterogeneous pattern of changes in the rate of returns to education across quantiles and across the different level of education. They also reveal the evidence of dissimilarities in the pattern of change in the returns to education between urban and rural areas.The marginal effects of education monotonically increase and are comparatively higher for upper quantiles (0.50, 0.75, 0.90). The return to primary education does not change much across quantile compared with those to secondary and tertiary education. This result is in line with findings showing that in countries that rapidly expand access to primary education, the returns to primary education fall, while returns to higher education rise (see for instance Psacharopoulos 1994, Psacharopoulos and Patrinos 2002). In contrast, "primary education continues to be the number one investment priority in developing countries" (Psacharopoulos and Patrinos (2002)).
Second, our decomposition results demonstrate a large and significant differences in consumption expenditures across quantiles between the urban and the rural sector. The high rural-urban inequality in Senegal is attributed in particular to the difference in returns to various covariates. However, only the difference in returns to education is still significant for lower quantiles. In contrast to the Vietnam's case, our findings report a weak contribution of the difference in covariates to the rural-urban inequality even for lower quantiles. Covariates such the households size and the gender

of the head of households largely contribute to the total difference in covariates for lower quantiles. These results demonstrate the need for a rural industrialization[17] to make education beneficial in rural sectors and to reduce the strong rural exodus in Senegal. This is expected to favor the creation of the appropriate higher-level jobs in rural sectors to attract rural migration and emigration and thereby to open up Dakar and other urban cities. China's Township and Village Enterprises (TVEs) provide an excellent model of how a rural industrialization has remarkably contributed to rural development in China. China's TVEs are private and collective owned enterprises established in rural and peri-urban areas. Since the industrial and agricultural reforms in China in the early 1980s, the growth of the TVEs has exploded in response to China's transition strategy[18]. There is a consensus agreement[19] that the TVEs have substantially contributed to China's overall economic growth and development, especially in rural areas[20].

Since the collective agreement of the international community to universal primary education, the two last decades have seen a strong expansion of the enrollment rate of primary education in most developing countries. In most developing countries, promoting education is not only for development policy and for eradicating poverty, but it is also an argument to attract institutional financing and other forms of aid from donors. Senegal witnessed one of the largest increase in the achievement of the second priority of the MDGs. The rate of primary education in Senegal climbed from 54 percent in 1994 to over 82 percent in 2005. This was accompanied by a substantial increase of the number of private schools in urban areas and of public primary schools in rural sectors. In Senegal, as well as in most developing countries, the quality of education in public schools has deteriorated following the increase of enrollment rates. Public schools record a higher frequency of school dropouts. In public schools, teaching materials are of poor quality and teachers lack appropriate skills. Private schools provide a better quality of education and are better equipped. The growing number of primary schools has partially contributed to the literacy and encouraged the education of girls. In contrast, the growing number of public primary schools disadvantages children from low-income families by the lack of educational resources.

Moreover, since the wealthiest households enroll their offspring in private schools, the growing number of private schools leads to increase inequalities in access to education. Hence, the strong socio-economic segregation of schools will increase social inequalities in the long run and will make poverty an intergenerational inheritance.

[17]Rural industrialization consists in urbanizing the rural areas by a combination of agriculture and industry, and of industry and trade. As argued by Zhang (1999), rural industrialization consists in "taking the road of leaving the land but not the village, entering the factory but not the city".

[18]the TVEs allowed rural communities to translate control over assets and resources into income, despite the absence of asset markets and without resorting to privatization. TVEs also facilitated access to capital on the part of start up firms.

[19]See Weitzman and Xu, 1994, Zhang, 1999, DaCosta and Carroll, 2001.

[20]Zhang (1999) noticed that "The gross output of the TVE sector registered an average annual growth of approximately 25 percent between 1980 and 1995. By 1995, TVEs accounted for approximately a quarter of China's gross domestic product (GDP), two-thirds of the total rural output, 45 percent of the gross industrial output, and more than one-third of Chinas export earnings."

