Poverty dynamics in Rwanda, 2006-2011

Preliminary, please do not cite

Christoph Lakner[1]

Abstract

In the absence of panel data, this paper uses an econometric technique to estimate poverty dynamics using repeated cross-sections. I estimate that between 2006 and 2011 around 15% of the population exit poverty, while around 8% fall into poverty, so headcount poverty falls by approximately 7pp. However, this poverty reduction starts from a high level of poverty (more than 50%), so the probability of leaving poverty *conditional* on being poor in the base period is relatively low (around 29%) compared with other countries. These conditional probabilities of exiting poverty are greater in urban areas, amongst educated household heads and in Kigali. The difference between female- and male-headed households, however, is small. When I exclude urban areas, living in a cluster with a greater coverage of the Crop Intensification Program increases the probability of exiting poverty and reduces the probability of falling into poverty. On the other hand, I find no substantive differences according to the rollout of a public works program. I also find that 20 years after the genocide, the districts where conflict was more intense have a lower probability of exiting poverty and a greater risk of becoming poor.

[1] World Bank, Development Research Group, clakner@worldbank.org. The opinions expressed in the paper are the author's, and should not be attributed to the World Bank and its affiliated organisations. I would like to thank Tom Bundervoet, Hai-Anh Dang, Peter Lanjouw and Roy van der Weide for very detailed comments on earlier drafts and help with the method and data. I would also like to thank Marijke Verpoorten for making the genocide data available on her website. This draft: 29 May 2014.

Introduction

Between 2006 and 2011, headcount poverty in Rwanda (using a basic-needs poverty line) dropped by 12pp from 57% to 45% (Table A.1). This paper measures the extent of poverty mobility over this time period. To be precise, I estimate the joint probabilities in the poverty transition matrix (see below).[2] By comparing the extent of poverty mobility across population subgroups, I assess where this poverty reduction has taken place and identify those groups which have remained in poverty.

Typically, we require panel data to measure poverty transitions because we need to observe the same household over time. However, over this time period in Rwanda there exist no good quality panel data. New panel data are planned to be released at some point in 2014, but they cover the time after 2011. Hartwig (2013) uses a two-round household panel survey between 2009 and 2011, but the data are not a general-purpose household survey and provide only a short panel.[3] Howe and McKay (2007) use qualitative research in the form of a participatory poverty assessment to identify the characteristics of the chronic poor in Rwanda. In a household survey they then investigate further characteristics of the chronic poor defined in this way. Using their method, one could obviously also look at changes in chronic poverty over time from repeated cross-sectional surveys. However, they are likely to underestimate chronic poverty because they need to use strict categories (e.g. very small ownership of land and livestock) to identify the chronic poor.

In the absence of panel data, this paper uses an econometric technique to construct a synthetic panel based on repeated cross-sections. Intuitively, this method imputes consumption in year 1 for every households observed in period 2, using an econometric consumption model. Hence for each household in period 2, the data now contain (imputed) consumption in period 1, i.e. we have created a synthetic panel data set. These data can be used directly to analyse poverty dynamics, i.e. the probabilities of being chronically poor or non-poor, exiting poverty, or falling into poverty. The method has been cross-validated in a number of countries from various regions.

[2] Consumption in periods 1 and 2 are denoted by y_{i1} and y_{i2}. Period 1 and period 2 poverty lines are z_1 and z_2 respectively.

[3] These data were collected to investigate the effects of a public works program, the Vision 2020 Umurenge Program (VUP).

This paper represents one of the first applications of synthetic panel methods to an African country.

Poverty transition matrix

		Poverty status in round 2	
		Poor: $y_{i2} < z_2$	Non-poor: $y_{i2} > z_2$
Poverty status in round 1	Poor: $y_{i1} < z_1$	*Chronic poor*	*Poverty exits*
	Non-poor: $y_{i1} < z_1$	*Poverty entrants*	*Persistently non-poor*

There exist two variants of the synthetic panel estimation methods. As I will explain in section 1 (and in more detail in Appendix 1), they differ in their assumption about the correlation between the error terms in the consumption models estimated for the two periods. The first method requires minimal assumptions but can only identify bounds which correspond to extreme assumptions about the error correlation. The upper bound on poverty mobility corresponds to a correlation of zero, while the lower bound corresponds to a perfect positive correlation. The second method derives a point estimate by obtaining the correlation coefficient from the data and assuming joint normality of the error term. I initially apply both methods to the data, but in the subgroup analysis I concentrate on the point estimates. This is because the normality assumption appears satisfied, so the point estimates strike the most reasonable balance between the two extreme assumptions associated with the bounds. Furthermore, the point estimates lie well within the bounds. Of course, the point estimates are also appealing because they are easier to communicate and derive policy implications.

This paper is structured in five parts. First, I give an intuitive explanation of the methodology. More details can be found in Appendix 1. Second, I describe the data set, particularly the selection of the sample and the definition of the variables. Section 3 chooses the consumption model used to impute consumption. In section 4, I present the results on the overall poverty dynamics comparing the bounds and point estimates. Finally, I estimate poverty dynamics by population subgroups in an attempt to get closer to policy implications. Note that the main results take sampling weights into account, while I report unweighted results in the Appendix Tables.[4]

1 Methodology

In this paper, I consider two estimation methods to impute period 1 consumption for households observed in period 2. First, the non-parametric approach by Dang et al. (2013) (DLLM) provides upper and lower bounds on the probabilities in a poverty transition matrix. Second, Dang and Lanjouw (2013) (DL) derive parametric point estimates under the additional assumption of joint normality of the error term.[5] I provide a general framework here, while the Appendix describes the two methods in more detail. The methodology, including notation, comes directly from DLLM and DL.

The linear projection of the consumption of household i in round 1 (y_{i1}) onto a vector of household characteristics (x_{i1}) can be written as

$$y_{i1} = \beta_1' x_{i1} + \varepsilon_{i1} \qquad (1)$$

Similarly, we can write the same model for period 2:

$$y_{i2} = \beta_2' x_{i2} + \varepsilon_{i2} \qquad (2)$$

It is important to note that these are not the same households because we do not have panel data and the model is estimated separately for two cross-sections. The vector of household characteristics, x_{i1} and x_{i2}, must be the same in both rounds. It contains time-invariant characteristics of the household and the household head (if his/her identity remains unchanged, which is an implied assumption). If recall questions exist in round 2, we can also use time-varying characteristics. For example, the variable "disability at the time of round 1" could be constructed for both rounds, if survey 2 asked a recall question referring to that period, or how

[4] It is common in this literature to report both sets of results as (e.g. see Dang and Lanjouw, 2013).
[5] Note that DLLM also present a parametric bounds approach, which I do not use in this paper. DLLM parameterise the correlation coefficient between the error terms using secondary data sources. In contrast, DL estimate this correlation from the data which can be considered an improvement.

long the household head had been suffering from this condition. More details about the consumption model and the variable construction are provided below.

This paper estimates for example the probability of being poor in period 1 and non-poor in period 2 (households which exit poverty), i.e. $P(y_{i1} < z_1 \; and \; y_{i2} > z_2)$, where z_1 and z_2 are the poverty lines in period 1 and 2. Of course, in the absence of panel data, we cannot observe y_{i1} and y_{i2} for the same household. Using Equations (1) and (2), we can re-write this expression as $P(\varepsilon_{i1} < z_1 - \beta_1' x_{i1} \; and \; \varepsilon_{i2} > z_2 - \beta_2' x_{i2})$. In other word, the probability of a household exiting poverty between rounds 1 and 2 depends on the joint distribution of the error terms.

The two estimation methods considered in this paper differ in their assumption about the correlation between the errors. The upper and lower bounds on mobility of the non-parametric method arise in the case of zero and perfect positive correlation. The parametric estimation imposes joint normality on the errors and estimates the correlation from the data. Therefore, the parametric method strikes a reasonable compromise between two extreme assumptions as long as the normality assumption is satisfied.

Intuitively, a weaker association between the error terms implies higher mobility. In the extreme case of perfect (positive) correlation, those households which have high consumption in the first period (conditional on a set of explanatory variables) will also have high consumption in period 2, i.e. mobility will be low. In contrast, when the association is zero, household consumption (conditional on household characteristics) in period 1 has no explanatory power for consumption in period 2, and mobility will be high. Hence the assumption of zero correlation corresponds to the upper bound on poverty mobility.

Both methods adopted in this paper need to assume that (1) the underlying population in rounds 1 and 2 is the same; and (2) the correlation in the error terms is non-negative.[6] The first assumption ensures that the distribution of time-invariant characteristics does not change over time, so that we can use these characteristics to predict consumption. I will test this assumption below. DLLM provide empirical support for the second assumption from panel data. Furthermore, they argue

[6] In DLLM it is assumed that the error terms are positive quadrant dependent which implies that their correlation cannot be negative. In DL it is also assumed that this correlation is non-negative.

that it could be justified (1) from the presence of household fixed effects in the error term; (2) from the persistence in consumption shocks (i.e. positive correlation over time); and (3) by arguing that while credit-constrained households might reduce consumption to finance lumpy consumption later, this is unlikely to be true for the population as a whole.

Appendix 1 explains the two estimation methods in more detail. The first set of results in section 5 compares the bounds and point estimates of poverty mobility for the whole population. When I subsequently analyse mobility by subgroup, I concentrate on the point estimates. This is because in the first part of the results, I show that the parametric assumptions required by the point identification approach are satisfied (section 3.3).

2 Data and summary statistics

I use the Rwanda Integrated Household Living Conditions Survey (or Enquête Intégrale sur les Conditions de Vie des Ménages - EICV), which is a cross-sectional household survey. There exist three rounds of the survey - 2000/1, 2005/6 and 2010/11. In this paper, I focus on the last two rounds, EICV2 and EICV3, because the questionnaires are more comparable. Note that I refer to EICV2 and EICV3 as year (or round) 1 and 2 respectively. Also note that the variables described here refer to the characteristics of the household head unless otherwise indicated.

2.1 Sample selection

The households included in the sample used for the analysis had to meet the following conditions:

- I exclude HHs whose head was enrolled in school in the 12 months prior of the survey. The consumption model includes only time-invariant characteristics and education is one of them. In EICV3, this affects 1.34% of observations, more than two-thirds of whom are enrolled in tertiary education.

- In EICV3, I excluded those HHs whose head had moved from abroad in the last six years.[7] In the synthetic panel analysis it is important that the population from which the household survey sample is drawn is defined consistently over time. The population in EICV2 are all households which are resident in Rwanda at the time of enumeration, i.e. excluding all those who lived abroad at that moment. This sample selection affects 0.98% of the sample in EICV3.
- In order to satisfy the assumptions of the synthetic panel analysis, DLLM suggest restricting the age of household heads to lie between 25 and 55 in the first round. Outside of this age range, poverty transitions might be harder to analyse because households are just being formed or start to dissolve. I choose the age range of 23 to 58 in round 1 because in Rwanda households form at a young age, particularly in the rural part of the country. After excluding the HH heads who are currently in school, 3.10% of the sample are younger than 23 (6.93% are younger than 25) and 17.87% are older than 58. Hence my adjustment drops just over 20% of the sample. Because the round 2 survey is five years later, I restrict the age range to lie between 28 and 63 in that round, as suggested by DL. After dropping HH heads in education and those who moved from abroad in the last six years, 12.11% of observations are younger than 28 and 13.81% are older than 63. Thus in round 2, my adjustment excludes just under 26% of the sample.

Table A.1 compares headcount poverty and average consumption across the different samples and over time. The estimation sample has somewhat higher poverty rates (56.9% vs. 56.7% in 2006, and 47.2% vs. 44.9% in 2011) and lower average consumption. For poverty, although not for average income, the differences arise as the result of the age restriction. Using my age range produces results which are more similar to the full sample compared with the alternative age restriction used by DLLM, who choose 25 to 55 in year 1.

In Figure A.1, I compare the consumption distributions across the two samples. Firstly, the density of the estimation sample is slightly to the left in both years, implying lower average income, as shown in Table A.1. However, there is no systematic difference otherwise. Secondly,

[7] The precise enumeration dates for the two survey rounds are Oct 2005 to Oct 2006 for EICV2 and Nov 2010 to Oct 2011 for EICV3. Therefore, the time between the start of round 1 and the end of round 2 is six years, which thus represents the most conservative time period to select.

the distribution shifted to the right over time, showing a growth in average income of some 16.6%.

2.2 Variable definitions

The dependent variable throughout is the logarithm of yearly consumption expenditures per adult equivalent, expressed in January 2001 prices. It is comparable across the survey waves and it is adjusted for regional differences in the cost of living. The main poverty line used is RWF64,000 per adult equivalent per year in January 2001 prices. Using market exchange rates, this equals USD0.49 per day.[8] There also exists an extreme poverty line of RWF48,000.

The variables included in the consumption model need to be time-invariant or time-deterministic (e.g. age). Furthermore, they need to be balanced across the two survey rounds (which will be formally tested in the next section), and should maximise the explanatory power of the consumption models (as for example measured by an R2).

The definition of the age and gender variables is straightforward. The birth-region variable has been more difficult to construct because of changes in the administrational divisions of Rwanda without a clear mapping between the two survey rounds.[9] I considered three potential variables, which are consecutively less detailed (but also require fewer assumptions).[10] I chose the most aggregated variable, because it requires no arbitrary assumptions about mapping the regions and because the gain in explanatory power as measured by an R2 was limited. It is defined as the Kigali, South, and West regions, the rest of Rwanda, neighbouring countries and other countries.[11]

[8] According the www.xe.com (retrieved on 12.12.2013), the exchange rate on 15 Jan 2011 was USD1.00= RWF357.23.

[9] The first survey records this information in terms of the 12 old regions, whereas the second survey uses the 30 new districts. In addition, there is a category for those born abroad. It is not possible to map the 30 new districts into the 12 old regions, the main problem being the old Kigali-Ngali (rural Kigali) region.

[10] Variable 1: 12 old regions. Variable 2: 4 new regions plus Kigali-Ngali.

[11] The new regions are Kigali, North, East, South and West. The abolition of the Kigali-Ngali region affected the North and East regions, which are thus grouped as “rest of Rwanda”.

I also include a disability dummy variable, which is defined as "Did you suffer from a disability *at the time of survey 1*?", i.e. it is time-invariant.[12] In survey 1, it is constructed directly from the contemporaneous question about disability. For survey 2, I make use of the question "How long have you been suffering from the disability?".[13]

The region of residence (and rural/urban dummy) faces a very similar issue. In order to be time-invariant, it should be defined as the "Region of residence *at the time of survey 1*". For the first survey round, it is simply the current region of residence. For survey round 2, I make use of the migration module of the questionnaire which asks for the previous residence and the time since you moved from the previous residence. Households which never moved or moved more than six years ago are assigned their current residence. All other households (i.e. those that moved within the last six years) take their previous residence. This assignment would be wrong for a household which arrived at the previous location less than four years ago. However, because I only observe the previous residence, and not the residence before that, I cannot construct the variable in any other way. The only option would be to exclude these households. I believe my approach is justified because (1) the proportion of households which arrived at their previous location less than four years ago is small (1.81% after dropping those who are still in school and those that moved from abroad in the last six years); and (2) it represents a conceptual improvement over simply using the current residence and effectively assuming no migration between the two survey rounds.

In the consumption model, I use educational attainment indicating the highest level of education (primary, vocational, secondary, tertiary) attended. I considered a number of alternative education variables: The four education dummy variables (any schooling, ability to read, write, or do

[12] In survey 2, there is a very similar question asking whether you have suffered from any health problems, and if so for how long. In survey 1, there is a similar question asking about any contemporaneous health problems. The averages are very different between the two survey rounds, and hence I do not incorporate this variable in the analysis. This might be explained by the fact that health problems are harder to remember than a disability, or that in survey round 2 respondents report the most recent health issue which did not occur since survey 1.

[13] The disability variable is coded as one if the respondent has been suffering from the disability for five or more years. Note that this cut-off time is the mid-point between the two survey rounds, and is different from the cut-off selected for dropping households moved from abroad. In the latter case, I wanted to be absolutely sure that I am excluding all households which were not in the population in survey round 1. For the disability variable, there could be a bias in both directions: First, missing a disability by choosing a six year window. Second, overstating a disability by choosing a four year window, i.e. the distance between the end of survey 1 and the beginning of survey 2. Taking the distance between the mid-points is the best compromise.

written calculations) are not balanced across the two survey rounds, and (not surprisingly) have a substantially lower R2. Using more detailed educational attainment (26 categories referring to the highest class attended) would increase the R2, but might be subject to greater measurement error.[14] Educational completion (i.e. the highest certificate obtained) has too many missing observations, which might be the result of measurement error (i.e. individuals failing to report a certificate they obtained) or simply confirm other evidence that educational completion rates are low in Rwanda (i.e. all missing observations are non-completers).[15] Finally, note that years of education could not be constructed from the survey because the highest category of educational attainment recorded in the survey includes a number of years.[16]

3 Choosing the consumption model

3.1 Testing for balance across 2006 and 2011

For the variables and sample used in the consumption model, Table 1 compares the mean and standard deviation in surveys 1 and 2. This is very similar to randomised controlled trials testing for differences in characteristics across the treatment and control groups. Given that the variables in the model are time-invariant and that I matched the age ranges in the two surveys (controlling for any birth cohort effects), there should not be any difference between the two means (abstracting from any sampling variation). Columns (4) and (5) show whether any differences we observe are statistically significant, taking into account population sampling weights and the complex survey design.[17]

[14] In other words, it seems plausible that the highest level (primary, secondary, etc) attended is more accurate than the exact class attended. The differences in the highest tertiary class attended between the surveys remain significant when using the more detailed attainment variable.
[15] According to World Bank (2013), which uses DHS data, Rwanda has the highest school attendance in francophone Africa, while primary completion is one of the lowest.
[16] For example, it is "Primary 6, 7, 8" in survey 2. If this arises out of an educational reform which extended primary schooling, years of schooling might have been constructed using the date of implementation of the reform and the birth cohort. Other issues include how to count vocational education and how to deal with individuals repeating a class, which is relatively common in Rwanda.
[17] For example, I regress the male dummy variable on an indicator for the 2011 survey and a constant. The p-value reported in Table 1 tests the null hypothesis that the coefficient on the year 2011 dummy is equal to zero, i.e. there is no difference between the means observed in survey rounds 1 and 2. The regression accounts for population sampling weights and the clustering and stratification of the survey.

