Poverty Dynamics – What They Teach Us and Why We'd Rather Study Income Dynamics

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Abstract

The literature on poverty dynamics is vast and covers many countries. Most studies built on the seminal work by Ravallion and Jalan (2000), who decompose poverty into a chronic and a transient component using panel data on household expenditures. For the case of Senegal, we redo their analysis, but we allow for a *continuum* of possible poverty lines accounting for the fact that the actual choice of the poverty line is inherently arbitrary. Comparing 100 poverty lines and three popular empirical models of poverty we come to doubt the hitherto established findings about poverty and its determinants. The analysis of poverty dynamics is plagued by (i) the vacuity of the binary poverty measure, (ii) the failure to control for the endogeneity of the determinants of income, and (iii) the focus on cross-sectional models to analyze poverty *dynamics*. To address these issues we estimate dynamic panel models of the determinants of household expenditure. In contrast to previous research we cannot find any effect of household demographics on per capita expenditure. Yet, per capita land holdings seem to play a very important role in rising household expenditure and growth and decreasing poverty. Our results suggest to analyze expenditure dynamics directly instead of artificially introducing poverty indicators. In line with Schultz (1980) we argue that permanently fighting poverty means addressing the rural poor when designing development interventions.

Keywords: Poverty/Expenditure Dynamics, GMM, Senegal, Convergence

JEL: D31, D63, I32, O15, O18

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1 Introduction

Poverty lines and indicators are simple and intuitive concepts that are appealing to policy-makers and donors. This paper argues that empirically these measures provide limited insights about the depth and determinants of poverty. Also it does not matter to households if they live above or below the poverty line. In fact for households poverty is not a binary reality but a question of absolute and relative income within peer groups. What matters to poor individuals –as to any other person– is how they do relative to their neighbors: Are they better or worse off? Do they catch up or fall behind? These questions relate to the two issues addressed in this paper. First, we investigate the usefulness of studying the determinants of poverty, rather than say expenditure levels. Second, we provide some evidence on expenditure dynamics in Senegal. Our empirical results suggest that there is no need to introduce artificial poverty measures, income/expenditure levels and their dynamics can be directly compared and policy conclusions be drawn.

The literature on poverty and its dynamics covers many countries, while using a relatively homogeneous methodology. Ravallion and Jalan (2000) were the first to decompose poverty into a chronic and a transient component. For the case of rural Senegal, we redo their analysis of poverty dynamics. We consider the differential impact of a set of standard control variables on overall, chronic, and transient poverty. However, we do not only consider one single poverty line. We introduce a *continuum* of possible poverty lines to account for the fact that the actual choice of poverty line is a arbitrary or even a political decision. In other words we are testing for the sensitivity of coefficients associated with the determinants of poverty to the choice of the poverty line. In addition to the comparison of 100 potential poverty lines we contrast three well-established empirical models and compare their estimation results. In the spirit of Ravallion and Jalan (2000) we apply censored quantile regressions. To account for unobserved heterogeneity at the village level we employ the linear fixed effects estimator and in order to correct for both effects jointly –the censored nature of the data and the fixed effects– we carry out a Mundlak type Tobit estimation. The coefficient estimates by and large overlap. Thus, no matter what poverty line is chosen, nor what estimation technique is used, we get statistically similar results. Across all poverty lines and all specifications we find no correlation between household demographics and poverty, but a strong negative correlation between overall poverty and per capita land holdings.

In addition, we address some more technical shortcomings in the poverty dynamics literature. Firstly, a binary measure is used to group individual households into rich and poor ones. By doing so, available income information is unnecessarily reduced. Secondly, the endogeneity of the determinants of poverty is rarely accounted for. A household's poverty level and variables such as household size or composition are simultaneously determined and subject to omitted variables. Thirdly, the cross-sectional models of poverty do not fully capitalize on the available panel data. We propose to estimate dynamic panel models of expenditure instead of analyzing poverty indicators. Employing GMM methods to study the determinants of income/expenditure we account for endogeneity and confirm the importance of land holdings in decreasing poverty. Per capita land holdings play an important role in rising both household expenditure levels and growth at least in the case of Senegal. We further show that there is no causal impact of household size or composition on per capita expenditure, except for the proportion of adolescents. In addition we find strong evidence of expenditure convergence in Senegalese rural households.