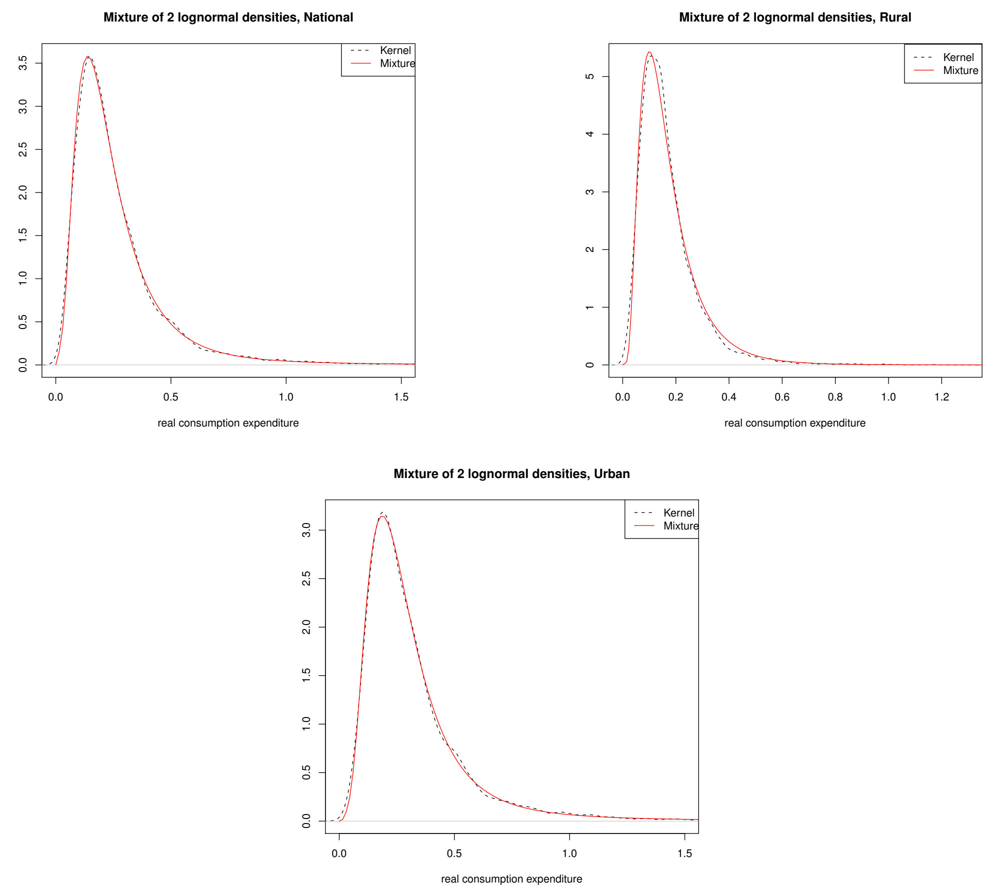
6. Sensitivity analysis: classical estimation

We present in this appendix the classical estimates based on the RIF-OLS suggested in Firpo et al. (2009). The estimates of the RIF-regression coefficients, $\hat{\beta}_\tau$ are obtained by an OLS regression.

$$\hat{\beta}_\tau = (X'X)^{-1} X' \widehat{RIF}(y, q_\tau, F). \tag{11}$$

where y is the vector of observations for Y and X is a matrix of observations for the exogenous variables. The density is estimated by using a kernel density estimator.

Figure 1: Mixture and kernel density estimations of the real consumption expenditure ESPS 2005-2006. Units are in 10^6.



The "classical RIF" estimates of Firpo et al. (2009) and the Bayesian RIF estimates presented above yield roughly the same marginal effects. This can be explained by the fact that distributions of consumption expenditures are well approximated by both Gaussian kernel density and mixture of normal densities. Results are not sensitive to extreme quantiles. However, the posterior standard deviations larger than a classical standard error.