For the first three variables I only report the summary statistics. Of course, we would expect that there are differences in terms of these variables over time, so I do not test for the difference in the mean. Average consumption (per adult equivalent) increased by 14.6% over this 5 year period. The average age of the household head obviously increases as the result of the sample restrictions (see section 2). Given that it is likely that household size is positively related to age, it is not surprising that it increases very slightly over time.

There are some significant differences in Table 1. For example, the no education category declined and tertiary attainment increased. The latter might be explained by the household heads being five years older. Note that the urban-rural difference was not significant when the analysis was done at the level of the household head, i.e. using only household weights, not population weights. In other words, the increase in the proportion of urban population was greater in terms of individuals than in terms of households. This is because household size increased faster for the urban observations.

3.2 Choosing the specification

Table 2 shows the estimates of the consumption model for 2006 and 2011. Tables A.2 and A.3 show the full set of results, reporting both population-weighted and un-weighted results. A number of different specifications are considered, which differ in the inclusion of the district of residence control and interaction effects of the included regressors. The interaction variables do not affect the R2 significantly, but do change some of the coefficient estimates as one would expect. For the all-Rwanda results, I compare the results for all four models. In the subgroup analysis, I concentrate on model 2, since the inclusion of the interaction effects in models 3 and 4 does not markedly improve the explanatory power nor does it significantly change the estimated poverty dynamics.

Some observations on the results:

- **Male:** The dummy variable for whether the household head is male is positive or statistically insignificant. A positive coefficient implies that male-headed households, conditional on all other controls, are better off. Note that the proportion of female-headed households seems high at around 21%.

- **Age:** Across all the specifications, age is significantly negative and convex. This suggests that the negative effect of an extra year on consumption increases with age.
- **Educational attainment:** The base category is having attained no education. Educational attainment is strongly significant. Moving between the different specifications, changes the coefficient estimates a fair bit, as educational attainment varies across gender and regions.
- **Birth region:** The base category is Kigali, the capital. In the baseline specification, the Southern region is poorest, Western region is less poor, and the rest of Rwanda (consisting of the new Northern and Eastern regions, as well as the old Kigali-Ngali region) is the least poor (after Kigali). The effect of being born abroad is somewhat volatile, but this is probably due to the fact that these are not many people.[18] Once the rural/urban dummy and the district of residence controls are included, the birth region variables flip sign (column 2). These effects are now identified off those observations which live in a region other than their birth region. Of course, the residence and birth region variables are strongly collinear, so the separate effects are hard to isolate.
- **Region of residence:** Not surprisingly, rural regions are poorer than urban regions. However, once I control for differences in educational attainment between rural and urban regions by including the interaction between educational attainment and rural, this effect disappears (i.e. compare models 3 and 4). This suggests that the overall negative region effect is driven by differences in educational attainment between rural and urban regions.
- **District of residence:** In some specifications, I also included controls for the district of residence (coefficients are shown in Tables A.2 and A.3). The baseline district is Nyarugenge, Kigali's business district. Not surprisingly, all other districts are no richer (i.e. coefficient is either negative or insignificant).

3.3 Testing the normality of residuals

The parametric point identification of the poverty transition matrix assumes that the error terms in the two years follow a bivariate normal distribution. We cannot test for bivariate normality

[18] For example, in 2006, the neighbouring-country effect flips sign moving from model 1 to 2. Furthermore, individuals born abroad in non-neighbouring countries had higher consumption in 2006, and lower consumption in 2011.

because we do not observe the same household in two years. However, we can test for the normality of the residuals in each year, which is a necessary condition for bivariate normality. Figure 1 shows the distribution of residuals (overlaid with a standard normal distribution) for the different specifications (see Figure A.2 for the unweighted residuals). The distribution of residuals is not very different across the different specifications. It seems reasonably close to a normal distribution, although the right-hand tail appears too fat and there is too much mass just below 0. Formal tests of normality fail at reasonable significance levels. However, it is important to realise that these formal tests are very stringent. Furthermore, in other methods which rely on a normality assumption, such as a probit model, one rarely tests for this assumption. In sum, while formal tests for normality are rejected, the distribution of residuals looks reasonably close to a normal distribution.

4 Results on poverty dynamics in the overall sample

To estimate the non-parametric bounds, I modified the estimation code posted on David McKenzie's website used in DLLM. The only substantive change was the inclusion of population weights in the consumption model (which was unweighted before). The estimation code for the point estimates was kindly provided by Hai-Anh Dang and has been used in DL. Note that there are some slight differences between the consumption models in Table 2 and the estimation of the poverty dynamics (Tables 3 and 4) but these only affect the standard errors.[19] Notation in the tables follows DL and DLLM: "Non-poor, poor" refers to observations being non-poor in period 1 and poor in period 2, i.e. those that fall into poverty. The literature on synthetic panels typically reports weighted and unweighted results (e.g. see DL). The main results (Tables 3 and 4) use population-weights which are the preferred specification. Unweighted results are reported in Tables A.4 and A.5.

The tables report joint probabilities, e.g. the probability of being poor in period 1 and non-poor in period 2. The bottom rows report the estimated marginal probabilities, i.e. the incidence of poverty in period 1. These are obtained by adding up the relevant joint probabilities, e.g.

[19] Population weights are included throughout. The bound estimates are clustered, but no adjustment is made for the complex survey design. The point estimates are neither clustered, nor adjusted for the complex survey design. This does not affect the point estimates of the consumption model or the estimates of the poverty transition matrix.

headcount poverty in period 1 is the sum of Pr(poor, poor) and Pr(poor, non-poor). It is also interesting to consider the probability of someone exiting poverty given that she is initially poor, which is given by

$$P(y_{i2} > z_2 \mid y_{i1} < z_1) = \frac{P(y_{i2} > z_2 \text{ and } y_{i1} < z_1)}{P(y_{i1} < z_1)}$$

where the numerator is the joint, and the denominator is the marginal probability.

4.1 Bounds on poverty transitions

Table 3 reports the upper and lower bounds on poverty mobility. These are wider than DLLM but not too dissimilar. For example in model 2 (the most complete model without interactions), the share of the population that exits poverty over this time period ranges from 9% to 22.8%, a difference of 13.8pp. For comparison, in the full model in DLLM, the proportion of the population that moves out of poverty between the two years ranges from 4% to 13% in Indonesia. Including the residence variables (i.e. moving from model 1 to 2) tightens the bounds. However, the inclusion of the interaction effects has no effect on the bounds.

4.2 Point identification under parametric assumptions

Table 4 shows the point estimates of poverty transitions under the parametric assumptions (DL method). I report the standard errors computed by the DL routine. These errors do not account for the complex survey design and are therefore too small. Similarly to the case of the bound estimates, the change in the point estimates is greatest between models 1 and 2. Across the different models, around 15% of persons exit poverty, with some 8% falling into poverty.[20] Therefore, the conditional probability of exiting poverty conditional on being poor in the first period is around 29%.[21] Or put differently, the probability of remaining poor given that one is

[20] Hence the model estimates a reduction in the poverty headcount by approximately 7pp based on the imputed consumption. This compares with 9.7pp using actual consumption but the same sample (Table A.1, row 3 "sample used in estimation").

[21] The conditional probability is calculated as follows (treating Table 4 as if it were a real panel, and using the estimates from model 2). $P(y_{i2} > z_2 \mid y_{i1} < z_1) = \frac{P(y_{i2}>z_2 \text{ and } y_{i1}<z_1)}{P(y_{i1}<z_1)} = \frac{P(y_{i2}>z_2 \text{ and } y_{i1}<z_1)}{P(y_{i2}>z_2 \text{ and } y_{i1}<z_1)+P(y_{i2}<z_2 \text{ and } y_{i1}<z_1)} = \frac{15.04\%}{15.04\%+36.78\%} = 29.02\%$

poor in the initial period, the rate of chronic poverty, is 71%. The probability of falling into poverty conditional on being non-poor in period 1 is approximately 16%.

We can also compare these poverty dynamics with other countries where comparable results exist. DLLM compare Bosnia-Herzegovina, Laos, Peru, the US and Vietnam. The joint probability of exiting poverty is relatively high compared with other countries (similar only to Laos). However, a relatively high rate of poverty in Rwanda implies that conditional on being poor in period 1, the probability of exiting poverty is close to the average of the other countries (slightly higher than Peru, somewhat less than Vietnam).

4.3 Comparing bounds and point estimates

Figure 2 compares the bounds and point estimates across the 4 different models. As noted above, the differences are greatest between models 1 and 2, and are most notable for the bound estimates. It is reassuring that the point estimate are all well within the bound estimates. In the top row of Figure 2 (poor, poor and poor, non-poor), the point estimates lie quite centrally within the bounds. In the bottom row, however, the point estimate is towards the lower bound (non-poor, poor) or the upper bound (non-poor, non-poor). In other words, if we take the mid-point of the bounds and compare it with the point estimates (for model 2), the difference is less than 1pp in the top row, but almost 3pp in the bottom row. Furthermore, compared with the mid-point, the point estimates overstate the persistently non-poor and understate those who fall into poverty.

While I concentrate on the weighted results in the main specification, Figure 2 (and Tables A.4 and A.5) also shows the unweighted results. The point estimates are very similar for the off-diagonal entries of the poverty transition matrix (i.e. [Poor, non-poor] and [Non-poor, poor]). However, the unweighted results underestimate those who remain poor and overestimate those who remain non-poor. This is not surprising given that the unweighted results underestimate poverty, especially in 2006.[22] The estimates are quite stable, so I concentrate on the weighted results which properly account for the stratified sampling.

[22] This can be explained by Kigali, which has low poverty, being over-sampled. In other words, ignoring sampling weights increases the population share of Kigali.

To assess the sensitivity of the results to the normality assumption I compare the parametric and non-parametric bound estimates. The bounds presented so far do not make any parametric assumption. Parametric bounds can be derived using the DL method: Instead of deriving the error correlation from the synthetic panel cohort-level correlation, I set it equal to 0 or 1 to derive the upper and lower bounds on poverty mobility respectively. Table A.6 reports the parametric bounds and Figure A.3 compares them with the non-parametric bounds (Table 3). The lower bounds in Figure A.3 are all very close. However, there are some differences in the upper bounds: Relative to the non-parametric bounds, the parametric bounds underestimate the upper bound of remaining poor and falling into poverty, while they overestimate the upper bound of remaining non-poor and exiting poverty. As a result, the parametric bounds underestimate poverty in period 2 relative to the non-parametric bounds. Results from Vietnam also find a bigger difference for the upper than the lower bounds. The percentage difference in the upper bounds is greater in Vietnam compared with my results. Overall, I conclude that the two types of bounds are quite similar to each other, so the parametric assumption appears reasonable.

In summary, the point estimates lie within the bounds in all specifications, and in most cases are close to the centre of the bounds. Furthermore, the residuals are approximately normal. Therefore, and because it makes the discussion of the results much easier, I concentrate on the point identification method from now on. The inclusion of the interaction effects does not affect the estimates in a significant way. Hence, I follow the suggestion by DLLM and choose the more parsimonious model 2 without the interaction effects.

5 Results by population sub-group

This chapter documents differences in poverty dynamics across sub-groups of the Rwandan population. It tries to get closer to policy recommendations by identifying those subgroups where poverty reduction has been particularly successful. Note that the sub-group estimates are derived from the same national consumption model (model 2 in Table 2, which excludes the interaction effects). While choosing a sub-group-specific model would be more flexible, it could provide quite unstable estimates due to small population sizes and over-fitting the data. In the sub-group estimates, I do not report standard errors because the standard errors derived in DL are not directly applicable to the subgroups.

5.1 Sub-groups defined over gender, age, education, occupation, residence, and VUP

Table 5 reports point estimates of poverty dynamics separated by gender, age, educational attainment and occupation of the household head. Table 6 breaks the population up by the province of residence and the Vision 2020 Umurenge Program (VUP). Note that the province variable is defined as the current province of residence. For the second survey round, this is different from the variable included in the consumption model, which is the (time-invariant) residence *at the time of survey 1*.

Figures 3 and 4 (and 5 and 6) report the conditional probabilities of exiting poverty and falling into poverty respectively. I concentrate on the conditional probabilities because they are probably more closely related to the policy objective. Furthermore, the conditional probabilities are normalised across subgroups which is important given that headcount poverty rates can be very different across the different subgroups. The latter is particularly true across the provinces, and urban and rural areas.

The conditional probability of exiting poverty (Figure 3) is quite similar between female- and male-headed households, which happens despite the poverty headcount in period 1 being greater for the female-headed households. At the same time, the probability of falling into poverty is the same (up to one decimal point) for male- and female-headed households. As a result, the decline in the poverty headcount is greater for the female-headed households (11pp vs. 7pp).

The probability of exiting poverty decreases with the age of the household head (except for the oldest age group), while the probability of falling into poverty is higher for older household heads.[23] Poverty is lowest amongst the youngest household heads in both periods. Not surprisingly, the conditional probability of moving out of (falling into) poverty is greater (lower) amongst the educated.

[23] Because of the age restrictions applied to the consumption model (Section 2.1), the youngest household heads in the second year sample are 28.

Figures 3 and 4 also show that within agriculture, those working on their own farm have a higher (lower) probability of exiting (falling into) poverty compared with agricultural labourers.[24] Within non-farm occupations, wage employees have a substantially lower probability of falling into poverty which is what we would expect if their incomes are more stable.

Table 6 and Figures 5 and 6 report the subgroup results for different regions and the VUP program. Not surprisingly, the conditional probability of moving out of (falling into) poverty is greater (lower) in urban areas. Kigali has the highest probability of exiting poverty, followed by the Northern, Eastern and Western Provinces. The Southern Province is the worst, and also had the highest intensity of the genocide, an issue which I address in detail below. The ranking of provinces is the same in terms of the conditional probability of falling into poverty (Figure 6), where Kigali now has the lowest conditional probability of falling into poverty.

However, it is important to bear in mind that Kigali starts from a relatively low poverty headcount rate (15%), which all else equal would increase the conditional probability of exiting poverty. Hence it is important to compare headcount poverty rates across provinces. The Provinces in increasing rates of poverty in period 1 are given by Kigali, Eastern, West, North and South. In period 2, the ranking of the Northern and Western Provinces reverses. This is consistent with the fact that the North has a higher probability of exiting poverty (33% v. 28%, Figure 5), and a lower risk of falling into poverty (14% v. 19%, Figure 6) than the West. Overall, the Northern region (bordering Uganda) appears to be the most successful, reducing poverty by 12pp.

Note that this comparison of headcount poverty rates is based on synthetic panel results, i.e. the imputed period 1 consumption. I can compare the results with what is obtained directly from the repeated cross-sections. In the synthetic panel, headcount poverty increased slightly in Kigali, which does not hold in the actual data, where it fell from 21% to 17%. However, the ranking of

[24] The occupation has been assigned according to the largest income source. The total number of observations is lower because for a number of households rents and transfers are the largest income source. Note that transfer income includes the wages earned as part of the VUP program. I exclude these groups because there are too few observations to offer precise estimates.

provinces by poverty level coincides for the synthetic panel and the cross-sectional data.[25] In the actual data, Kigali reduced poverty the least (4pp) and the Northern Province the most (18pp), which corresponds to the ranking for poverty changes in the synthetic panel.[26]

Finally, the last two subgroups refer to whether or not the enumeration area (EA) was located in a sector where the VUP program was active. This information is derived from the survey and not from administrative records about program implementation, so there could be some measurement error. The VUP program was started in July 2009 and rolled out in stages across the country, starting from the poorest sectors defined according to lack of infrastructure and food insecurity (Hartwig, 2013). Sectors are administrative regions which are larger than EAs. The VUP program is targeted at the poorest households, and it contains both a public works and social safety net component. VUP clusters appear to have lower initial poverty rates, contrary to the targeting scheme (Table 6). In the full data set, the poverty headcounts are more similar (45.2% for VUP and 44.8% for non-VUP). Furthermore, it is important to bear in mind that the targeting is based on infrastructure and food security characteristics, not headcount poverty. The conditional probability of exiting (entering) poverty is greater (smaller) in VUP-EAs. However, the difference is very small and is driven by the difference in the estimated initial poverty headcounts (whose ranking reverses in the actual data).[27] The absence of any effect could be explained by the fact that the VUP was still small-scale in 2011.

5.2 Investigating the impact of the Crop Intensification Program (CIP)

Table 7 and Figures 7 and 8 compare poverty mobility between EAs which were affected by the Crop Intensification Program (CIP) and those which were not. The CIP included a number of measures to improve agricultural output, such as land consolidation (combining adjacent plots), regionalisation of crops (specialisation of crops suitable for a certain climate) and measures

[25] We may also compare this with the results in Table 2, although these show differences in average consumption between birth regions, not regions of residence. The ranking of Kigali, West and South are consistent with the poverty rankings. In that specification, the residual region includes North and East.

[26] Of course, it might also be argued that deep-rooted poverty becomes harder to eliminate as the poverty rate falls, so this might not be surprising.

[27] The latter can be seen from the fact that the comparison of the joint probabilities Pr(poor, non-poor) and Pr(non-poor, poor) actually goes the opposite way.

against soil erosion, the development of marshlands, improved irrigation and use of fertilizers.[28] It started in 2007, i.e. in-between the two survey rounds. The regional roll-out of the CIP depended on the agro-ecological environment, e.g. it was implemented more on flat than hilly land, since the former makes land consolidation easier.

Because we lack information on the geographic roll-out of the CIP, we use a question in EICV3 which asks about participation in the program. This is very similar to the way I defined the VUP implementation above. I defined two variables at the EA level: First, a binary variable which captures whether anybody in the EA has participated in the program. Second, I define an intensity variable which measures the fraction of plots affected by the program. In the second survey round, I assign every household the CIP measures of its EA.