The reminder of the paper is structured as follows. In section 2 we briefly describe the squared poverty gap index and the decomposition into its chronic and transient component. Section 3 reviews some selected studies from the broad literature on poverty dynamics and carefully addresses their main challenges and drawbacks. In section 4 we present the dataset, and section 5 outlines the empirical specifications and the identification problems. In section 6 we discuss the results from the three different estimation techniques while making use of the *continuum* of 100 poverty lines. In section 7 we focus on the analysis of expenditure dynamics rather than poverty dynamics. We use dynamic panel models to identify causal determinants. Results of the expenditure dynamics are presented in section 8. Section 9 concludes.

2 The squared poverty gap and its decomposition

In the first part of our analysis we use the poverty decomposition measures as proposed by Ravallion and Jalan. These measures are based on the squared poverty gap for two reasons: Firstly, the index is additive both in time and across households. Secondly, it is a measure of the severity of poverty since it gives more weight to the poorest households. The squared poverty gap for household i at time t with a normalized per capita income y_{it} is calculated as follows:

$$p(y_{it}) = \begin{cases} (1-y_{it})^2 & \text{for } y_{it} < 1 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Normalization is relative to the poverty line. Households at or above the poverty line are indexed zero. Thus, the overall poverty index for any single household obtains by taking the time mean of equation (1):

$$Pov_i = E_t[p(y_{it})].$$

Decomposing the above poverty index, a household's level of chronic poverty is $Ch_i = p(\overline{y}_i)$, where $E_t[y_{it}] = \overline{y}_i$ is the time mean of normalized per capita income. As the computation suggests chronic poverty is supposed to cover the persistent component of poverty. Transient poverty, in turn, measures the volatility in the exposure to poverty. It is the time mean over the deviation from long-term poverty and is calculated as follows: $Tr_i = E_t[p(y_{it}) - p(\overline{y}_i)]$. By construction, the poverty indices collapse the time series information of the data into a cross-section. These indicators are then regressed on time-averages and variations of household characteristics. The idea is to identify whether individual control variables have differential effects on the overall poverty index and its chronic and transient component.

3 A Careful Review of Existing Findings

After Ravallion and Jalan's seminal study of the poverty dynamics in rural China, poverty and its dynamics have been analyzed for a wide range of countries (e.g. Argentina, Brazil, South Africa, etc.). Cruces and Wodon (2003) quickly followed up using the same methodology for the case of Brazil. Their study roughly confirms the findings of Ravallion and Jalan. For the case of Nepal Bhatta and Sharma (2006) find that chronic poverty is mainly driven by low human capital. Ribas and Machado (2007) analyze transient and chronic poverty in the Brazilian context using pseudo panel methods. For the case of Rwanda, Muller (1997) studies poverty dynamics with respect to seasonal fluctuations.[1]

Ravallion and Jalan find that wealth and land holdings significantly reduce both transient and chronic poverty. In addition, the household's stage of the life cycle seems to matter for the two types of poverty. Yet, there is little indication that education, household demographics, or local characteristics affect transient poverty. In contrast, chronic poverty is significantly affected by household demographics such as household size, age composition or education. These findings imply that the two types of poverty should be addressed with fundamentally different policy instruments. Their study suggests that chronic poverty can be alleviated by standard income generating programs, whereas transient poverty needs to be addressed by counter-cyclical policies, insurance mechanisms and buffer stocks.

Although these findings are intuitively plausible, they might originate from spurious regressions. In particular, most coefficient estimates may be biased due to endogeneity. For instance, the finding that education does not reduce transient poverty might be driven by omitted variables, such as unobserved ability, that biases the coefficient to zero. Reverse

[1] A series of papers and methods is featured on the website http://www.chronicpoverty.org/

causality is likely to be at work between the wealth variables and the poverty index. If a household faces a transitory poverty shock, it might sell some wealth holdings to smooth consumption. Thus, the reduction in wealth is a consequence of the poverty spell, instead of the poverty spell being caused by low initial wealth. To reduce the sources of endogeneity, fixed effects at the village level could be employed. To address reverse causality, instrumental variables or panel GMM methods offer possible solutions.