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Table 9: RIF-OLS estimates using kernel density estimation

	OLS Mean	Lowest .10	Lower middle .25	Median .50	Upper middle .75	Highest .90
Intercept	12.835***	11.951***	12.392***	12.800***	13.284***	13.821***
	(0.050)	(0.105)	(0.070)	(0.061)	(0.070)	(0.097)
primary	0.104***	0.040	0.075***	0.113***	0.120***	0.101***
	(0.014)	(0.031)	(0.021)	(0.019)	(0.019)	(0.027)
secondary	0.338***	0.067*	0.177***	0.284***	0.445***	0.615***
	(0.012)	(0.031)	(0.020)	(0.017)	(0.020)	(0.031)
tertiary	0.791***	0.138*	0.278***	0.547***	0.951***	1.680***
	(0.025)	(0.055)	(0.034)	(0.031)	(0.033)	(0.050)
age	−1.093***	−0.881*	−1.059***	−1.146***	−1.187***	−1.513***
	(0.195)	(0.409)	(0.270)	(0.240)	(0.265)	(0.3673))
age^2	0.999***	0.852*	0.945***	1.107***	1.098***	1.314***
	(0.175)	(0.372)	(0.247)	(0.220)	(0.243)	(0.335)
size	−0.032***	−0.022***	−0.026***	−0.030***	−0.036***	−0.045***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
female	0.099***	0.094**	0.128***	0.125***	0.102***	0.055*
	(0.012)	(0.029)	(0.020)	(0.020)	(0.020)	(0.027)
rural	−0.500***	−0.717***	−0.602***	−0.523***	−0.389***	−0.278***
	(0.010)	(0.022)	(0.015)	(0.013)	(0.014)	(0.020)
married	0.065***	0.088**	0.093***	0.089***	0.043·	0.043
	(0.016)	(0.033)	(0.023)	(0.017)	(0.020)	(0.027)

Significant codes: *** 0.01; ** 0.05; * 0.1. Standard errors in parentheses.

Table 10: Classical RIF-Probit estimates

	Lowest .10	Lower middle 0.25	Median .50	Upper middle .75	Highest .90
Intercept	18.169***	6.517***	2.991***	1.228**	−4.174**
	(1.660)	(0.567)	(0.374)	(0.519)	(1.420)
primary	0.494	0.463***	0.530***	0.838***	2.169***
	(0.443)	(0.141)	(0.093)	(0.132)	(0.405)
secondary	1.403**	1.564***	1.389***	2.309***	6.060***
	(0.550)	(0.180)	(0.102)	(0.127)	(0.344)
tertiary	5.700***	4.078***	3.628***	4.679***	11.298***
	(1.650)	(0.553)	(0.270)	(0.237)	(0.490)
age	−0.693**	−0.415***	−0.307***	−0.253**	0.083
	(0.283)	(0.090)	(0.065)	(0.090)	(0.271)
age^2	0.030**	0.017***	0.014***	0.013**	0.002
	(0.010)	(0.002)	(0.003)	(0.004)	(0.012)
size	−0.221***	−0.148***	−0.167***	−0.374***	−1.464***
	(0.017)	(0.008)	(0.006)	(0.013)	(0.050)
female	1.467***	0.919***	0.613***	0.739***	1.631***
	(0.460)	(0.151)	(0.091)	(0.125)	(0.341)
rural	−8.121***	−3.255***	−2.414***	−3.127***	−6.330***
	(0.317)	(0.096)	(0.070)	(0.130)	(0.472)
married	1.308***	0.682***	0.476***	0.501***	2.189***
	(0.501)	(0.163)	(0.101)	(0.135)	(0.371)

Significant codes: *** 0.01; ** 0.05; * 0.1. Standard errors in parentheses.