Because this is an agricultural intervention, I only include rural areas. The conditional probability of exiting poverty is higher amongst observations affected by the CIP (Figure 7). The conditional probability of exiting poverty increases with the intensity of the CIP. Having the CIP reduces the conditional probability of falling into poverty which falls with the intensity of the program (Figure 8). I can also compare the non-CIP and CIP observations according to poverty in periods 1 and 2 (Table 7). In all specifications (except the at least 30% category), poverty in the base-year is higher amongst CIP than non-CIP. As a result of the differential rates of poverty exit and entry, this reverses in some cases in period 2, particularly in the areas where the CIP was more intense.

5.3 Differentiating by genocide intensity

This part of the analysis looks at the effects of the Rwandan genocide on poverty mobility almost 20 years after its end. I investigate poverty mobility across districts classified by their genocide intensity. Like the rest of the subgroup analysis, the districts are the districts of current residence, not the time-invariant variables used in the consumption model. Verpoorten (2012) uses records from the Rwandan transitional justice scheme instituted in the aftermath of the genocide. These records provide data on genocide suspects and survivors, which she combines to a genocide

[28] For more information, see http://www.minagri.gov.rw/index.php?id=31.

intensity index using a Principal Component Analysis (PCA).[29] Using a PCA instead of the underlying measures arguably combines the information from different variables in the most useful way. The data are provided for roughly 1400 geographic units (called sectors). Because the micro data can only be matched at the level of the 30 districts, I have to aggregate the genocide data to that level.[30]

I classify districts into three genocide intensity groups according to the value of the PCA. Using the sector information, I compute four summary statistics at the district-level: Verpoorten (2012) computes two PCA indices (including or excluding the distance to mass grave). For each of the indices, I compute the district mean and median.[31] The groups are chosen in such a way that the ranking does not depend on which of these summary statistics is used. In other words, the high intensity group includes the top 5 districts regardless of which PCA index is chosen or whether the mean or median is taken over the sectors within a district.

All districts with the highest intensity of the genocide are located in the Southern region. By contrast all the districts in the Northern region have a low intensity. The three districts in the Kigali province all have a medium intensity of the genocide.

Table 8 reports the results including and excluding Kigali and using the three detailed groups as well as two-group classifications. When Kigali is included, the effect of the genocide is very clear: The higher the intensity of the genocide, the lower is the probability of exiting poverty and the higher is the risk of falling into poverty.

However, the exclusion of Kigali from the medium group pushes the conditional probability of exiting (entering) poverty below (above) the value of the high-intensity category (Figures 9 and 10). As can be seen from Table 8, this is mostly explained by the increase in poverty in period 1 (the denominator in the conditional probability) rather than a change in Pr(Poor, Non-poor). The rankings for the two category classifications are robust to excluding Kigali.

[29] The PCA uses six variables: Category 1, 2 and 3 suspects, and widowed, orphaned and disabled survivors. She also presents an alternative index where she uses the log distance to mass grave in addition.
[30] The micro data has finer regional units such as enumeration areas, but they are anonymized so they cannot be matched to the sectors.
[31] Alternatively, I could have estimated the PCA at the district-level using the average district characteristics. However, that way I would have lost some statistical power by limiting the variation the PCA uses.

6 Conclusion

This paper has estimated poverty mobility in Rwanda between 2006 and 2011, a period of strong reduction of the poverty headcount nationally. Because of the absence of panel data, I have used repeated cross-sectional surveys to estimate a consumption model and thus create a synthetic panel. The probability of exiting poverty conditional on being poor in the base period is around 29%, or put differently almost three quarters of individuals who are initially poor remain in poverty. The probability of exiting poverty is greater in urban areas, amongst educated household heads and in Kigali, but the difference between female- and male-headed households is negligible. Clusters with a greater coverage of the Crop Intensification Program have a higher probability of exiting poverty and a lower risk of falling into poverty. But I find no effect for the VUP program. Finally, those districts where conflict was more intense have a lower probability of exiting poverty and a greater risk of becoming poor, which certainly requires more investigation.

7 Tables and Figures

[See attached]

Appendix: Details on the empirical methodology

Non-parametric bounds

Upper bound for poverty mobility, i.e. $corr(\varepsilon_{i1}, \varepsilon_{i2}) = 0$

I obtain an upper bound on poverty mobility in the following four steps. First, I estimate equation (1) using the data in year 1, saving the estimated coefficients $\widehat{\beta_1}$ and the predicted residuals $\widehat{\varepsilon_{i1}}$. Second, let $\widehat{\widehat{\varepsilon_{i1}}}$ denote a random draw (with replacement) from the observed distribution of $\widehat{\varepsilon_{i1}}$. Using this information, I can then estimate consumption in round 1 for those households which are observed in round 2:

$$\widehat{y_{i1}^{2U}} = \widehat{\beta_1}' x_{i2} + \widehat{\widehat{\varepsilon_{i1}}} \qquad (3)$$

where the superscript denotes households observed in round 2 and the fact that it is an upper-bound estimate; the subscript indicates period 1 consumption as before. For every household in round 2, equation (3) imputes round 1 consumption using the characteristics of that household, and assuming that the relationship between those characteristics and consumption is the same as what was actually observed in period 1. In the third step, I can estimate the elements of the poverty transition matrix for the households observed in period 2, replacing y_{i1} with y_{i1}^{2U}.

In the final step of deriving the upper bounds, I repeat steps two and three 500 times, because each of them is based on a particular random draw from the $\widehat{\varepsilon_{i1}}$ distribution, so will be subject to random variability. Hence I get 500 estimates of the poverty transition matrix, which I average to derive the upper bounds.

Note that the upper bound for poverty mobility corresponds to a lower bound for poverty immobility. This means in terms of the poverty transition matrix, that the assumption $corr(\varepsilon_{i1}, \varepsilon_{i2}) = 0$ gives an upper bound for the off-diagonal elements and a lower bound for the diagonal entries. Intuitively, this happens because the rows have to add up to the (observed) marginal probability of being poor, so if one of the estimates is an upper bound, the other must be a lower bound.[32]

<u>Lower bound for poverty mobility, i.e. $corr(\varepsilon_{i1}, \varepsilon_{i2}) = 1$</u>

Under the assumption of perfectly correlated errors, I can obtain a lower bound for poverty mobility in three steps. First, I simply estimate equations (1) and (2), the consumption models for year 1 and 2. From this I obtain $\widehat{\beta_1}$ and $\widehat{\beta_2}$, and the estimated standard deviation of the residuals, $\widehat{\sigma_{\varepsilon_1}}$ and $\widehat{\sigma_{\varepsilon_2}}$. Second, I impute year 1 consumption for the households observed in period 2 as

$$\widehat{y_{i1}^{2L}} = \widehat{\beta_1}' x_{i2} + \gamma \widehat{\varepsilon_{i2}} \qquad (4)$$

where the superscript denotes the lower-bound estimate and $\gamma = \frac{\widehat{\sigma_{\varepsilon_1}}}{\widehat{\sigma_{\varepsilon_2}}}$. Similarly to the upper bound estimates, I use the estimated coefficients from period 1 and the characteristics from

[32] In other words, in the transition matrix where y_{i1} is replaced by y_{i1}^{2U}, the marginal probability of a household being poor in the second period which is observed, is given by $P(y_{i2} < z_2) = P(y_{i1}^{2U} > z_1 \; and \; y_{i2} < z_2) + P(y_{i1}^{2U} < z_1 \; and \; y_{i2} < z_2)$. Given that the first term (the measure of poverty mobility) is an upper bound, the second term (the measure of poverty immobility or chronic poverty in this case) must be a lower bound.

period 2. The error term, however, is different: When the errors are perfectly correlated, I can simply use the error observed in period 2. γ is a scaling factor which accounts for the differences in the standard deviation between the years. Furthermore, because I use the household-specific residual, rather than a random draw from the distribution of residuals, there is no need to repeat the procedure 500 times.

In the final step, I can again use $\widehat{y_{i1}^{2L}}$ and y_{i1} to estimate the poverty transition matrix. As above, the lower bound for poverty mobility is equivalent to an upper bound for poverty immobility.

Parametric point estimates

If we assume that ε_{i1} and ε_{i2} follow a bivariate normal distribution, the joint probability of a household being poor in period 1 and non-poor in period 2 (i.e. escaping poverty) is given by

$$P(y_{i1} < z_1 \; and \; y_{i2} > z_2) = \Phi_2\left(\frac{z_1-\beta_1' x_{i2}}{\sigma_{\varepsilon_1}}, -\frac{z_2-\beta_2' x_{i2}}{\sigma_{\varepsilon_2}}, -\rho\right) \qquad (5)$$

where $\Phi_2(\cdot)$ is the bivariate normal cumulative distribution function, and ρ is the correlation coefficient between ε_{i1} and ε_{i2}. DL propose a way to estimate ρ. Above I derived bounds by considering the two extreme cases of perfect and zero correlation (ignoring any negative association).

DL show that the correlation coefficient is given by

$$\rho = \frac{\rho_{y_{i1}y_{i2}}\sqrt{var(y_{i1})var(y_{i2}) - \beta_1' var(x_i)\beta_2}}{\sigma_{\varepsilon_1}\sigma_{\varepsilon_2}} \qquad (6)$$

where $var(x_i)$ is the variance of household characteristics in one of the survey rounds[33], and $\rho_{y_{i1}y_{i2}}$ is the correlation between household consumption in period 1 and 2, which is unobserved in the absence of panel data. DL argue that it can be approximated by the synthetic panel cohort-level correlation coefficient: $\rho_{y_{i1}y_{i2}} \approx \rho_{y_{c1}y_{c2}}$, where c indicates a particular birth cohort.

To summarise, in order to obtain point estimates, I follow the following steps: First, I estimate equations (1) and (2), and obtain $\widehat{\beta_1}$, $\widehat{\beta_2}$, $\widehat{\sigma_{\varepsilon_1}}$ and $\widehat{\sigma_{\varepsilon_2}}$. Second, in both years I aggregate the data

[33] By the assumption that the population is the same in the two years, the choice of survey round is irrelevant. However, in a practical application this might not hold exactly.

by birth cohort (of the household head). In round 2, I need to adjust the age restriction in round 1 upwards by the gap between the two surveys. For example if I limit the sample to household heads between the ages of 23 and 58 in the first year, five years later I should select household heads between 38 and 63. $\rho_{y_{c1}y_{c2}}$ is then the correlation coefficient computed over the average birth-cohort household consumption. I can combine this information to estimate equation (6) and finally back out the joint probabilities using equations such as (5).

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Table 1: Summary statistics and balancing test						
	Average				Standard Deviation	
variable	**mean '06**	**mean '11**	**p-value**		**sd '06**	**sd '11**
Yearly consumption expenditure per adult equivalent (2011 prices, RWF)	98,099	112,389			201,658	216,484
Age	41.24	43.80			9.27	9.57
Household size	6.00	6.01			2.24	2.15
Number of observations	5,439	10,368				
Time-invariant variables included in the regression						
Gender is male	0.785	0.789	0.592		0.411	0.408
Disabled at the time of round 1	0.065	0.058	0.146		0.247	0.234
Educational attainment:						
no education	0.296	0.270	0.008	***	0.456	0.444
some primary education	0.590	0.604	0.172		0.492	0.489
some vocational education	0.050	0.048	0.639		0.218	0.213
some secondary education	0.058	0.058	0.956		0.233	0.234
some tertiary education	0.007	0.020	0.000	***	0.083	0.141
At the time of round 1, residence is …						
… urban	0.158	0.177	0.040	**	0.365	0.382
… rural	0.842	0.823	0.040	**	0.365	0.382
At the time of round 1, district of residence:						
Nyarugenge	0.024	0.031	0.079	*	0.153	0.173
Gasabo	0.042	0.049	0.317		0.200	0.217
Kicukiro	0.027	0.028	0.775		0.162	0.166
Nyanza	0.030	0.026	0.659		0.170	0.160
Gisagara	0.027	0.033	0.456		0.163	0.178
Nyaruguru	0.027	0.026	0.876		0.163	0.160
Huye	0.044	0.031	0.176		0.205	0.174
Nyamagabe	0.040	0.031	0.264		0.195	0.172
Ruhango	0.029	0.026	0.714		0.167	0.159
Muhanga	0.038	0.032	0.528		0.191	0.177
Kamonyi	0.025	0.030	0.543		0.157	0.170
Karongi	0.033	0.032	0.895		0.180	0.177
Rutsiro	0.029	0.030	0.914		0.167	0.170
Rubavu	0.038	0.038	0.979		0.192	0.191
Nyabihu	0.030	0.032	0.870		0.171	0.175
Ngororero	0.036	0.031	0.596		0.187	0.175
Rusizi	0.034	0.041	0.356		0.182	0.199
Nyamasheke	0.044	0.038	0.479		0.205	0.191
Rulindo	0.034	0.029	0.583		0.181	0.168
Gakenke	0.032	0.035	0.731		0.176	0.183
Musanze	0.032	0.038	0.484		0.177	0.191
Burera	0.039	0.034	0.630		0.194	0.182
Gicumbi	0.043	0.054	0.378		0.202	0.226
Rwamagana	0.030	0.027	0.675		0.171	0.161
Nyagatare	0.043	0.035	0.419		0.202	0.185
Gatsibo	0.029	0.043	0.125		0.168	0.204
Kayonza	0.024	0.029	0.474		0.153	0.167
Kirehe	0.028	0.028	0.927		0.166	0.164
Ngoma	0.039	0.027	0.173		0.194	0.162
Bugesera	0.029	0.036	0.432		0.168	0.185
Region of birth:						
Kigali	0.018	0.038	0.000	***	0.132	0.192
Southern	0.305	0.285	0.302		0.461	0.451
Western	0.248	0.256	0.648		0.432	0.437
Rest of Rwanda	0.393	0.380	0.573		0.488	0.485
neighbouring countries	0.037	0.040	0.613		0.188	0.196
other foreign countries	0.000	0.000	0.309		0.008	0.015

Notes: Population sampling weights are included throughout. The test for differences in the mean accounts for the complex survey design. The individual-level characteristics are those of the household head. The age of the household head is restricted to between 23 and 58 in survey round 1, and 28 and 63 in survey round 2.

Table 2: Consumption model in 2006 and 2011

	2006				2011			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Gender is male	0.036	0.066***	-0.637	-0.667	-0.025	-0.016	0.075	0.076
	(0.027)	(0.025)	(0.402)	(0.406)	(0.018)	(0.017)	(0.217)	(0.220)
Age (Years)	-0.096***	-0.090***	-0.090***	-0.091***	-0.079***	-0.074***	-0.072***	-0.072***
	(0.011)	(0.010)	(0.010)	(0.010)	(0.007)	(0.007)	(0.007)	(0.007)
age2	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Disabled at the time of EICV2	-0.044	-0.025	-0.026	-0.027	-0.103***	-0.063*	-0.065*	-0.067*
	(0.051)	(0.045)	(0.046)	(0.045)	(0.037)	(0.036)	(0.036)	(0.036)
educattain==some primary educ	0.292***	0.250***	0.935**	1.047**	0.227***	0.206***	0.061	0.226
	(0.026)	(0.025)	(0.403)	(0.441)	(0.022)	(0.022)	(0.217)	(0.302)
educattain==some vocational educ	0.803***	0.632***	1.314***	1.326***	0.705***	0.613***	0.447**	0.538*
	(0.058)	(0.052)	(0.405)	(0.443)	(0.044)	(0.040)	(0.222)	(0.310)
educattain==some secondary educ	1.202***	0.955***	1.619***	1.642***	1.139***	0.992***	0.817***	0.887***
	(0.068)	(0.060)	(0.404)	(0.451)	(0.046)	(0.052)	(0.214)	(0.284)
educattain==some tertiary educ	2.471***	1.957***	2.612***	2.847***	2.212***	1.931***	1.777***	1.971***
	(0.157)	(0.145)	(0.366)	(0.362)	(0.090)	(0.110)	(0.197)	(0.203)
birthreg3==Southern	-0.477***	0.352***	0.351***	0.321***	-0.268***	0.197***	0.196***	0.164**
	(0.092)	(0.097)	(0.097)	(0.096)	(0.054)	(0.071)	(0.071)	(0.070)
birthreg3==Western	-0.427***	0.242**	0.243**	0.204**	-0.225***	0.226***	0.226***	0.195**
	(0.095)	(0.100)	(0.100)	(0.099)	(0.055)	(0.078)	(0.078)	(0.076)
birthreg3==Rest	-0.383***	0.204**	0.203**	0.180*	-0.158***	0.170**	0.169**	0.142*
	(0.089)	(0.095)	(0.095)	(0.093)	(0.052)	(0.075)	(0.075)	(0.073)
birthreg3==neighboring countries	-0.197*	0.271**	0.275***	0.236**	0.127*	0.386***	0.384***	0.348***
	(0.108)	(0.105)	(0.105)	(0.104)	(0.072)	(0.084)	(0.084)	(0.083)
birthreg3==others	1.437***	1.185***	1.196***	1.429***	-0.610***	-0.489***	-0.488***	-0.569***
	(0.095)	(0.108)	(0.108)	(0.115)	(0.177)	(0.152)	(0.156)	(0.146)
region==rural		-0.450***	-0.450***	-0.334		-0.209***	-0.211***	-0.200
		(0.062)	(0.062)	(0.307)		(0.047)	(0.047)	(0.212)
Constant	13.062***	13.184***	13.198***	12.991***	12.792***	12.915***	12.949***	12.759***
	(0.223)	(0.220)	(0.220)	(0.229)	(0.164)	(0.158)	(0.158)	(0.161)
Observations	5439	5439	5439	5439	10368	10368	10368	10368
R-squared	0.214	0.318	0.319	0.323	0.293	0.355	0.357	0.361
Adjusted R-squared	0.212	0.313	0.313	0.317	0.292	0.352	0.354	0.358
District of residence		Yes	Yes	Yes		Yes	Yes	Yes
Educ. attain x male			Yes	Yes			Yes	Yes
Educ. attain x rural				Yes				Yes

Dependent variable is ln(Yearly consumption expenditure per adult equivalent (2011 prices, RWF)).