Another concern with the current methodology is the poverty line. Ravallion and Jalan use both the official poverty line and a poverty line that's based on the average nutritional requirement plus a non-food component. Furthermore, they then increase the poverty line artificially to the point that the number of households classified as non-poor remains low enough to estimate the empirical model precisely. The rational is that since non-poor households enter as zeros in the dependent variable, the estimation becomes imprecise once the poverty line is chosen too low. In fact, Ravallion and Jalan argue that results are not sensitive to the choice of the poverty line. In this paper we go a step further and argue that if the choice of the poverty line has indeed no effects on the results, the need for it becomes obsolete. Then, transient and chronic poverty are simply twisted proxies of income and deviations of the same from a trend. As already indicated, we work through this argument using a continuum of 100 poverty lines.

Few studies discuss thoroughly the importance of poverty lines in measuring poverty dynamics. Kurosaki (2006) investigates the sensitivity of various poverty decompositions with respect to the poverty line and expected welfare levels. His paper underlines the theoretical and empirical importance of incorporating prudent risk preferences (e.g. Constant-Relative-Risk Aversion) to make sure that transient poverty is increasing in chronic poverty and that the decomposition is more robust to the poverty line. Rather than studying the sensitivity of different poverty lines with respect to the decomposition itself, our paper concentrates on the sensitivity of estimates of poverty determinants with respect to reasonable ranges of the poverty line.

Other papers have tried to refine measures of chronic and transient poverty in response to the simple methodology by Ravallion and Jalan (2000). McCulloch and Calandrino (2003) augment measures of poverty by measuring high vulnerability of being poor rather than a low level of consumption in itself. Results indicate that both mean consumption and high vulnerability are driven by similar determinants for the case of China. In another study on a rich Chinese panel dataset, Duclos, Araar, and Giles (2010) propose a new method of measuring chronic and transient poverty and correcting for statistical bias due to a small number of time periods. Their measures are money metric measures of low average well-being (i.e. chronic poverty) and risk (i.e. transient poverty) that make up total deprivation (i.e. total poverty). These measures define total poverty as the sum of mean poverty and inequality in poverty, as well as they express inequality in poverty as a sum of between- and within-individual poverty. For the case of China, results show that different measures of transient and chronic poverty provide significantly different policy implications.

4 Data

Our analysis is based on a household panel of 565 rural households from 7 Senegalese regions[2], 35 rural communities, and 71 villages. The regions are all located in the North and North-West of the country, with the exception of Tambacounda which is located in the North-East of Senegal. The sample covers 50 % of Senegal's regions including those with the highest population density in the country. The survey was conducted between January 2004 and June 2005. During that time, surveys were repeated on a biannual basis. Data were collected as part of the impact evaluation of the *Programme national d'infrastructures rurales* ("National Rural Infrastructures Program"[3]) which is a decentralized rural development program initiated by the World Bank and IFAD. As a consequence of the relatively short time span of six months between consecutive survey rounds, we are able to follow households over at least three periods.

Table 1 presents summary statistics. Note that the summary statistics are averages of household averages over the four survey periods. As the survey covers only rural areas, households are large with an average of about 11 members and a maximum of 31 members. According to the World Development Indicators[4] Senegalese women had on average 5.26 children in 2004. In our sample high fertility is reflected in the substantial proportion of infants and children per households. On average 41.5 percent of household members are under the age of 14 years and 50 percent are younger than 25 years. These summary statistics confirm well known household demographics in rural West-Africa. Additionally, as in most traditional societies, households are headed by men, only 10.6 percent of the sampled households have a female household head. The age of the household head varies between 28 and 106 years with an average of 62 years. Per capita agricultural land is 0.45 hectars (4484.31 square meters). However, variation is notable with a standard deviation of 0.48 hectares indicating a high degree of heterogeneity in land holdings. As this study tries to challenge previous findings we aim at a high comparability of our empirical model with the seminal specification by Ravallion and Jalan (2000). Yet, we do not have