Table 11: RIF-OLS estimates decomposition rural-urban inequality

	OLS	Lowest	Lower middle	Median	Upper middle	Highest
	Mean	.10	.25	.50	.75	.90
Differences	0.643***	0.650***	0.604***	0.592***	0.625***	0.675***
	(0.0274)	(0.020)	(0.014)	(0.012)	(0.014)	(0.018)
return effect						
total	0.551***	0.603	0.568**	0.509***	0.507**	0.527
	(0.140)	(0.524)	(0.257)	(0.187)	(0.241)	(0.408)
Intercept	0.650***	0.743***	0.479***	0.578***	0.671***	0.754***
	(0.146)	(0.283)	(0.198)	(0.168)	(0.191)	(0.248)
primary	0.013***	0.020**	0.026***	0.019***	0.010	0.005
	(0.005)	(0.010)	(0.007)	(0.006)	(0.007)	(0.009)
secondary	0.040***	0.030**	0.059***	0.048***	0.042***	0.039***
	(0.007)	(0.015)	(0.010)	(0.008)	(0.009)	(0.012)
tertiary	0.016***	−0.003	0.016*	0.012*	0.023***	0.040***
	(0.006)	(0.012)	(0.008)	(0.007)	(0.008)	(0.010)
age	−0.030	−0.098	0.129	−0.084	0.030	−0.099
	(0.308)	(0.595)	(0.417)	(0.356)	(0.404)	(0.526)
age^2	0.040	0.060	−0.045	0.079	−0.016	0.046
	(0.142)	(0.274)	(0.192)	(0.164)	(0.186)	(0.242)
size	−0.083***	−0.058*	−0.038	−0.092***	−0.142***	−0.145***
	(0.050)	(0.095)	(0.067)	(0.058)	(0.066)	(0.086)
female	−0.021	−0.011	−0.013	−0.022**	−0.045***	−0.035***
	(0.008)	(0.017)	(0.011)	(0.010)	(0.011)	(0.014)
married	−0.073	−0.079	−0.045	−0.029	−0.065	−0.078
	(0.034)	(0.067)	(0.046)	(0.039)	(0.044)	(0.056)
covariate effect						
total	0.092	0.047***	0.036***	0.083***	0.117***	0.148***
	(0.0115)	(0.0230)	(0.0157)	(0.0127)	(0.0145)	(0.0181)
primary	0.005	−0.001	−0.001	0.003	0.008**	0.010**
	(0.0030)	(0.0061)	(0.0041)	(0.0033)	(0.0038)	(0.0048)
secondary	0.022	0.010	−0.006	0.014***	0.031***	0.047***
	(0.0062)	(0.0125)	(0.0085)	(0.0069)	(0.0078)	(0.0098)
tertiary	0.028	0.020	0.008	0.022***	0.030***	0.041***
	(0.0056)	(0.0112)	(0.0076)	(0.0062)	(0.0070)	(0.0088)
age	0.001***	0.001	0.001	0.001***	0.002***	0.002***
	(0.0004)	(0.0019)	(0.0006)	(0.0005)	(0.0005)	(0.0007)
age^2	−0.002	−0.002	−0.002	−0.002***	−0.004***	−0.003**
	(0.0018)	(0.0027)	(0.0011)	(0.0009)	(0.0010)	(0.0013)
size	0.030***	0.021***	0.029***	0.029***	0.032***	0.035***
	(0.0018)	(0.0047)	(0.0025)	(0.0020)	(0.0023)	(0.0029)
female	0.025***	0.019**	0.026***	0.028***	0.034***	0.030***
	(0.0049)	(0.0109)	(0.0067)	(0.0055)	(0.0062)	(0.0078)
married	−0.018***	−0.022**	−0.019***	−0.012***	−0.016***	−0.014***
	(0.0048)	(0.0106)	(0.0066)	(0.0053)	(0.0060)	(0.0076)

Significant codes: *** 0.01; ** 0.05; * 0.1