Standard errors in parentheses. Regressions account for complex survey design (clustering and stratification).

Regressions are weighted using population sampling weights.

** p<0.1; ** p<0.05; *** p<0.01*

Figure 1:

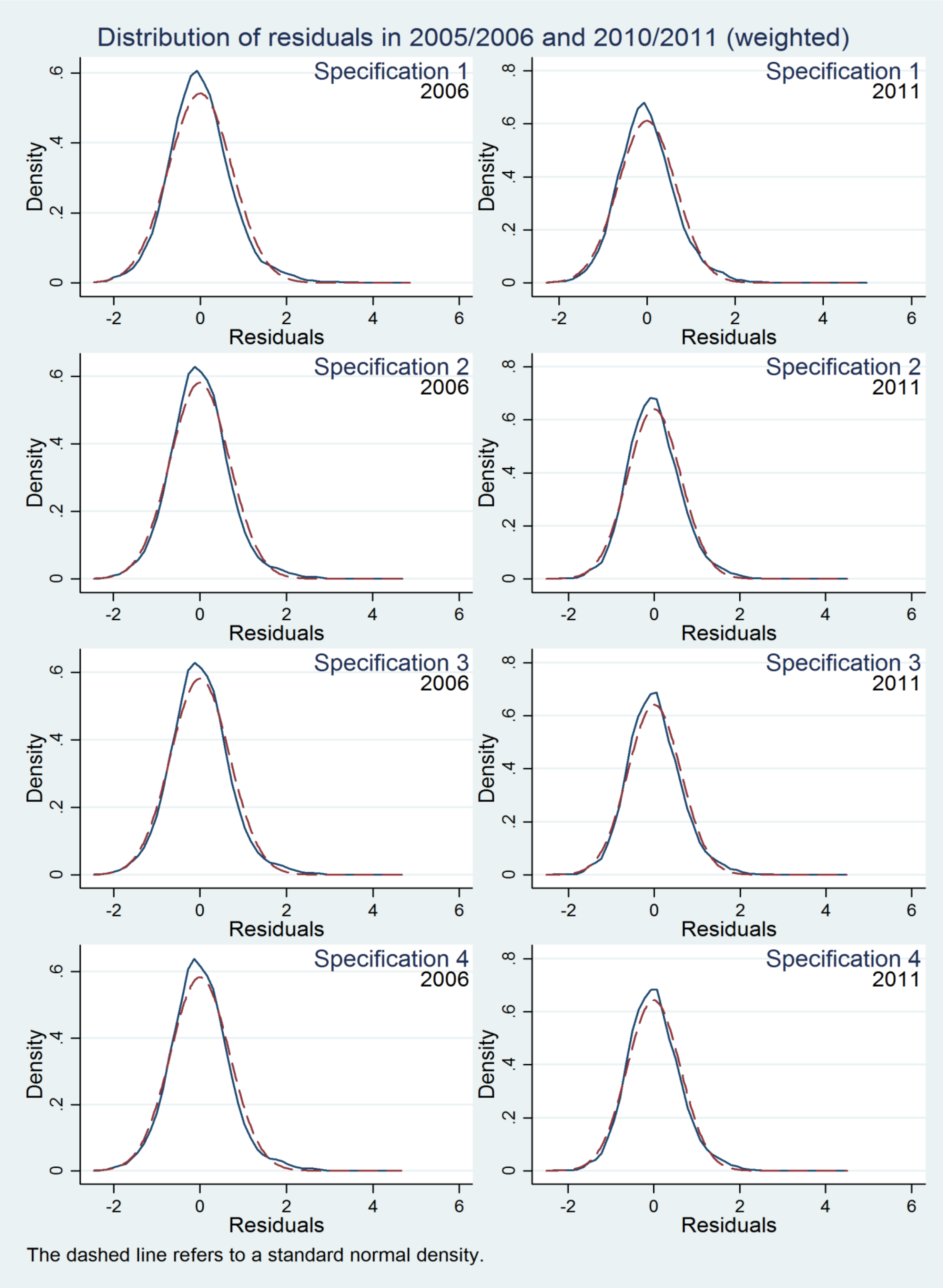

Distribution of residuals in 2005/2006 and 2010/2011 (weighted)
Specification 1
2006
Specification 1
2011
Specification 2
2006
Specification 2
2011
Specification 3
2006
Specification 3
2011
Specification 4
2006
Specification 4
2011
Density
Residuals
0
.2
.4
.6
.8
-2
0
2
4
6
The dashed line refers to a standard normal density.

Table 3: Bounds on poverty transitions								
	Non-parametric lower bound				Non-parametric upper bound			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel A: Joint and marginal probabilities								
Poor, Poor	47.1	46.2	46.2	46.2	25.2	27	27	27.1
Poor, Non-poor	7.9	9	9	9	22.7	22.8	22.8	23
Non-poor, Poor	0.1	1	1	1	22	20.2	20.2	20.1
Non-poor, Non-poor	44.9	43.8	43.8	43.8	30.1	30	30	29.8
N	10368	10368	10368	10368	10368	10368	10368	10368
Poor in period 1	55	55.2	55.2	55.2	47.9	49.8	49.8	50.1
Poor in period 2	47.2	47.2	47.2	47.2	47.2	47.2	47.2	47.2
Panel B: Conditional probabilities								
Poor --> Poor	85.6	83.7	83.7	83.7	52.6	54.2	54.2	54.1
Poor --> Non-poor	14.4	16.3	16.3	16.3	47.4	45.8	45.8	45.9
Non-poor --> Poor	0.2	2.2	2.2	2.2	42.2	40.2	40.2	40.3
Non-poor --> Non-Poor	99.8	97.8	97.8	97.8	57.8	59.8	59.8	59.7

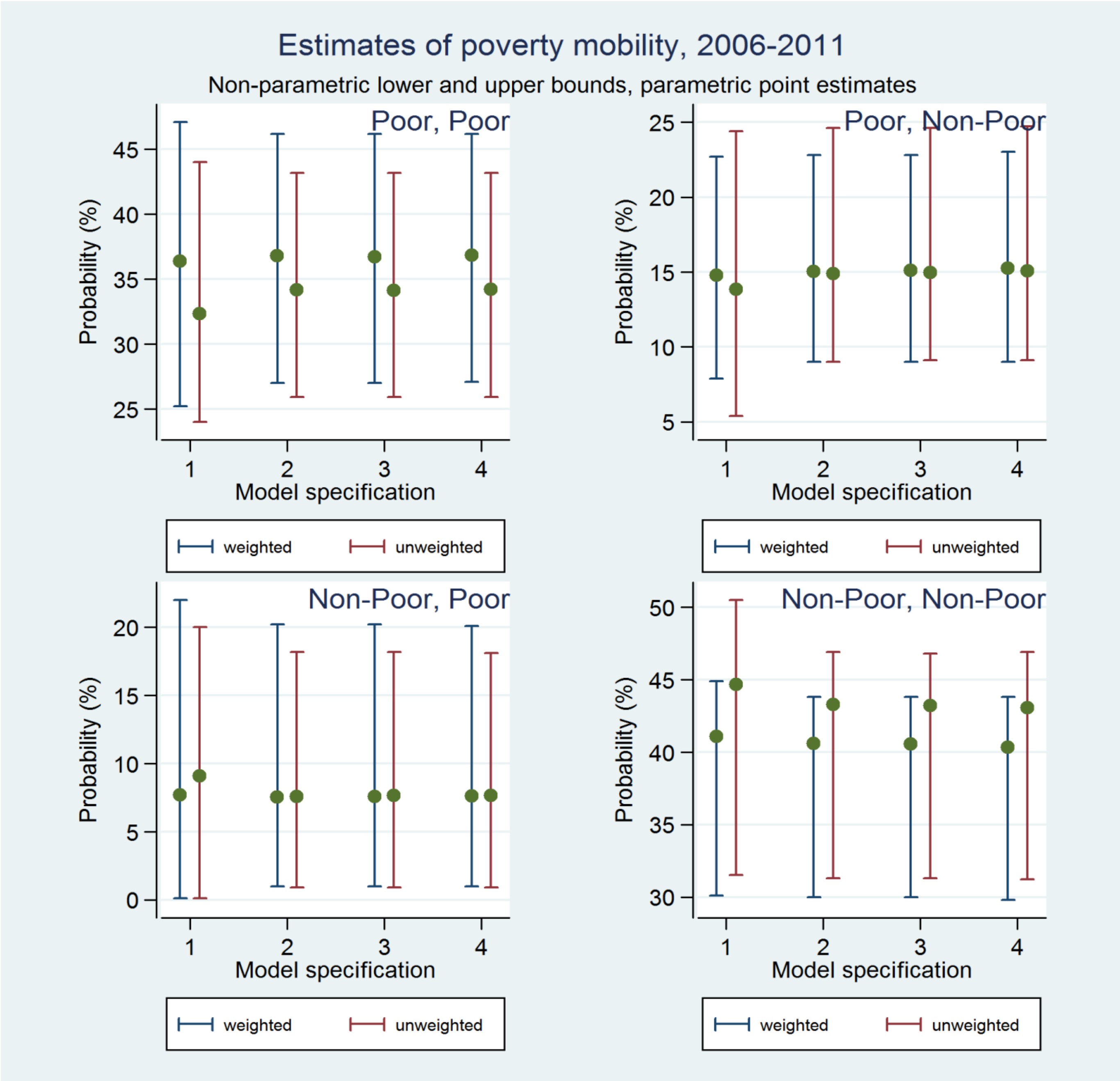
Regressions account for population sampling weights and clustering, but not for complex survey design (stratification). However, this will not affect the point estimates. For the upper bound, I chose 500 replications. Pr(poor, non-poor) is the probability of being poor in period 1 and non-poor in period 2.The table shows the number of observations in year 2.The column numbers refer to the different consumption model.

Table 4: Point estimates of poverty transitions

	(1)	(2)	(3)	(4)
Panel A: Joint and marginal probabilities				
Poor, Poor	36.40	36.78	36.74	36.83
se	0.15	0.18	0.18	0.17
Poor, Non-poor	14.80	15.04	15.10	15.24
se	0.04	0.07	0.07	0.07
Non-poor, Poor	7.70	7.56	7.59	7.61
se	0.03	0.04	0.04	0.05
Non-poor, Non-poor	41.10	40.62	40.57	40.32
se	0.18	0.22	0.22	0.21
N	10368	10368	10368	10368
Poor in period 1	51.20	51.82	51.84	52.07
Poor in period 2	44.11	44.34	44.33	44.44
Panel B: Conditional probabilities				
Poor --> Poor	71.10	70.98	70.88	70.73
Poor --> Non-poor	28.90	29.02	29.12	29.27
Non-poor --> Poor	15.78	15.69	15.77	15.88
Non-poor --> Non-Poor	84.22	84.31	84.23	84.12

Regressions account for population sampling weights, but not clustering or the complex survey design (stratification). This will not affect the point estimates, but the reported SEs will be too low. I chose 500 replications to estimate standard errors. Pr(poor, non-poor) is the probability of being poor in period 1 and non-poor in period 2.The table shows the number of observations in year 2.The column numbers refer to the different consumption models.

Figure 2:



Estimates of poverty mobility, 2006-2011
Non-parametric lower and upper bounds, parametric point estimates
Poor, Poor
Poor, Non-Poor
Non-Poor, Poor
Non-Poor, Non-Poor
Probability (%)
Model specification
1
2
3
4
25
30
35
40
45
5
10
15
20
0
50
weighted
unweighted

Table 5: Point estimates of poverty transitions by subgroups (characteristics of HH head)

	Gender		Age				Education		Occupation			
	Female	Male	28-30	31-40	41-50	50+	None	some	Farm own	Farm wage	NF own	NF wage
Panel A: Joint and marginal probabilities												
Poor, Poor	40.57	35.77	29.54	34.49	40.79	37.18	51.06	31.51	41.08	44.68	29.09	24.85
Poor, Non-poor	17.31	14.43	14.67	15.03	15.14	15.05	16.24	14.60	16.12	16.77	13.79	11.71
Non-poor, Poor	6.62	7.81	7.74	7.25	7.34	8.10	7.37	7.63	7.95	7.56	7.19	6.48
Non-poor, Non-poor	35.50	41.99	48.06	43.23	36.73	39.66	25.34	46.26	34.85	30.99	49.94	56.96
N	2698	7670	1226	3311	2922	2909	2912	7456	6433	711	1169	1672
Poor in period 1	57.88	50.20	44.21	49.52	55.93	52.23	67.30	46.11	57.19	61.45	42.87	36.56
Poor in period 2	47.20	43.58	37.28	41.74	48.12	45.29	58.43	39.14	49.03	52.23	36.28	31.33
Panel B: Conditional probabilities												
Poor --> Poor	70.10	71.25	66.82	69.64	72.93	71.19	75.87	68.34	71.82	72.70	67.84	67.97
Poor --> Non-poor	29.90	28.75	33.18	30.36	27.07	28.81	24.13	31.66	28.18	27.30	32.16	32.03
Non-poor --> Poor	15.72	15.68	13.87	14.37	16.65	16.96	22.53	14.16	18.58	19.60	12.59	10.21
Non-poor --> Non-Poor	84.28	84.32	86.13	85.63	83.35	83.04	77.47	85.84	81.42	80.40	87.41	89.79

Regressions account for population sampling weights, but not clustering or the complex survey design (stratification). However, this will not affect the point estimates. All results use model 2 which is estimated for the whole sample. Pr(poor, non-poor) is the probability of being poor in period 1 and non-poor in period 2.The table shows the number of observations in year 2. Gender, age and education refer to characteristics of the HH head. Occupation is defined according to the largest HH income source.