[2]Djourbel, St. Louis, Tambacounda, Fatick, Thies, Louga, Kaolack

[3]For further information about the *Programme national d'infrastructures rurales* see IFAD (1999) and Arcand and Bassole (2007)

[4]World Bank: WDI 2004/2005

information on the educational attainment of the household head. Therefore, we proxy the propensity to get schooling with a set of dummy variables for the walking distance to the nearest primary school. As it becomes apparent from the summary statistics most households, namely 87.6 percent, have a walking distance of over 30 minutes or are not even aware of the next primary school. This confirms common knowledge of development practitioners and international organizations that in rural Senegal access to schooling is difficult for the large majority of households.

Our dependent variables are the three poverty indices, namely overall poverty, as well as its decomposition into chronic and transient poverty. The indices are constructed as described in section 2. Since income was not included in the survey, we use expenditures in terms of adult equivalents as basis for the calculation of the poverty indices. Knowing that rural communities do not have access to well-functioning credit markets the two variables are close empirical substitutes.

As emphasized before, we allow the poverty line to vary. Therefore, the poverty indices which constitute our dependent variable vary accordingly. Instead of tabulating them for all 100 poverty lines we present their evolution across poverty lines graphically. This is illustrated in Figure 1, which depicts the evolution of the three poverty indices (Column 1) and the evolution of the number of people that is considered non-poor (Column 2) as the poverty line increases. The vertical axis depicts the average level of poverty in terms of overall poverty (Column 1, Row 1), chronic (Column 1, Row 2) and transient poverty (Column 1, Row 3). The horizontal axis corresponds to the chosen poverty line. The lowest poverty line starts at FCFA $4,500$. We then increase the poverty line in steps of FCFA 500 up to a poverty line of FCFA $54,500$. As Column 1 of Figure 1 shows the average of overall poverty increases from 0.008 at the lowest poverty line to 0.364 at the highest poverty line. The average poverty is depicted as the solid line, the two dotted lines show the standard deviation. For the entire range of poverty lines the variability of poverty is high, yet at lower levels of the poverty line it is still relatively small as a result of the way the poverty indicator is constructed. At a poverty line of FCFA $4,500$ the standard deviation of overall poverty is 0.040 and for a poverty line of FCFA $54,500$ it is 0.167. The further the poverty line is increased the more households are considered as poor, yet their degree of poverty differs introducing the increase in the variation. Average chronic poverty across the sample and across poverty lines evolves in a similar fashion as average overall poverty. Average transient poverty does not display a big variation across the different poverty lines. This is partly explained by the fact that transient poverty is a variational measure. While the average overall and chronic poverty increase in the level of the poverty line, the number of households classified as non-poor ($\widehat{=}$ poverty index of zero) decreases only up to a poverty line of roughly FCFA 40,000 and then (almost) stagnates. Column 2 in Figure 1 depicts that evolution of households coded non-poor across the different poverty lines and for each of the three poverty indicators. At a poverty line of FCFA $4,500$, 89 percent of the households in the sample live above the poverty line. However, at a poverty line which is equivalent to a household income per adult equivalent of FCFA $54,500$ only 1 percent of the sampled households is considered non-poor. As can be seen in the graph, once the poverty line surpasses roughly FCFA $40,000$, the slope flattens as only few 'rich' outliers are left. Hence, the chosen *range* of poverty lines is appropriate for two reasons: (i) choosing a poverty line below FCFA $4,500$ results in (almost) all households in the sample being classified as non-poor and no analysis can be carried out as there is not sufficient variation in the dependent variable;[5] (ii) the official poverty line over the period of interest is set at FCFA $47,667$. Given our range of possible poverty lines we capture a wide area around this official line and are thus able to address the sensitivity of the officially set poverty line.