Figure 3: Conditional probability by population subgroup

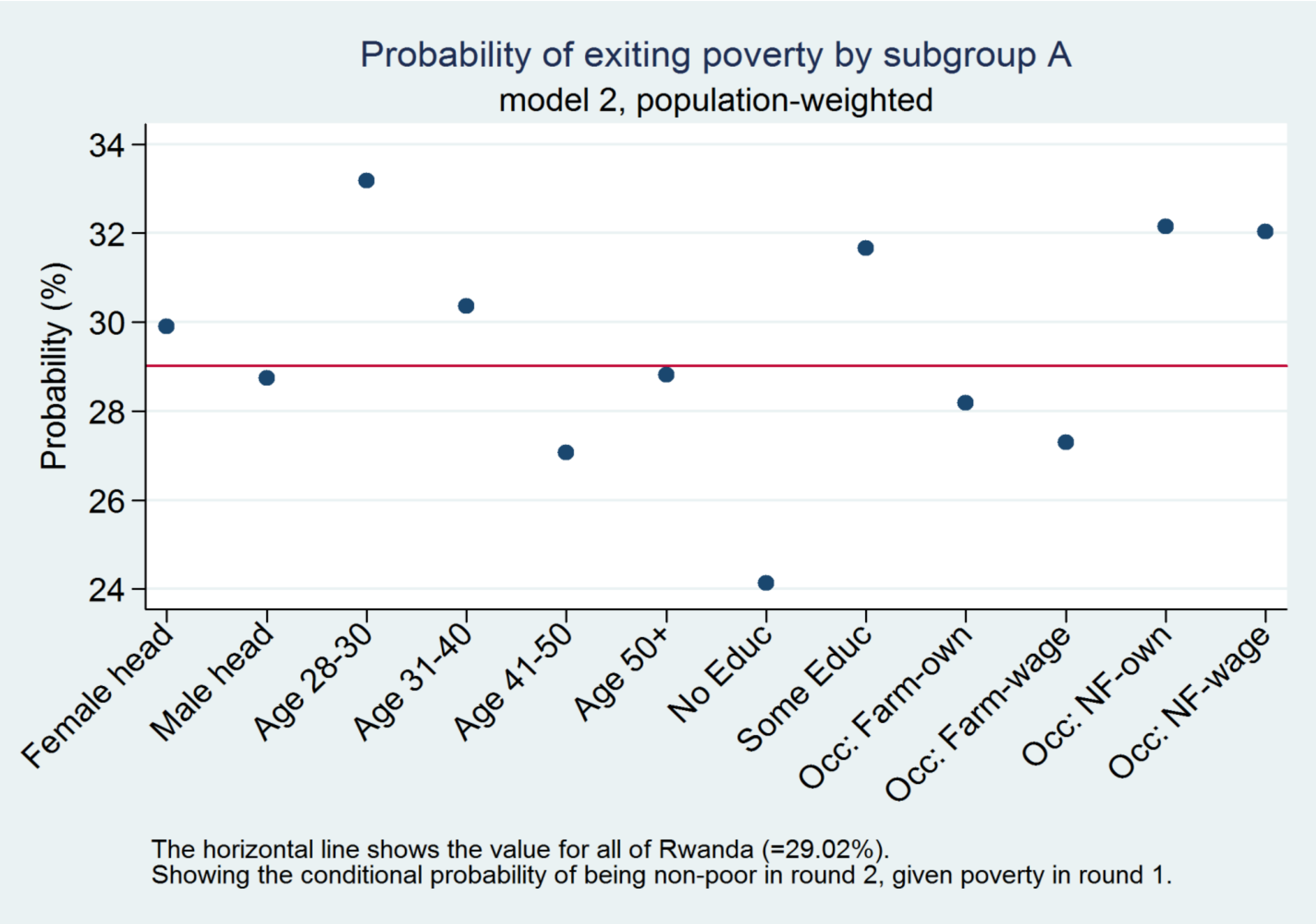


Figure 4: Conditional probability by population subgroup

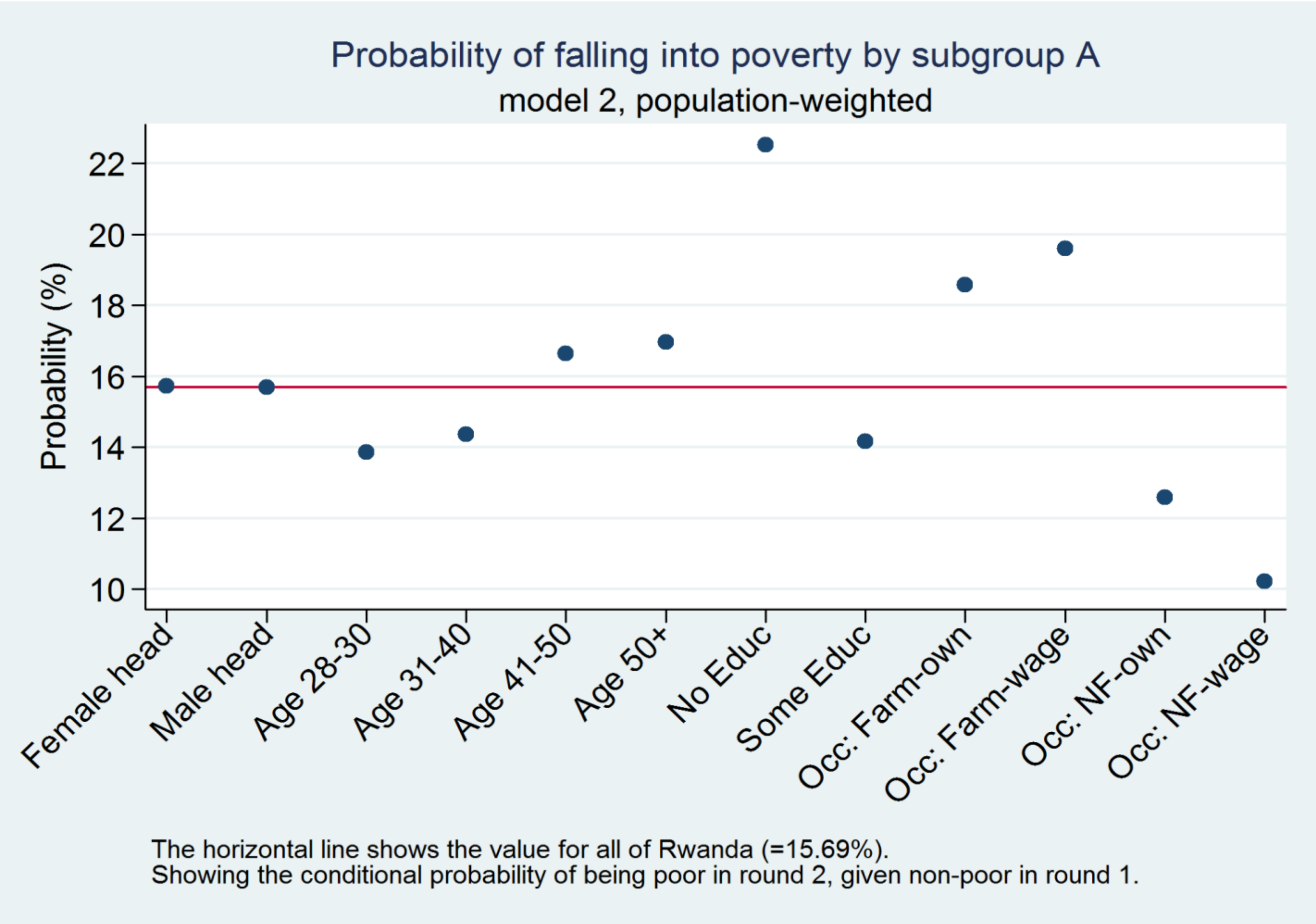


Table 6: Point estimates of poverty transitions by subgroups (regions and VUP program)

	Urbanisation		Provinces					VUP program	
	Urban	Rural	Kigali	South	West	North	East	Non-VUP	VUP
Panel A: Joint and marginal probabilities									
Poor, Poor	14.68	40.45	9.83	46.15	39.23	37.67	34.83	37.31	34.60
Poor, Non-poor	7.16	16.35	5.66	15.28	15.19	18.38	15.69	15.19	14.40
Non-poor, Poor	7.81	7.52	6.61	7.78	8.71	6.14	7.63	7.51	7.79
Non-poor, Non-poor	70.35	35.68	77.90	30.79	36.87	37.81	41.85	39.99	43.21
N	1553	8815	971	2840	2392	1677	2488	8232	2136
Poor in period 1	21.84	56.80	15.49	61.43	54.42	56.05	50.53	52.50	49.01
Poor in period 2	22.49	47.97	16.44	53.93	47.93	43.81	42.46	44.81	42.39
Panel B: Conditional probabilities									
Poor --> Poor	67.23	71.22	63.47	75.12	72.08	67.21	68.94	71.06	70.61
Poor --> Non-poor	32.77	28.78	36.53	24.88	27.92	32.79	31.06	28.94	29.39
Non-poor --> Poor	9.99	17.40	7.83	20.18	19.10	13.98	15.41	15.80	15.27
Non-poor --> Non-Poor	90.01	82.60	92.17	79.82	80.90	86.02	84.59	84.20	84.73

Regressions account for population sampling weights, but not clustering or the complex survey design (stratification). However, this will not affect the point estimates. All results use model 2 which is estimated for the whole sample. Pr(poor, non-poor) is the probability of being poor in period 1 and non-poor in period 2.The table shows the number of observations in year 2.

Figure 5: Conditional probability by population subgroup

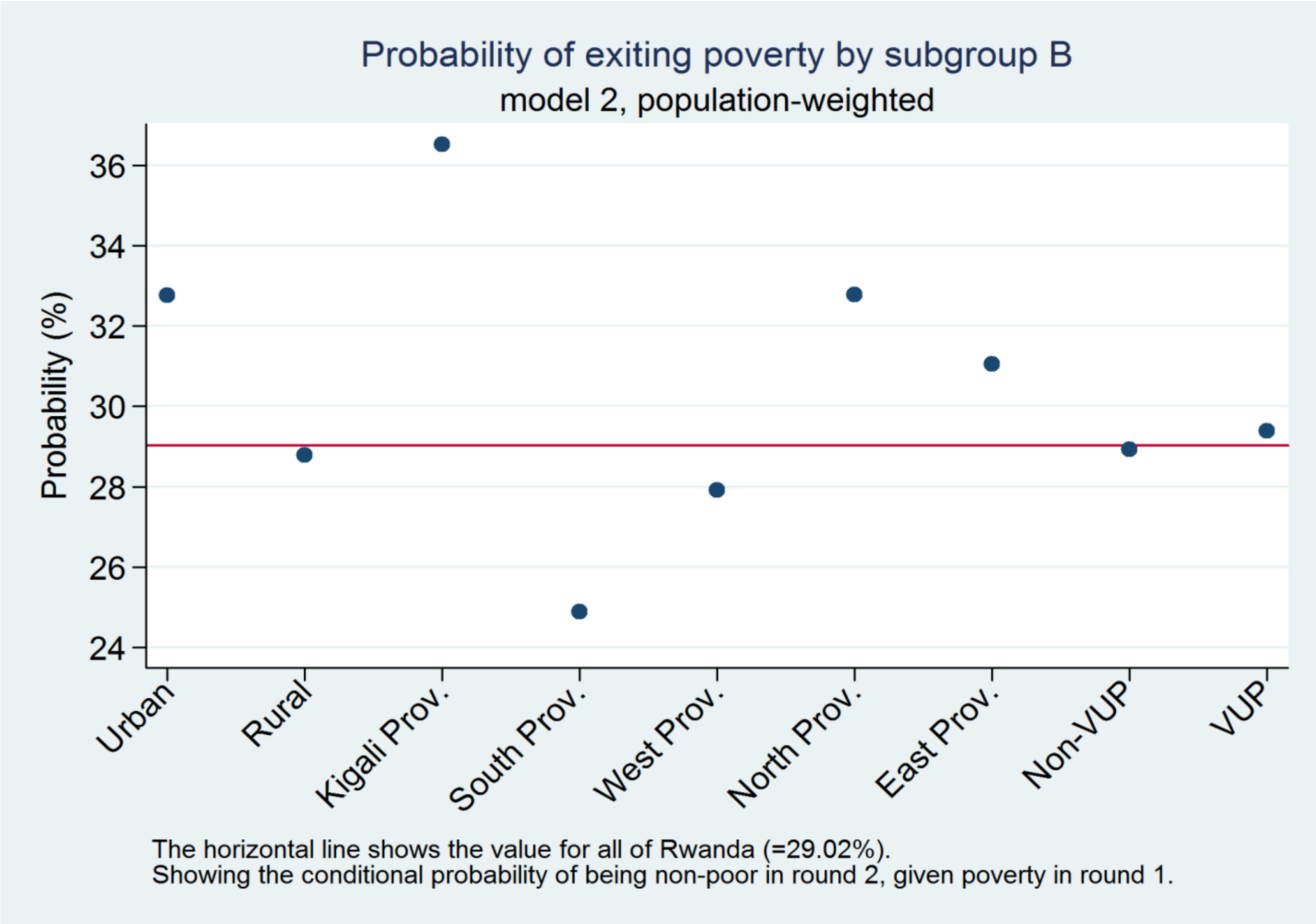


Figure 6: Conditional probability by population subgroup

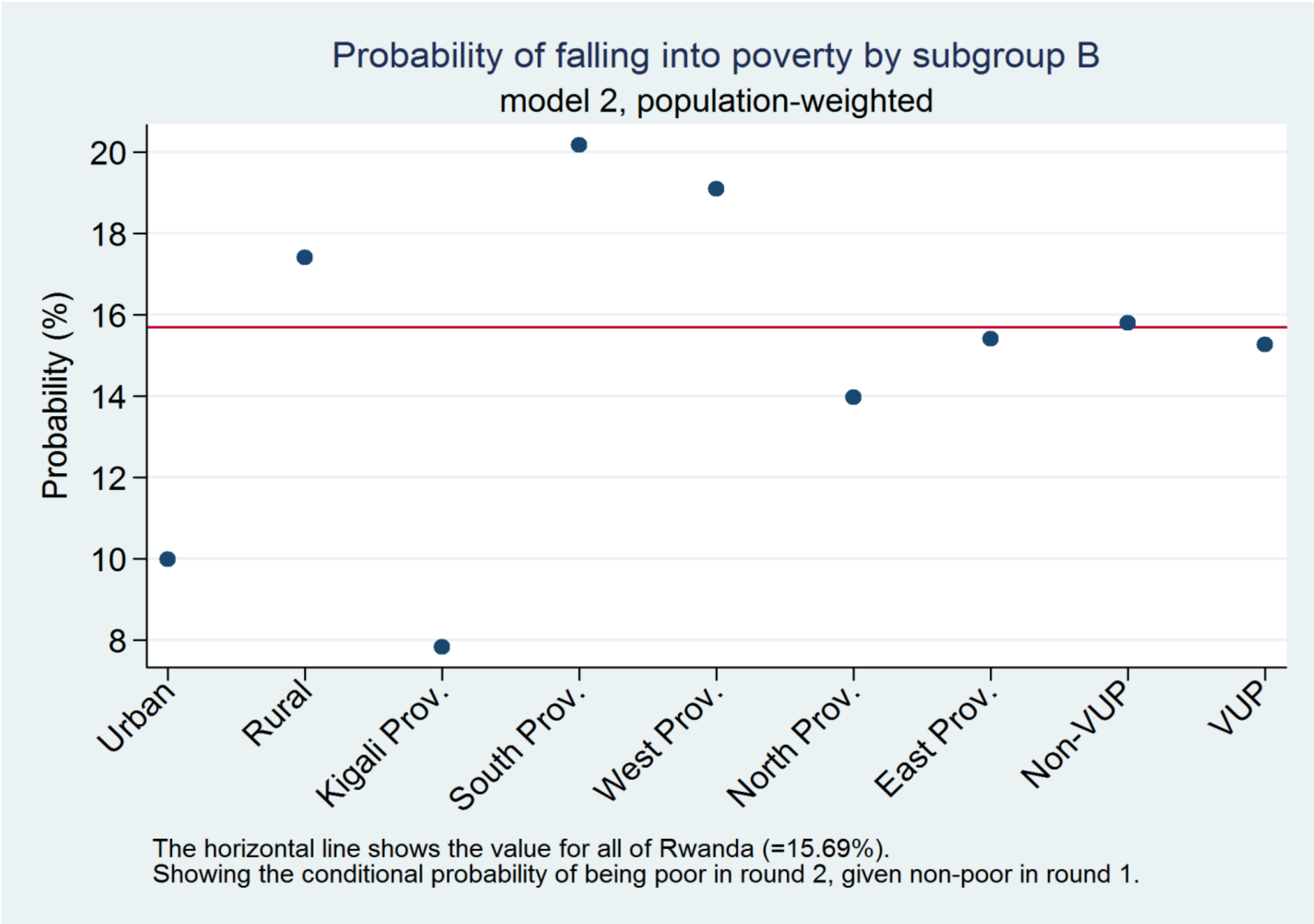


Table 7: Point estimates of poverty transitions by participation in Crop Intensification Program (CIP) *[only rural areas]*

	any plots		at least 10%		at least 20%		at least 30%	
	Non-CIP	**CIP**	**Non-CIP**	**CIP**	**Non-CIP**	**CIP**	**Non-CIP**	**CIP**
Panel A: Joint and marginal probabilities								
Poor, Poor	39.23	40.90	40.70	40.03	40.88	38.74	40.87	36.50
Poor, Non-poor	14.59	16.99	15.27	18.18	15.66	19.05	15.97	19.92
Non-poor, Poor	8.34	7.22	8.07	6.59	7.89	6.05	7.72	5.59
Non-poor, Non-poor	37.85	34.89	35.96	35.21	35.56	36.16	35.44	38.00
N	2453	6362	5713	3102	7248	1567	8094	721
Poor in period 1	53.81	57.89	55.97	58.21	56.55	57.79	56.84	56.42
Poor in period 2	47.56	48.12	48.77	46.62	48.77	44.79	48.59	42.08
Panel B: Conditional probabilities								
Poor --> Poor	72.89	70.65	72.71	68.77	72.30	67.03	71.91	64.70
Poor --> Non-poor	27.11	29.35	27.29	31.23	27.70	32.97	28.09	35.30
Non-poor --> Poor	18.05	17.14	18.32	15.76	18.15	14.34	17.90	12.81
Non-poor --> Non-Poor	81.95	82.86	81.68	84.24	81.85	85.66	82.10	87.19

Regressions account for population sampling weights, but not clustering or the complex survey design (stratification). However, this will not affect the point estimates. All results use model 2 which is estimated for the whole sample. Pr(poor, non-poor) is the probability of being poor in period 1 and non-poor in period 2.The table shows the number of observations in year 2.CIP treatment is defined in three ways: (1) any plots in cluster treated; (2) at least 10%; (3) at least 20%; (4) at least 30%. Only rural areas because this is an agricultural intervention.

Figure 7: Conditional probability by population subgroup

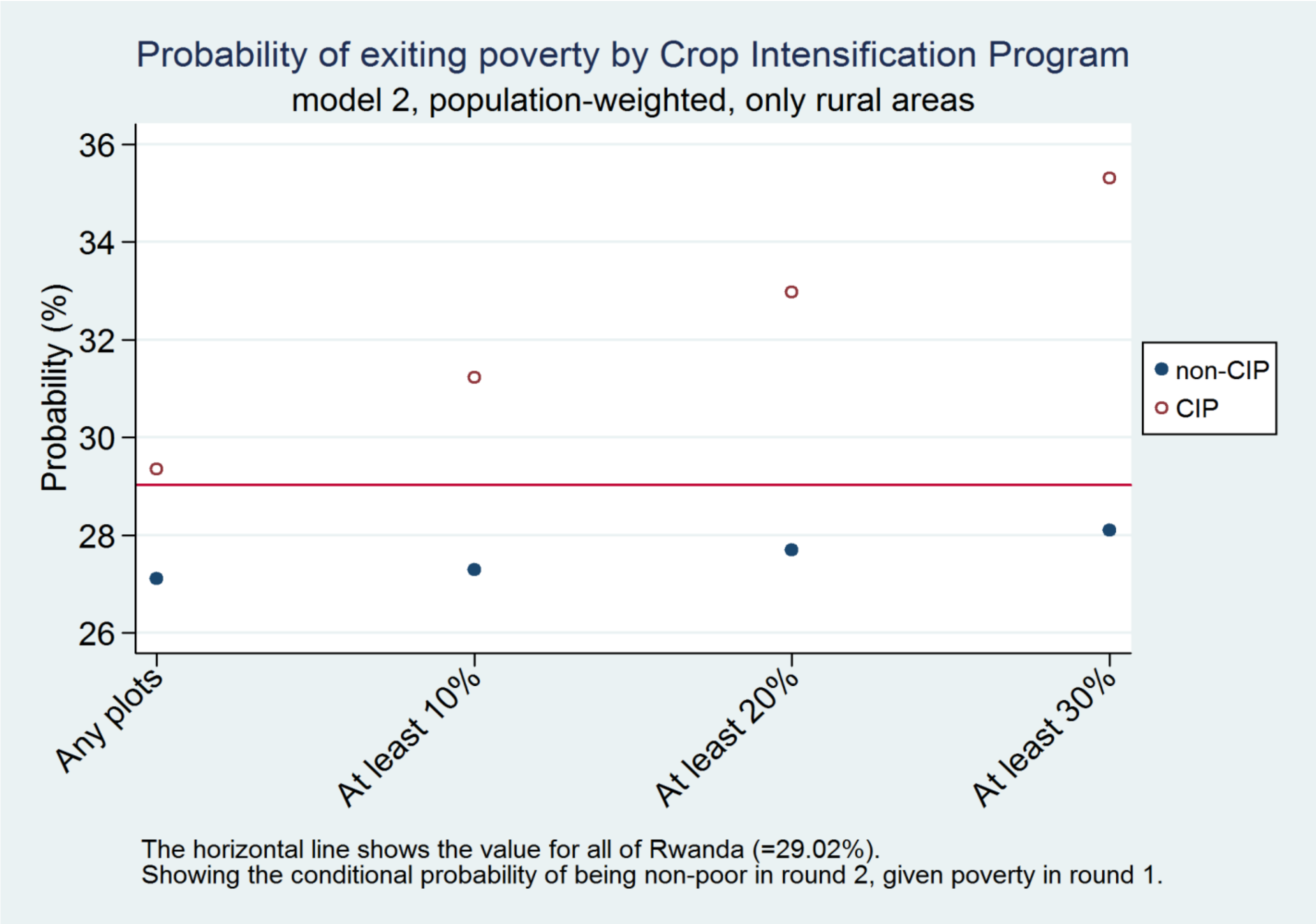


Figure 8: Conditional probability by population subgroup

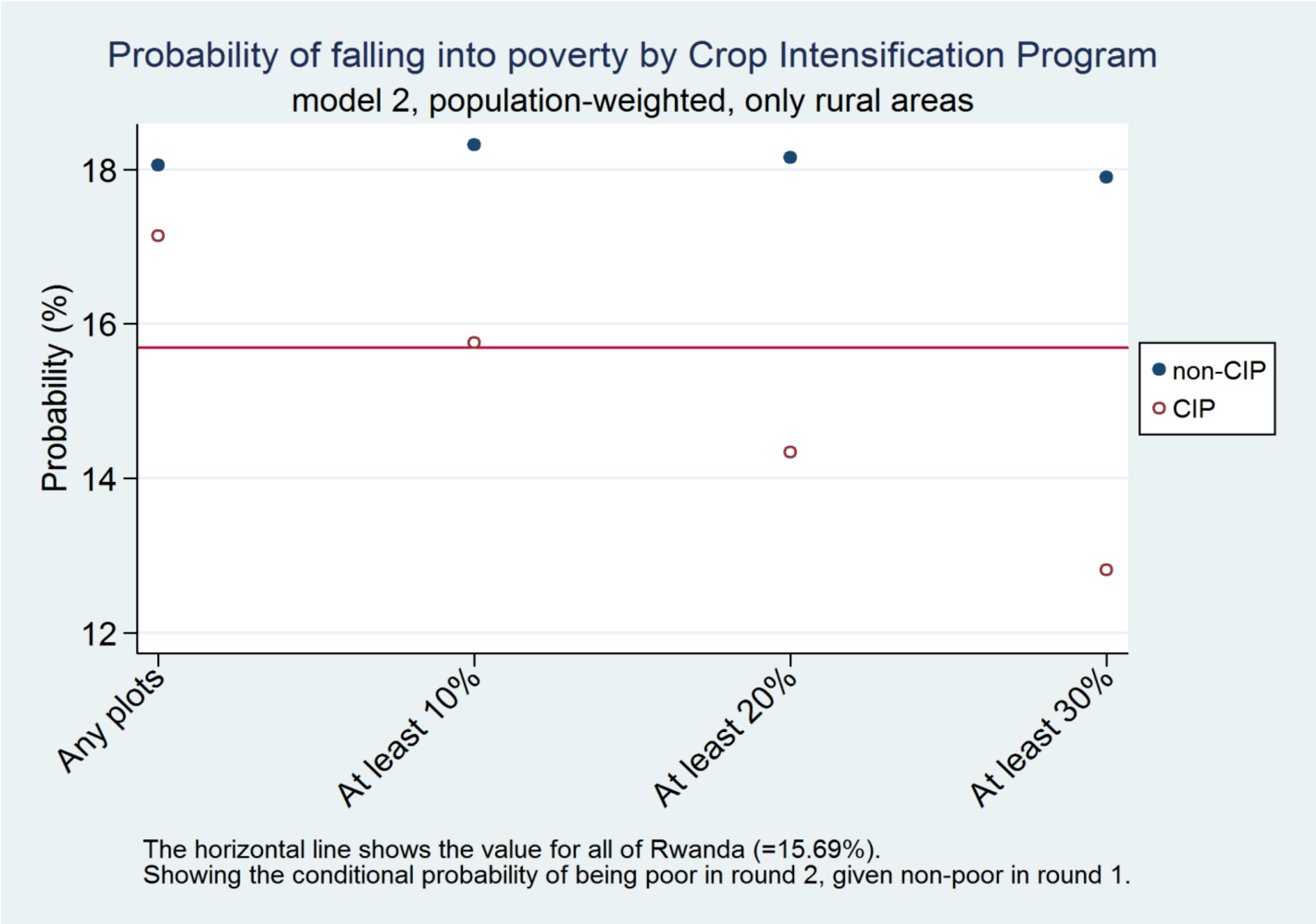
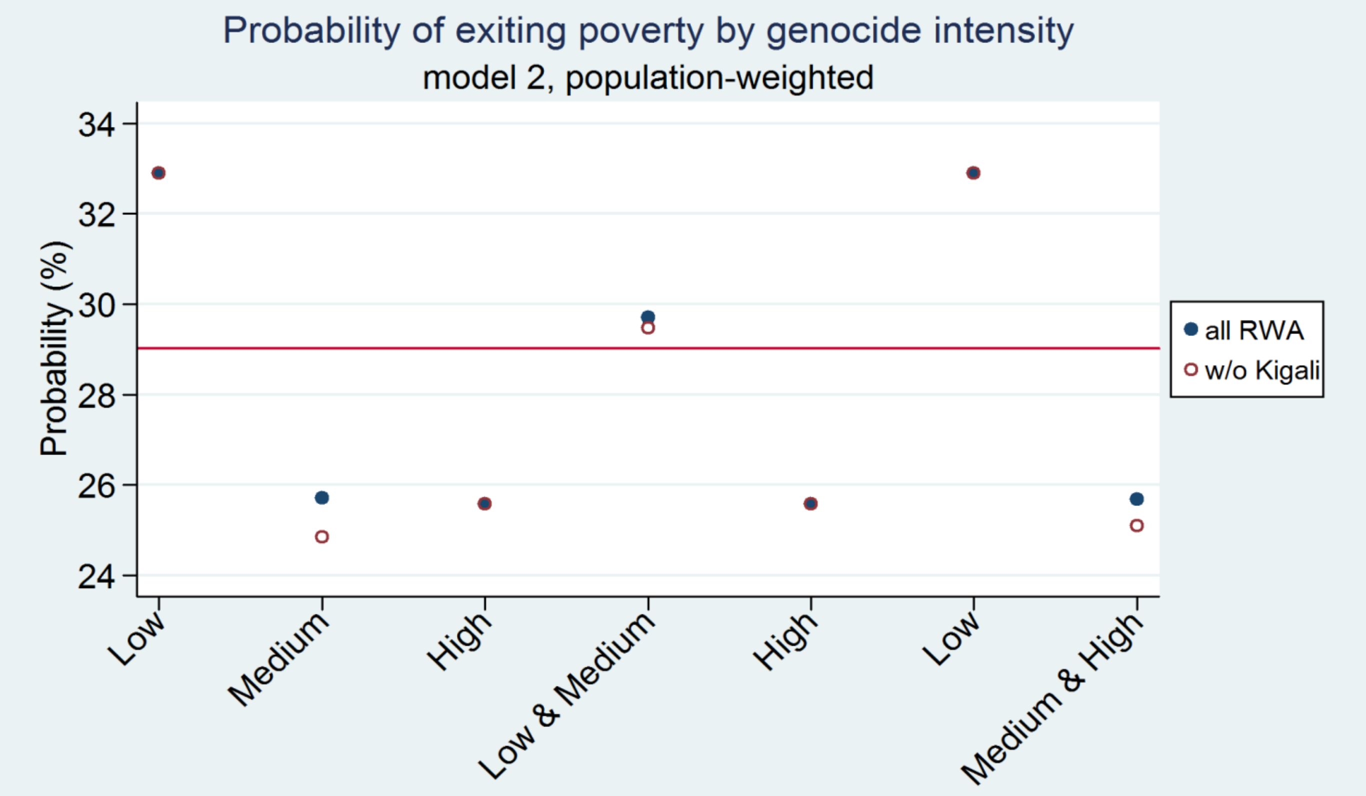


Table 8: Point estimates of poverty transitions by genocide intensity

	Whole Sample							Excluding Kigali						
	Detailed groups			Two groups		Two groups		Detailed groups			Two groups		Two groups	
	Low	Medium	High	Low & Medium	High	Low	Medium & High	Low	Medium	High	Low & Medium	High	Low	Medium & High
Panel A: Joint and marginal probabilities														
Poor, Poor	37.03	33.96	44.25	35.52	44.25	37.03	36.59	37.03	40.72	44.25	38.62	44.25	37.03	41.80
Poor, Non-poor	18.16	11.76	15.21	15.01	15.21	18.16	12.64	18.16	13.47	15.21	16.14	15.21	18.16	14.00
Non-poor, Poor	6.44	8.61	7.87	7.51	7.87	6.44	8.42	6.44	9.17	7.87	7.62	7.87	6.44	8.77
Non-poor, Non-poor	38.37	45.67	32.67	41.96	32.67	38.37	42.35	38.37	36.64	32.67	37.62	32.67	38.37	35.43
N	4117	4508	1743	8625	1743	4117	6251	4117	3537	1743	7654	1743	4117	5280
Poor in period 1	55.19	45.72	59.46	50.53	59.46	55.19	49.23	55.19	54.19	59.46	54.76	59.46	55.19	55.80
Poor in period 2	43.48	42.57	52.12	43.03	52.12	43.48	45.01	43.48	49.89	52.12	46.24	52.12	43.48	50.57
Panel B: Conditional probabilities														
Poor --> Poor	67.10	74.28	74.42	70.30	74.42	67.10	74.32	67.10	75.15	74.42	70.53	74.42	67.10	74.91
Poor --> Non-poor	32.90	25.72	25.58	29.70	25.58	32.90	25.68	32.90	24.85	25.58	29.47	25.58	32.90	25.09
Non-poor --> Poor	14.38	15.86	19.41	15.18	19.41	14.38	16.58	14.38	20.01	19.41	16.83	19.41	14.38	19.84
Non-poor --> Non-Poor	85.62	84.14	80.59	84.82	80.59	85.62	83.42	85.62	79.99	80.59	83.17	80.59	85.62	80.16

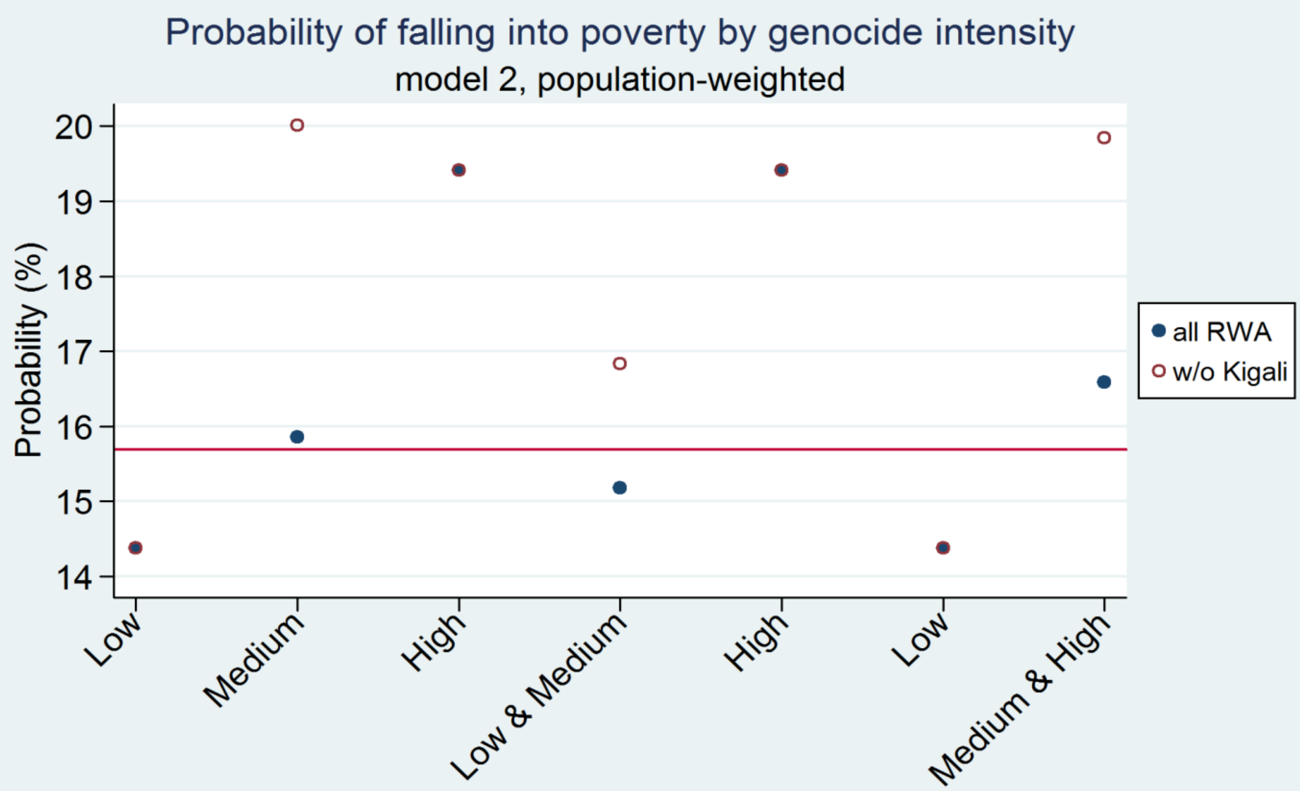
Regressions account for population sampling weights, but not clustering or the complex survey design (stratification). However, this will not affect the point estimates. All results use model 2 which is estimated for the whole sample. Pr(poor, non-poor) is the probability of being poor in period 1 and non-poor in period 2.The table shows the number of observations in year 2. Districts are ranked according to genocide intensity as measured by PCA. The number of districts is as follows: Low:12, Medium: 13, High: 5. The three Kigali districts are all in the intermediate category.

Figure 9: Conditional probability by population subgroup



The horizontal line shows the value for all of Rwanda (=29.02%).
Showing the conditional probability of being non-poor in round 2, given poverty in round 1.
The three Kigali districts are all in the intermediate category.

Figure 10: Conditional probability by population subgroup



The horizontal line shows the value for all of Rwanda (=15.69%).
Showing the conditional probability of being poor in round 2, given non-poor in round 1.
The three Kigali districts are all in the intermediate category.

Table A.1: Comparing poverty across different samples

	Poverty		Extreme Poverty		Mean consumption	
	2006	**2011**	**2006**	**2011**	**2006**	**2011**
Full sample	56.67%	44.91%	39.75%	27.57%	99,749	116,262
Sample restrictions without age restrictions	56.98%	45.35%	39.95%	27.84%	96,817	111,818
Sample used in estimation	56.88%	47.17%	40.31%	29.38%	98,099	112,389
Alternative age restriction (25-55 in year 1)	57.64%	47.99%	41.20%	30.15%	97,569	111,444

Using population weights throughout. Poverty line is 64000, Extreme poverty line 48000. Consumption is measured as yearly consumption expenditure per adult equivalent (2011 prices, RWF).The estimation sample restricts the age of the household head to between 23 and 58 in 2006 and 28 and 63 in 2011.

Figure A.1: Comparing the distribution of consumption in full sample and estimation sample