5 Identification

In section 3 we address some of the drawbacks of the existing literature on poverty dynamics. We argue that the commonly employed estimation techniques fail to account for unobserved heterogeneity. Therefore, we wish to tackle that issue by jointly applying *three* different empirical models and comparing their results. Not only do we test for the sensitivity of the results with respect to the chosen poverty line, we also test for the sensitivity of the results with respect to the empirical specification. In order to analyze the determinants of each of the three poverty indices (overall, chronic, transient) over the range of 100 different poverty lines we use the following three empirical models: (i) censored quantile regressions as employed by Ravallion and Jalan (2000), (ii) a fixed effects linear regression specification to account for unobserved heterogeneity, and (iii) a Mundlak type Tobit estimation procedure to jointly account for the censored nature of the data in addition to the unobserved heterogeneity. Our baseline model is the censored quantile regression, which is commonly used in the literature. Initially we restrict the anaylsis to the 85th quantile.[6] Instead of minimizing the sum of squared residuals as in the classical OLS framework, quantile regressions minimize the sum of absolute residuals (compare Koenker and Hallock, 2001 and Koenker, 2008). The conditional quantile function is specified as follows:

$$Q_{P_{iv}|X_{iv}}(\tau|X_{iv}) = F^{-1}(\tau) + \beta X_{iv} \tag{2}$$

[5] Already below a poverty line of FCFA $13,500$ some of the estimations fail.

[6] Ravallion and Jalan (2000) pick this quantile as it allows precise estimation in the presence of a lot of zeros. In this study we carried out a number of robustness checks for different quantiles. We could verify that the estimates are qualitively equivalent across quantiles, although the precision of the confidence bounds varies slightly. Results for different quantiles are available upon request.

where we observe the poverty indicator $P_{iv} = \max(C_i, P^*_{iv})$ with censoring values C_i for all households $i = 1, ..., n$. The latent index originating from a poverty latent index model is denoted with P^*_{iv}. The quantile to be estimated is given by τ and F is an iid distribution function of the disturbance term in the linear latent index model: $P^*_{iv} = \beta X_{iv} + \varepsilon_{iv}$. The matrix X_{iv} contains the household control variables such as household size and household composition variables, the age of the household head and the squared age, a dummy for the gender of the household head, per capita land holdings, dummies to control for the distance to the nearest primary school and the standard deviation of the household size and the standard deviation of per capita land holdings. The latter two are included to account for variations in these variables. The censoring value is a constant in our application to poverty dynamics and takes the value of zero. Thus, the censored quantile specification accommodates the excess number of zeros and allows to analyze the data at different population quantiles.

The weakness of the censored quantile model –as discussed above– is that we do not control for unobserved village heterogeneity. Therefore we specify a linear fixed effects model which allows us to account for village effects that are time fixed and identical to all households within a given village. Thus, we account for unobserved heterogeneity by only looking at within village variation. We estimate the following specification:

$$P_{iv} = \beta X_{iv} + \nu_v + \varepsilon_{iv} \tag{3}$$

where P_{iv} is the vector associated with one of the three poverty indicators, overall Pov_i, chronic Ch_i or transient Tr_i poverty. The village fixed effect is captured by ν_v and control variables are collected in the matrix X_{iv}. By focusing at within village variation we remove the bias originating from village-level unobservables. Unfortunately, the linear fixed effects specification only solves part of the problem as it doesn't account for the excess amount of zeros we observe in the data. Therefore, we also estimate a random effects Tobit model. To control for unobserved heterogeneity at the village level without running into incidental parameter problems we employ a simple Mundlak procedure:

$$P_{iv} = \beta X_{iv} + \nu \overline{X}_v + \xi_v + \varepsilon_{iv} \tag{4}$$

$$\text{with} \quad P_{iv} = \begin{cases} 0 & \text{if } P^*_{iv} \leq 0 \\ P^*_{iv} & \text{if } P^*_{iv} > 0 \end{cases},$$

where P^*_{iv} is a latent index variable of poverty, X_{iv} is the vector of explanatory variables including the above stated household characteristics, $\overline{X}_v$ are average village characteristics of X_{iv}, the random effect is represented by ξ_v. By including averages of all explanatory variables in the random effects Tobit model we fit a model that controls for village-level unobservables.[7] If the latent variable is bigger than zero we have a household living below the poverty line and observe the actual level of poverty according to the index. If the latent variable is smaller or equal to zero the household under observation is non-poor as defined by the respective poverty line.

In short, we use three very different empirical models to identify the determinants of poverty and its chronic and transient component. As these empirical specifications have different theoretical and practical limitations, we can address the sensitivity of the determinants of poverty with respect to the empirical model. In the next section we present graphical results for each coefficient estimate across the 100 possible poverty lines and for two of the three models; namely the censored and the Tobit model. In the graphical representation we stick to these two results for the sake of clarity in the exposition.

6 Empirical Results of the Poverty Estimation

In this section we present the impact of varying the poverty line on the size and the significance level of the various coefficient estimates in the overall, chronic and transient poverty regression models. Before we start with the interpretation of the coefficient estimates, we briefly revise the evolution of the dependent variables themselves across the different poverty lines. Figure 1 Column 1 shows that the averages of the three poverty measures are positively correlated with the poverty line. In other words, as the number of households coded as non-poor falls, the average poverty level increases mechanically. This trend is least pronounced in the transient poverty measure. Figure 1 Column 2 points to a considerable movement into poverty between the poverty lines of FCFA 10,000 and 40,000. As the poverty line surpasses FCFA 40,000, the number of non-poor households decreases only marginally across the three poverty indices (see section 4 for further details). In the discussion of the results we will therefore concentrate on the range of most variation between FCFA 10,000 and 40,000.

We start of with some general observations that hold across all coefficient estimates. For illustrative purposes we consider the coefficient estimates of household size in Figure 2 Column 1. In each graph, the vertical axis depicts the coefficients and confidence bands for household size as a function of the poverty line, where the latter is depicted on the horizontal axis. The censored quantile model is drawn in black, the Tobit specification

[7]More specifically, we are running a random effects Tobit with village means to control for unobserved heterogeneity at the village level. This involves a relatively mild linearity assumption in terms of the manner in which village-specific unobservables enter the specification (see for instance Wooldridge (2001), pp.487 for a discussion).

is colored blue. Solid lines represent coefficient estimates, dotted lines the 95 percent confidence bounds. The zero line is displayed in red. For the sake of clarity in exposition we do not show fixed effects results in the graphs. Yet, we allude to them in the text. When interpreting a single graph it is important to keep in mind that all the other *simultaneously* included co-variates are presented in separate graphs. Some selected ones are shown in the subsequent graphs. Besides, it is reassuring that at high poverty lines, the coefficient estimates and confidence bands across the empirical specifications converge. This observation holds for the two depicted specifications as well as for the fixed effects results. In fact, especially the fixed effects and the Tobit specification nicely overlap once the number of non-poor households is small. For instance after a poverty line of 40,000 the number of zeros ($\widehat{=}$ non-poor) becomes so small that mechanically Tobit estimates and fixed effects estimates become identical. The coefficient estimates according to the censored quantile regression are systematically smaller, yet statistically undistinguishable from the others. Only the confidence bands of the fixed effects specification (not shown) are smooth, the confidence bands of the other two specifications are spiky as they result from bootstrap approximations. Again, these general observations apply to all coefficient estimates, not just to the coefficient associated with household size.

Results for the impact of household size on *overall poverty* are presented at the top of Figure 2 Column 1. According to the Tobit model, household size is positively correlated with overall poverty. This confirms findings by Ravallion and Jalan. Bigger households are on average poorer. The effect is more pronounced the higher the poverty line is. Already at a poverty line of FCFA 27,500 the effect is significant. The fixed effects model, although not depicted in the graph, shows similar results. Comparing, however *all three* empirical models (censored quantile, fixed effects, Tobit) estimates are statistically equal across models and lines, the size of the coefficient is not sensitive to the poverty line, and the impact is always zero. In the center of Figure 2 Column 1, we present results for the correlation between household size and *chronic poverty*. Starting at a poverty line of roughly FCFA 19,500, all three models suggest that an increase in household size leads to chronic poverty. Estimates are for the most part significant and also statistically equivalent across models and lines. It is noteworthy to record that although the three estimates from the different models give statistically identical coefficients, considering only the censored quantile result would lead us to base subsequent policy conclusions on a coefficient that is about 0.1 smaller than the coefficient resulting from a fixed effects or Tobit estimation. The bottom graph of Figure 2 Column 1 implies that household size has no statistically significant effect on *transient poverty* up to a poverty line of roughly FCFA 29,500 for the quantile model, and 34,500 for the Tobit specification. Therafter an increase in household size dampens transient poverty. The findings for the impact of household size on the three poverty indicators are qualitatively in line with Ravallion and

Jalan. Yet we demonstrate that the choice of the poverty line, although it does not seem to have a profound impact on the coefficient size, it can trigger statistical significance.