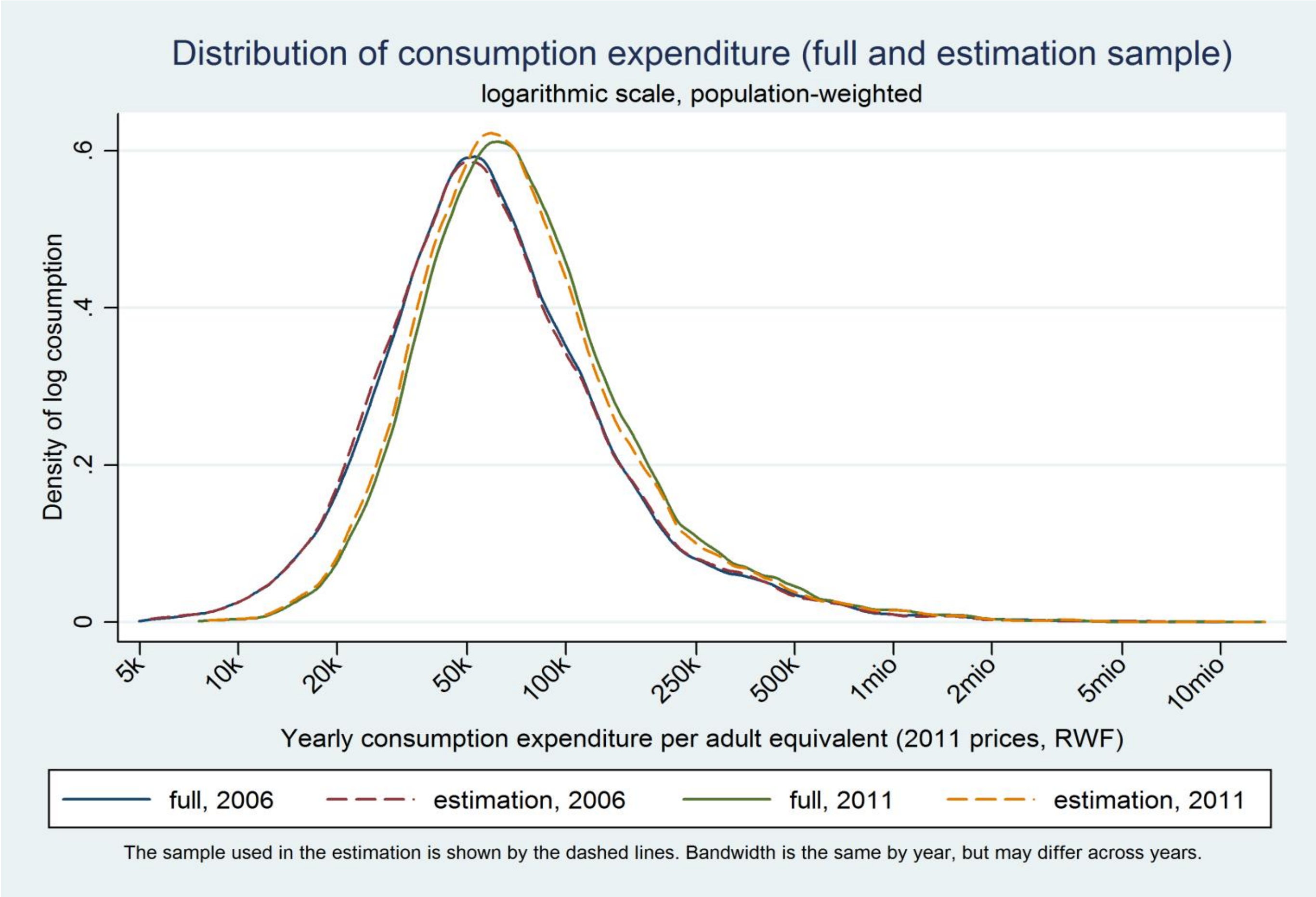


Table A.2: Full consumption model in 2006								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	weighted				unweighted			
Gender is male	0.036	0.066***	-0.637	-0.667	0.037	0.077***	-0.782	-0.786
	(0.027)	(0.025)	(0.402)	(0.406)	(0.025)	(0.023)	(0.558)	(0.557)
Age (Years)	-0.096***	-0.090***	-0.090***	-0.091***	-0.108***	-0.093***	-0.092***	-0.093***
	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)
age2	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Disabled at the time of EICV2	-0.044	-0.025	-0.026	-0.027	-0.032	-0.030	-0.031	-0.031
	(0.051)	(0.045)	(0.046)	(0.045)	(0.046)	(0.038)	(0.039)	(0.038)
educattain==some primary educati	0.292***	0.250***	0.935**	1.047**	0.335***	0.251***	1.079*	1.204*
	(0.026)	(0.025)	(0.403)	(0.441)	(0.025)	(0.023)	(0.559)	(0.617)
educattain==some vocational educ	0.803***	0.632***	1.314***	1.326***	0.952***	0.678***	1.516***	1.541**
	(0.058)	(0.052)	(0.405)	(0.443)	(0.056)	(0.049)	(0.560)	(0.611)
educattain==some secondary educ	1.202***	0.955***	1.619***	1.642***	1.432***	1.030***	1.839***	1.904***
	(0.068)	(0.060)	(0.404)	(0.451)	(0.063)	(0.056)	(0.566)	(0.623)
educattain==some tertiary educati	2.471***	1.957***	2.612***	2.847***	2.826***	2.232***	3.013***	3.205***
	(0.157)	(0.145)	(0.366)	(0.362)	(0.134)	(0.134)	(0.544)	(0.545)
birthreg3==Southern	-0.477***	0.352***	0.351***	0.321***	-0.462***	0.387***	0.384***	0.368***
	(0.092)	(0.097)	(0.097)	(0.096)	(0.085)	(0.097)	(0.097)	(0.095)
birthreg3==Western	-0.427***	0.242**	0.243**	0.204**	-0.448***	0.297***	0.295***	0.272***
	(0.095)	(0.100)	(0.100)	(0.099)	(0.086)	(0.095)	(0.095)	(0.094)
birthreg3==Rest	-0.383***	0.204**	0.203**	0.180*	-0.400***	0.204**	0.202**	0.192**
	(0.089)	(0.095)	(0.095)	(0.093)	(0.083)	(0.091)	(0.091)	(0.090)
birthreg3==neighboring countries	-0.197*	0.271**	0.275***	0.236**	-0.178	0.295***	0.293***	0.274**
	(0.108)	(0.105)	(0.105)	(0.104)	(0.112)	(0.108)	(0.108)	(0.108)
birthreg3==others	1.437***	1.185***	1.196***	1.429***	1.375***	1.077***	1.099***	1.302***
	(0.095)	(0.108)	(0.108)	(0.115)	(0.085)	(0.109)	(0.109)	(0.115)
region==rural		-0.450***	-0.450***	-0.334		-0.504***	-0.505***	-0.458
		(0.062)	(0.062)	(0.307)		(0.062)	(0.062)	(0.331)
residence==Gasabo		-0.130	-0.133	-0.106		-0.089	-0.094	-0.083
		(0.094)	(0.094)	(0.093)		(0.099)	(0.100)	(0.098)
residence==Kicukiro		-0.178*	-0.185*	-0.163		-0.215**	-0.218**	-0.202**
		(0.106)	(0.106)	(0.102)		(0.096)	(0.097)	(0.094)
residence==Nyanza		-0.689***	-0.689***	-0.623***		-0.771***	-0.769***	-0.721***
		(0.121)	(0.121)	(0.120)		(0.119)	(0.118)	(0.118)
residence==Gisagara		-0.933***	-0.933***	-0.874***		-0.957***	-0.957***	-0.920***
		(0.123)	(0.124)	(0.124)		(0.123)	(0.123)	(0.123)
residence==Nyaruguru		-1.027***	-1.025***	-0.969***		-1.105***	-1.102***	-1.067***
		(0.108)	(0.109)	(0.108)		(0.110)	(0.110)	(0.110)
residence==Huye		-0.732***	-0.730***	-0.663***		-0.751***	-0.753***	-0.715***
		(0.113)	(0.114)	(0.116)		(0.131)	(0.128)	(0.128)
residence==Nyamagabe		-0.862***	-0.864***	-0.801***		-0.939***	-0.940***	-0.900***
		(0.118)	(0.119)	(0.117)		(0.117)	(0.117)	(0.116)
residence==Ruhango		-0.657***	-0.658***	-0.595***		-0.719***	-0.719***	-0.675***
		(0.105)	(0.106)	(0.105)		(0.105)	(0.105)	(0.104)
residence==Muhanga		-0.563***	-0.564***	-0.512***		-0.615***	-0.618***	-0.583***
		(0.106)	(0.106)	(0.104)		(0.108)	(0.108)	(0.107)
residence==Kamonyi		-0.520***	-0.520***	-0.456***		-0.560***	-0.556***	-0.512***
		(0.101)	(0.102)	(0.101)		(0.104)	(0.103)	(0.103)
residence==Karongi		-0.431***	-0.435***	-0.363***		-0.541***	-0.544***	-0.495***
		(0.130)	(0.131)	(0.131)		(0.121)	(0.121)	(0.121)
residence==Rutsiro		-0.479***	-0.484***	-0.419***		-0.620***	-0.625***	-0.584***
		(0.137)	(0.137)	(0.136)		(0.124)	(0.124)	(0.123)
residence==Rubavu		-0.590***	-0.597***	-0.539***		-0.571***	-0.580***	-0.548***
		(0.126)	(0.126)	(0.126)		(0.114)	(0.114)	(0.114)
residence==Nyabihu		-0.492***	-0.493***	-0.422***		-0.541***	-0.546***	-0.502***
		(0.115)	(0.115)	(0.117)		(0.113)	(0.114)	(0.115)
residence==Ngororero		-0.410**	-0.414**	-0.351*		-0.474***	-0.479***	-0.439**

		(0.186)	(0.185)	(0.185)		(0.174)	(0.173)	(0.173)
residence==Rusizi		-0.447***	-0.449***	-0.381***		-0.558***	-0.561***	-0.516***
		(0.142)	(0.143)	(0.143)		(0.136)	(0.136)	(0.136)
residence==Nyamasheke		-0.552***	-0.554***	-0.489***		-0.591***	-0.593***	-0.549***
		(0.132)	(0.132)	(0.133)		(0.127)	(0.127)	(0.127)
residence==Rulindo		-0.370***	-0.369***	-0.316**		-0.389***	-0.388***	-0.355***
		(0.137)	(0.137)	(0.136)		(0.128)	(0.128)	(0.128)
residence==Gakenke		-0.468***	-0.468***	-0.415***		-0.471***	-0.470***	-0.436***
		(0.124)	(0.125)	(0.124)		(0.121)	(0.122)	(0.121)
residence==Musanze		-0.409***	-0.408***	-0.353***		-0.469***	-0.471***	-0.437***
		(0.132)	(0.132)	(0.130)		(0.127)	(0.127)	(0.126)
residence==Burera		-0.699***	-0.700***	-0.644***		-0.718***	-0.720***	-0.687***
		(0.116)	(0.117)	(0.117)		(0.118)	(0.118)	(0.119)
residence==Gicumbi		-0.541***	-0.541***	-0.480***		-0.600***	-0.602***	-0.563***
		(0.111)	(0.111)	(0.109)		(0.122)	(0.122)	(0.119)
residence==Rwamagana		-0.132	-0.134	-0.090		-0.165	-0.169	-0.145
		(0.124)	(0.125)	(0.121)		(0.120)	(0.120)	(0.117)
residence==Nyagatare		-0.273**	-0.275**	-0.224**		-0.279**	-0.282**	-0.254*
		(0.113)	(0.113)	(0.112)		(0.134)	(0.134)	(0.133)
residence==Gatsibo		-0.394***	-0.395***	-0.340***		-0.342**	-0.344**	-0.310**
		(0.124)	(0.124)	(0.124)		(0.135)	(0.135)	(0.135)
residence==Kayonza		-0.212*	-0.214*	-0.157		-0.237**	-0.238**	-0.202*
		(0.118)	(0.119)	(0.119)		(0.120)	(0.121)	(0.121)
residence==Kirehe		-0.501***	-0.504***	-0.449***		-0.604***	-0.606***	-0.572***
		(0.156)	(0.156)	(0.156)		(0.148)	(0.149)	(0.148)
residence==Ngoma		-0.391***	-0.392***	-0.328***		-0.382***	-0.386***	-0.349***
		(0.114)	(0.114)	(0.111)		(0.115)	(0.116)	(0.115)
residence==Bugesera		-0.521***	-0.527***	-0.467***		-0.546***	-0.551***	-0.513***
		(0.128)	(0.128)	(0.128)		(0.136)	(0.136)	(0.136)
1b.educattain#0b.male			0.000	0.000			0.000	0.000
			(.)	(.)			(.)	(.)
1b.educattain#1.male			0.668*	0.690*			0.793	0.788
			(0.403)	(0.407)			(0.559)	(0.557)
2.educattain#0b.male			-0.742*	-0.773*			-0.911	-0.916
			(0.403)	(0.408)			(0.560)	(0.558)
2o.educattain#1o.male			0.000	0.000			0.000	0.000
			(.)	(.)			(.)	(.)
3.educattain#0b.male			-0.715*	-0.757*			-0.939*	-0.957*
			(0.406)	(0.411)			(0.543)	(0.544)
3o.educattain#1o.male			0.000	0.000			0.000	0.000
			(.)	(.)			(.)	(.)
4.educattain#0b.male			-0.578	-0.636			-0.800	-0.817
			(0.419)	(0.421)			(0.576)	(0.575)
4o.educattain#1o.male			0.000	0.000			0.000	0.000
			(.)	(.)			(.)	(.)
5o.educattain#0b.male			0.000	0.000			0.000	0.000
			(.)	(.)			(.)	(.)
5o.educattain#1o.male			0.000	0.000			0.000	0.000
			(.)	(.)			(.)	(.)
1b.educattain#0b.region_2				0.000				0.000
				(.)				(.)
1b.educattain#1.region_2				0.110				0.159
				(0.307)				(0.332)
2.educattain#0b.region_2				0.132				0.084
				(0.305)				(0.327)
2o.educattain#1o.region_2				0.000				0.000
				(.)				(.)
3.educattain#0b.region_2				0.454				0.300
				(0.311)				(0.328)
3o.educattain#1o.region_2				0.000				0.000

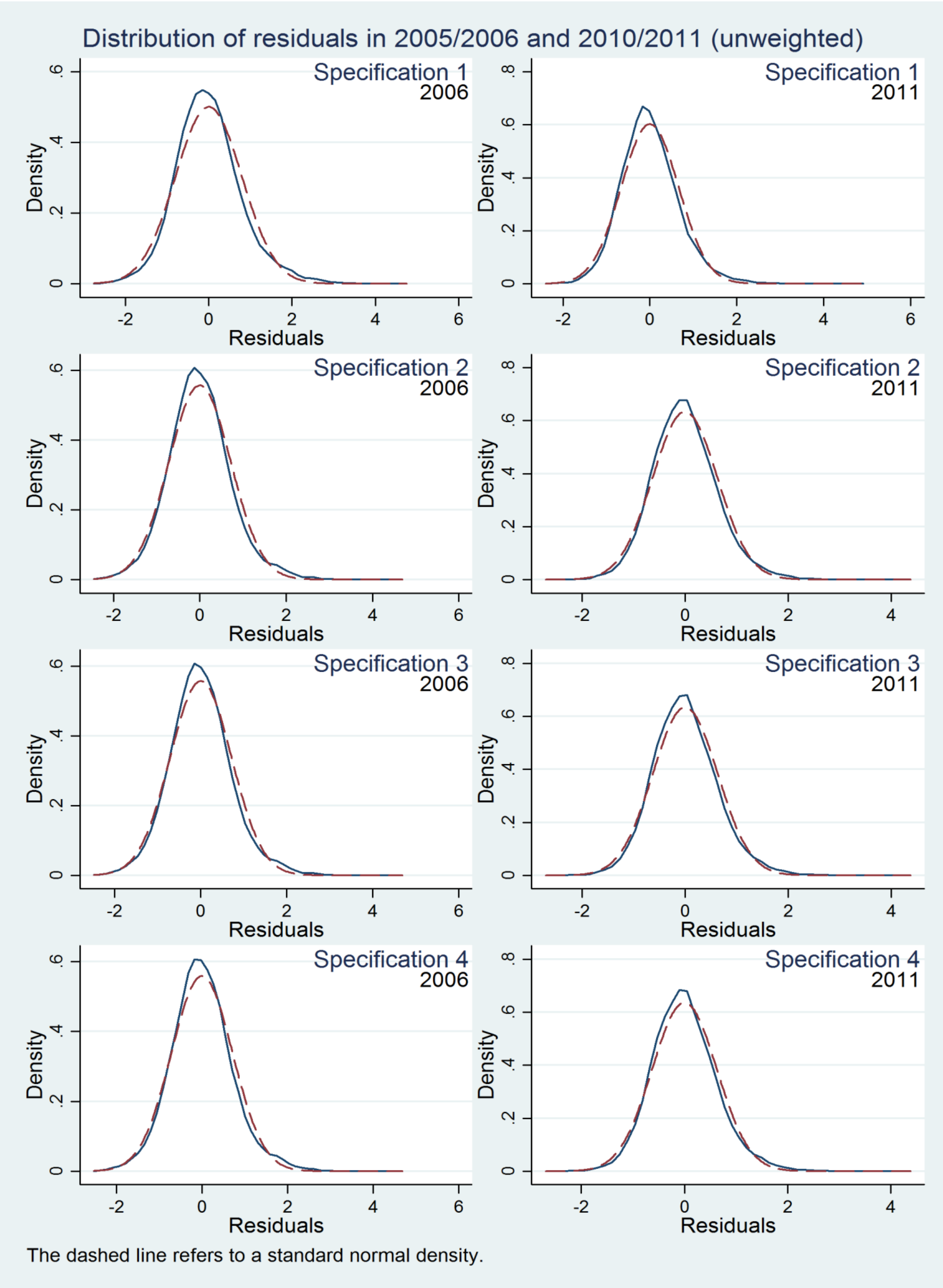
				(.)				(.)
4.educattain#0b.region_2				0.341				0.173
				(0.314)				(0.333)
4o.educattain#1o.region_2				0.000				0.000
				(.)				(.)
5o.educattain#0b.region_2				0.000				0.000
				(.)				(.)
5o.educattain#1o.region_2				0.000				0.000
				(.)				(.)
Constant	13.062***	13.184***	13.198***	12.991***	13.407***	13.367***	13.396***	13.220***
	(0.223)	(0.220)	(0.220)	(0.229)	(0.211)	(0.195)	(0.197)	(0.205)
Observations	5439	5439	5439	5439	5439	5439	5439	5439
r2	0.214	0.318	0.319	0.323	0.299	0.432	0.434	0.436
District of residence		Yes	Yes	Yes		Yes	Yes	Yes
Educ. attain x male			Yes	Yes			Yes	Yes
Educ. attain x rural				Yes				Yes
Dependent variable is ln(Yearly consumption expenditure per adult equivalent (2011 prices, RWF)).								
Standard errors in parentheses. Regressions account for complex survey design (clustering and stratification).								
Columns (1) to (4) are weighted using population sampling weights. Columns (5) to (8) are unweighted.								
** p<0.1; ** p<0.05; *** p<0.01*								