We also include the variation in household size as a control variable. Results indicate that the variability of household size does not matter for overall and chronic poverty. Conversely, the variability of household size seems to expose households to increased transient poverty, but only at poverty lines of FCFA 35,500 and higher. These results obtain no matter which of the three empirical models is employed.[8] In sum the two household size coefficients –level and variation– demonstrate that the estimated effect on overall and chronic poverty is robust to the choice of poverty line, whereas in the case of transient poverty it is not.

It is standard in the literature on poverty dynamics to also look at the impact of household composition on the different indices. We present the coefficients associated with the proportion of infants in Figure 2 Column 2, the coefficients associated with the proportion of children and those for the proportion of adolescents in a household are shown in Figure 3. Even at a glance one can see that for none of the poverty indices and none of the empirical specifications there is a significant correlation between household demographics and poverty. Although the Tobit specification shows a small kink around a poverty line of FCFA 37,000, the coefficient estimates of the different empirical models are by and large identical and the confidence bounds do always overlap. These results are in sharp contrast to previous findings that constitute a negative impact of the proportion of children and adolescents on overall poverty and its decomposition into chronic and transient poverty.

We also consider the effect of a female household head on poverty. A priori the effect might go both ways. Either female heads are more careful in the household's labor market, income and expenditure decisions and try to allocate as much of the household revenues as possible to improve family well-being leading to a positive coefficient; or households with a female head are socially and economically excluded from the village. Therefore, their families are in an even worse situation, implying a negative coefficient. Figure 4 Column 1 depicts the coefficient associated with the female head dummy. Again, throughout empirical specifications and poverty indicators the impact of a female household head on all dimensions of poverty seems to be zero.

Ravallion and Jalan stress that cultivated land helps to escape from overall and chronic poverty, however land holdings have no effect on transient poverty. Our results for the effect of land per capita on *overall poverty* are presented in the top of Figure 4 Column

[8] Detailed results and graphs are provided by the authors upon request.

2. Again, all three empirical models produce very similar coefficient estimates across poverty lines. It is striking that despite substantial changes in the number of households coded as non-poor ($\widehat{=}$ zeros), the size and significance of the coefficients remains almost unchanged. In particular, the censored quantile and the fixed effects model (the latter is not shown in the graph) confirm the results by Ravallion and Jalan for a wide array of poverty lines. Land per capita is significantly[9] and negatively correlated with overall poverty. Also note that the confidence bands of the censored quantile and the fixed effects model overlap. There is weaker evidence of a statistically significant effect for the Tobit model in particular in the region of the poverty line between FCFA 19,500 and 38,500. Next we consider the impact of land per capita on *chronic poverty*, presented in the center of Figure 4 Column 2. As expected results are comparable to the ones for overall poverty discussed right before. In line with Ravallion and Jalan we find that land holdings can significantly decrease chronic poverty for a wide array of poverty lines and across models. Again, coefficient estimates are statistically equal and robust to changes in the poverty line or the empirical model. Results for transient poverty are more borderline. There is some weaker statistical evidence in the region above a poverty line of FCFA 34,500 that land holdings increase transient poverty. Yet the impact is not statistically significant. We also looked at the impact of the *variation* in land per capita on poverty to the effect that we find nothing.