Table A.3: Full consumption model in 2011								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	weighted				unweighted			
Gender is male	-0.025	-0.016	0.075	0.076	-0.023	-0.018	0.016	0.017
	(0.018)	(0.017)	(0.217)	(0.220)	(0.015)	(0.015)	(0.199)	(0.201)
Age (Years)	-0.079***	-0.074***	-0.072***	-0.072***	-0.086***	-0.084***	-0.081***	-0.081***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
age2	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Disabled at the time of EICV2	-0.103***	-0.063*	-0.065*	-0.067*	-0.081***	-0.035	-0.036	-0.036
	(0.037)	(0.036)	(0.036)	(0.036)	(0.028)	(0.027)	(0.027)	(0.027)
educattain==some primary edu	0.227***	0.206***	0.061	0.226	0.204***	0.176***	0.099	0.272
	(0.022)	(0.022)	(0.217)	(0.302)	(0.015)	(0.014)	(0.200)	(0.264)
educattain==some vocational e	0.705***	0.613***	0.447**	0.538*	0.670***	0.561***	0.477**	0.586**
	(0.044)	(0.040)	(0.222)	(0.310)	(0.038)	(0.035)	(0.204)	(0.267)
educattain==some secondary e	1.139***	0.992***	0.817***	0.887***	1.154***	0.970***	0.876***	0.943***
	(0.046)	(0.052)	(0.214)	(0.284)	(0.041)	(0.037)	(0.204)	(0.267)
educattain==some tertiary edu	2.212***	1.931***	1.777***	1.971***	2.371***	2.020***	1.934***	2.136***
	(0.090)	(0.110)	(0.197)	(0.203)	(0.075)	(0.069)	(0.191)	(0.199)
birthreg3==Southern	-0.268***	0.197***	0.196***	0.164**	-0.304***	0.216***	0.212***	0.183***
	(0.054)	(0.071)	(0.071)	(0.070)	(0.049)	(0.059)	(0.059)	(0.057)
birthreg3==Western	-0.225***	0.226***	0.226***	0.195**	-0.281***	0.188***	0.186***	0.157**
	(0.055)	(0.078)	(0.078)	(0.076)	(0.050)	(0.066)	(0.066)	(0.064)
birthreg3==Rest	-0.158***	0.170**	0.169**	0.142*	-0.223***	0.179***	0.175***	0.151***
	(0.052)	(0.075)	(0.075)	(0.073)	(0.049)	(0.057)	(0.057)	(0.055)
birthreg3==neighboring countr	0.127*	0.386***	0.384***	0.348***	0.116*	0.410***	0.405***	0.370***
	(0.072)	(0.084)	(0.084)	(0.083)	(0.066)	(0.071)	(0.071)	(0.070)
birthreg3==others	-0.610***	-0.489***	-0.488***	-0.569***	-0.201	0.143	0.138	0.076
	(0.177)	(0.152)	(0.156)	(0.146)	(0.394)	(0.437)	(0.437)	(0.450)
region==rural		-0.209***	-0.211***	-0.200		-0.236***	-0.237***	-0.236
		(0.047)	(0.047)	(0.212)		(0.041)	(0.041)	(0.169)
residence==Gasabo		-0.215***	-0.215***	-0.203***		-0.174**	-0.174**	-0.164**
		(0.072)	(0.072)	(0.070)		(0.074)	(0.074)	(0.072)
residence==Kicukiro		-0.053	-0.050	-0.067		-0.007	-0.006	-0.024
		(0.075)	(0.075)	(0.074)		(0.072)	(0.072)	(0.072)
residence==Nyanza		-0.590***	-0.589***	-0.547***		-0.594***	-0.593***	-0.542***
		(0.087)	(0.087)	(0.085)		(0.081)	(0.081)	(0.080)
residence==Gisagara		-0.560***	-0.555***	-0.517***		-0.547***	-0.542***	-0.500***
		(0.089)	(0.089)	(0.088)		(0.084)	(0.084)	(0.083)
residence==Nyaruguru		-0.649***	-0.647***	-0.609***		-0.646***	-0.642***	-0.600***
		(0.087)	(0.087)	(0.085)		(0.083)	(0.083)	(0.082)
residence==Huye		-0.484***	-0.479***	-0.439***		-0.433***	-0.428***	-0.387***
		(0.092)	(0.092)	(0.091)		(0.088)	(0.087)	(0.086)
residence==Nyamagabe		-0.765***	-0.762***	-0.720***		-0.795***	-0.793***	-0.748***
		(0.088)	(0.088)	(0.085)		(0.082)	(0.081)	(0.080)
residence==Ruhango		-0.648***	-0.642***	-0.606***		-0.621***	-0.615***	-0.573***
		(0.085)	(0.084)	(0.083)		(0.082)	(0.081)	(0.081)
residence==Muhanga		-0.514***	-0.509***	-0.469***		-0.508***	-0.503***	-0.462***
		(0.095)	(0.094)	(0.091)		(0.088)	(0.088)	(0.086)
residence==Kamonyi		-0.424***	-0.422***	-0.380***		-0.426***	-0.423***	-0.378***
		(0.085)	(0.085)	(0.084)		(0.080)	(0.080)	(0.078)
residence==Karongi		-0.696***	-0.695***	-0.658***		-0.610***	-0.608***	-0.564***
		(0.093)	(0.093)	(0.091)		(0.091)	(0.091)	(0.090)
residence==Rutsiro		-0.578***	-0.577***	-0.540***		-0.534***	-0.533***	-0.492***
		(0.094)	(0.094)	(0.092)		(0.087)	(0.087)	(0.086)
residence==Rubavu		-0.350***	-0.348***	-0.303***		-0.315***	-0.313***	-0.262***
		(0.096)	(0.097)	(0.095)		(0.091)	(0.092)	(0.091)
residence==Nyabihu		-0.318***	-0.318***	-0.279***		-0.293***	-0.294***	-0.249***
		(0.095)	(0.095)	(0.092)		(0.088)	(0.087)	(0.086)
residence==Ngororero		-0.491***	-0.491***	-0.452***		-0.449***	-0.449***	-0.406***

		(0.098)	(0.098)	(0.096)		(0.091)	(0.091)	(0.089)
residence==Rusizi		-0.478***	-0.475***	-0.444***		-0.380***	-0.376***	-0.340***
		(0.092)	(0.092)	(0.089)		(0.089)	(0.089)	(0.087)
residence==Nyamasheke		-0.673***	-0.676***	-0.637***		-0.614***	-0.616***	-0.572***
		(0.097)	(0.097)	(0.095)		(0.087)	(0.087)	(0.086)
residence==Rulindo		-0.390***	-0.387***	-0.348***		-0.386***	-0.383***	-0.340***
		(0.088)	(0.088)	(0.085)		(0.083)	(0.082)	(0.081)
residence==Gakenke		-0.559***	-0.555***	-0.518***		-0.571***	-0.567***	-0.525***
		(0.090)	(0.090)	(0.087)		(0.082)	(0.082)	(0.080)
residence==Musanze		-0.133	-0.132	-0.102		-0.147*	-0.146*	-0.108
		(0.089)	(0.089)	(0.085)		(0.079)	(0.079)	(0.078)
residence==Burera		-0.424***	-0.421***	-0.383***		-0.404***	-0.403***	-0.361***
		(0.090)	(0.091)	(0.088)		(0.083)	(0.083)	(0.083)
residence==Gicumbi		-0.456**	-0.451**	-0.412**		-0.535***	-0.531***	-0.487***
		(0.193)	(0.193)	(0.190)		(0.091)	(0.092)	(0.090)
residence==Rwamagana		-0.203**	-0.199**	-0.161**		-0.197**	-0.194**	-0.154**
		(0.084)	(0.084)	(0.082)		(0.078)	(0.078)	(0.077)
residence==Nyagatare		-0.290***	-0.286***	-0.254***		-0.311***	-0.309***	-0.270***
		(0.096)	(0.096)	(0.093)		(0.088)	(0.088)	(0.087)
residence==Gatsibo		-0.330***	-0.328***	-0.293***		-0.374***	-0.369***	-0.329***
		(0.094)	(0.093)	(0.090)		(0.083)	(0.082)	(0.081)
residence==Kayonza		-0.337***	-0.334***	-0.299***		-0.305***	-0.299***	-0.259***
		(0.086)	(0.086)	(0.084)		(0.082)	(0.081)	(0.080)
residence==Kirehe		-0.433***	-0.434***	-0.401***		-0.428***	-0.429***	-0.392***
		(0.086)	(0.086)	(0.083)		(0.082)	(0.082)	(0.080)
residence==Ngoma		-0.399***	-0.396***	-0.363***		-0.392***	-0.388***	-0.354***
		(0.081)	(0.081)	(0.079)		(0.076)	(0.076)	(0.076)
residence==Bugesera		-0.432***	-0.426***	-0.391***		-0.473***	-0.469***	-0.429***
		(0.095)	(0.095)	(0.094)		(0.084)	(0.083)	(0.082)
1b.educattain#0b.male			0.000	0.000			0.000	0.000
			(.)	(.)			(.)	(.)
1b.educattain#1.male			-0.195	-0.198			-0.129	-0.129
			(0.220)	(0.223)			(0.200)	(0.203)
2.educattain#0b.male			0.008	0.008			-0.030	-0.030
			(0.218)	(0.221)			(0.200)	(0.203)
2o.educattain#1o.male			0.000	0.000			0.000	0.000
			(.)	(.)			(.)	(.)
3.educattain#0b.male			0.124	0.110			-0.000	-0.007
			(0.238)	(0.240)			(0.213)	(0.215)
3o.educattain#1o.male			0.000	0.000			0.000	0.000
			(.)	(.)			(.)	(.)
4.educattain#0b.male			0.217	0.212			0.062	0.041
			(0.228)	(0.232)			(0.216)	(0.219)
4o.educattain#1o.male			0.000	0.000			0.000	0.000
			(.)	(.)			(.)	(.)
5o.educattain#0b.male			0.000	0.000			0.000	0.000
			(.)	(.)			(.)	(.)
5o.educattain#1o.male			0.000	0.000			0.000	0.000
			(.)	(.)			(.)	(.)
1b.educattain#0b.region_2				0.000				0.000
				(.)				(.)
1b.educattain#1.region_2				0.190				0.195
				(0.211)				(0.173)
2.educattain#0b.region_2				0.025				0.023
				(0.205)				(0.167)
2o.educattain#1o.region_2				0.000				0.000
				(.)				(.)
3.educattain#0b.region_2				0.253				0.225
				(0.228)				(0.183)
3o.educattain#1o.region_2				0.000				0.000

				(.)				(.)
4.educattain#0b.region_2				0.268				0.273
				(0.202)				(0.179)
4o.educattain#1o.region_2				0.000				0.000
				(.)				(.)
5o.educattain#0b.region_2				0.000				0.000
				(.)				(.)
5o.educattain#1o.region_2				0.000				0.000
				(.)				(.)
Constant	12.792***	12.915***	12.949***	12.759***	13.067***	13.195***	13.210***	13.023***
	(0.164)	(0.158)	(0.158)	(0.161)	(0.147)	(0.150)	(0.150)	(0.153)
Observations	10368	10368	10368	10368	10368	10368	10368	10368
r2	0.293	0.355	0.357	0.361	0.311	0.377	0.379	0.382
District of residence		Yes	Yes	Yes		Yes	Yes	Yes
Educ. attain x male			Yes	Yes			Yes	Yes
Educ. attain x rural				Yes				Yes
Dependent variable is ln(Yearly consumption expenditure per adult equivalent (2011 prices, RWF)).								
Standard errors in parentheses. Regressions account for complex survey design (clustering and stratification).								
Columns (1) to (4) are weighted using population sampling weights. Columns (5) to (8) are unweighted.								
** p<0.1; ** p<0.05; *** p<0.01*								

Figure A.2:



Distribution of residuals in 2005/2006 and 2010/2011 (unweighted)
Specification 1
2006
Specification 1
2011
Specification 2
2006
Specification 2
2011
Specification 3
2006
Specification 3
2011
Specification 4
2006
Specification 4
2011
Density
Residuals
The dashed line refers to a standard normal density.

Table A.4: Bounds on poverty transitions (unweighted)								
Poverty Status	**Non-parametric lower bound**				**Non-parametric upper bound**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Poor, Poor	44	43.2	43.2	43.2	24	25.9	25.9	25.9
Poor, Non-poor	5.4	9	9.1	9.1	24.4	24.6	24.6	24.7
Non-poor, Poor	0.1	0.9	0.9	0.9	20	18.2	18.2	18.1
Non-poor, Non-poor	50.5	46.9	46.8	46.9	31.5	31.3	31.3	31.2
Adjusted R2	0.31	0.374	0.376	0.379				
N	10368	10368	10368	10368	10368	10368	10368	10368
Poor in period 1	49.4	52.2	52.3	52.3	48.4	50.5	50.5	50.6
Poor in period 2	44.1	44.1	44.1	44.1	44	44.1	44.1	44

Regressions account for clustering, but not for sampling weights or the complex survey design (stratification). For the upper bound, I chose 500 replications. Pr(poor, non-poor) is the probability of being poor in period 1 and non-poor in period 2.The table shows the number of observations in year 2.The column numbers refer to the different consumption model.

Table A.5: Point estimates of poverty transitions (unweighted)

	(1)	(2)	(3)	(4)
Poor, Poor	32.35	34.19	34.13	34.23
se	0.14	0.17	0.17	0.17
Poor, Non-poor	13.86	14.90	14.98	15.06
se	0.04	0.07	0.07	0.07
Non-poor, Poor	9.11	7.60	7.66	7.66
se	0.03	0.04	0.04	0.04
Non-poor, Non-poor	44.68	43.31	43.23	43.05
se	0.18	0.22	0.22	0.22
N	10368	10368	10368	10368
Poor in period 1	46.21	49.10	49.11	49.29
Poor in period 2	41.46	41.79	41.79	41.88

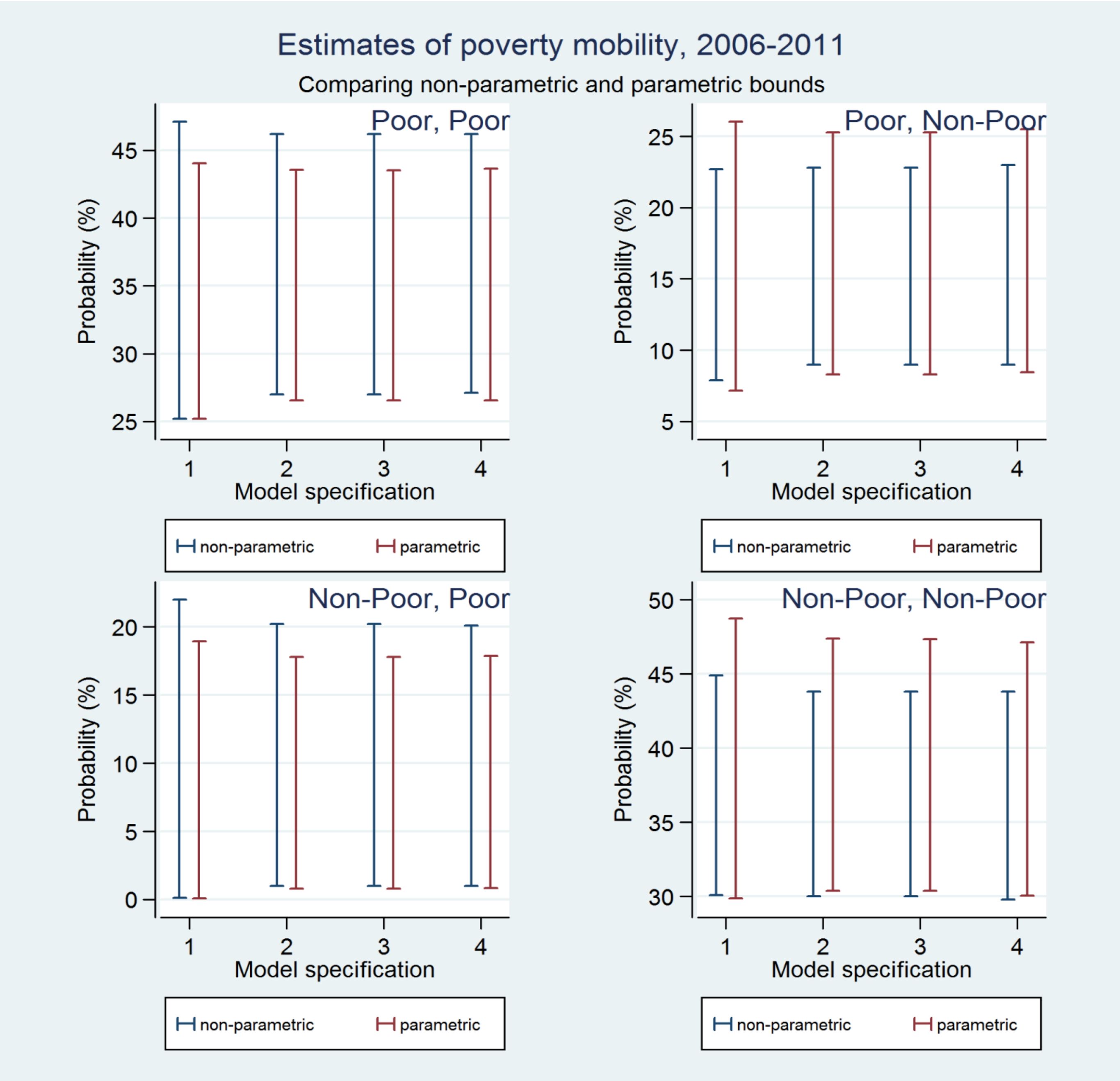
Regressions are unweighted and do not account for clustering or the complex survey design (stratification). This will not affect the point estimates, but the reported SEs will be too low. I chose 500 replications to estimate standard errors. Pr(poor, non-poor) is the probability of being poor in period 1 and non-poor in period 2.The table shows the number of observations in year 2.The column numbers refer to the different consumption model.

Table A.6: Parametric bounds on poverty transitions

Poverty Status	Parametric lower bound				Parametric upper bound			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Poor, Poor	44.05	43.54	43.53	43.62	25.18	26.54	26.56	26.56
se	0.22	0.41	0.41	0.41	0.13	0.16	0.16	0.16
Poor, Non-poor	7.15	8.28	8.31	8.44	26.02	25.28	25.28	25.50
se	0.04	0.09	0.09	0.09	0.06	0.09	0.09	0.09
Non-poor, Poor	0.06	0.80	0.81	0.82	18.93	17.80	17.78	17.88
se	0.01	0.03	0.03	0.03	0.05	0.07	0.07	0.07
Non-poor, Non-poor	48.74	47.37	47.35	47.11	29.87	30.37	30.39	30.05
se	0.23	0.42	0.42	0.42	0.21	0.24	0.24	0.24
N	10368	10368	10368	10368	10368	10368	10368	10368
Poor in period 1	51.20	51.82	51.84	52.07	51.20	51.82	51.84	52.07
Poor in period 2	44.11	44.34	44.33	44.44	44.11	44.34	44.33	44.44

Regressions account for population sampling weights, but not clustering or the complex survey design (stratification). This will not affect the point estimates, but the reported SEs will be too low. I chose 500 replications to estimate standard errors. Pr(poor, non-poor) is the probability of being poor in period 1 and non-poor in period 2.The table shows the number of observations in year 2.The column numbers refer to the different consumption model.

Figure A.3:



Estimates of poverty mobility, 2006-2011
Comparing non-parametric and parametric bounds
Poor, Poor
Poor, Non-Poor
Non-Poor, Poor
Non-Poor, Non-Poor
Probability (%)
Model specification
non-parametric
parametric