Last but not least it is often argued that the age of the household head matters in poverty reduction because it proxies the head's experience as well as his/her acceptance and social status within the household and the village. Therefore, we include age and age square in all empirical models. Yet, we do not find a significant impact of age on poverty. The same holds for the distance to the next primary school.[10]

Thus, the overall message from the exercise of varying the poverty line 100 times and carrying out the analysis of poverty dynamics with three different empirical models is threefold: First, for the majority of estimates and poverty lines, censored quantile, fixed effects, and Tobit estimates are statistically equivalent. These results are not driven by a relatively homogeneous sample. In fact, the movements in and out of poverty as one varies the poverty line from very high to very low levels are substantial. Second, comparing the three empirical models the choice of the poverty line has virtually no effect on coefficient sizes and some weak effect on significance levels. Yet, taking any single model alone one may get spurious results. Taking only the Tobit model into account some coefficients are huge in size and appear to be significant for ranges of the poverty line between FCFA 35,000 and 45,000. This holds, especially when it comes to

[9]In fact, the p-values fluctuate around the 5% level, staying well below 10%.

[10]Results are not shown here for the sake of brevity. They are provided by the authors upon request.

household composition variables. As the actual Senegalese poverty line over the sample period is FCFA 47,667 and thus close to the critical area, equivocal policy implications might be drawn, depending on the choice of model. Thus, drawing on the knowledge from implementing a continuum of poverty lines we wonder about the robustness of the results from previous studies of poverty dynamics as they only employ one empirical specification and one poverty line. Third, the analysis so far has not addressed the probable endogeneity of most of the explanatory variables. The imprecise estimates might be consequences of endogeneity bias. Jointly the results imply that instead of carrying out a *static analysis* of *poverty dynamics*, the study of the determinants, growth, convergence and variance of income/expenditure could provide more insight. In addition, exploiting the panel dimension of the data in greater depth will allow us to control for endogeneity.

7 Exploiting the Panel Dimension: Identification through lagged Variables

As argued above the empirical models employed so far only allow us to account for unobserved heterogeneity at the village level. Nevertheless two problems remain: First of all, some rich panel information is ignored by collapsing the data into one single indicator. Second, multiple sources of endogeneity remain at the household level and from time varying unobservables. Both issues can be plausibly addressed with GMM panel methods estimating an equation of the following type:

$$y_{ivt} = \beta X_{ivt} + \eta_i + \lambda_t + \varepsilon_{ivt}, \tag{5}$$

where y_{ivt} is log per capita expenditure of household i in village v at time t and the matrix X_{ivt} contains the control variables introduced in section 5. The specification allows us to control for household fixed effects η_i and for period specific effects λ_t. Instead of estimating equation (5) by Ordinary Least Squares we transform the equation into first differences Δy_{ivt}. By first differencing we remove the household fixed effect η_i without introducing a persistent correlation between the transformed dependent variable and the transformed disturbance term. Consistent coefficient estimates can be obtained by (i) assuming that the disturbance term ε_{ivt} is serially uncorrelated and (ii) imposing initial conditions X_{iv1} that are uncorrelated to subsequent disturbances ε_{ivt} for $t = 2, 3, ..., T$. Consequently, the correlation between the explanatory variables and the disturbance term can be addressed. Accordingly, the lagged level of X_{it-2} is uncorrelated with $\Delta\varepsilon_{ivt}$ and serves as instrument. The first-differenced GMM estimator by Arellano and Bond (1991) can then be used to obtain consistent coefficient estimates and we are able to address the endogeneity problem of the explanatory variables with their own past observations and without the need to search for additional exogenous instruments.

In the same spirit as the expenditure equation (5) we estimate an expenditure growth regression with lagged expenditure as explanatory variable:

$$g_{ivt} = \alpha \, y_{iv(t-1)} + \beta X_{ivt} + \eta_i + \lambda_t + \varepsilon_{ivt}, \tag{6}$$

where g_{ivt} is expenditure growth of household i in village v between period t and $(t-1)$. The remaining variables are as described before. This specification allows us to address the robustness of our results and to allude to the income convergence literature.

8 Empirical Results of the Expenditure Estimation

In this section we present results from the expenditure and growth models. We concentrate on the variables household size and land holdings per capita and contrast the results with the insights from the poverty dynamics. In Table 2 we regress per capita household expenditure on its lag, per capita land holdings as well as a series of household characteristics that have been included in the poverty estimations as well. As discussed in the previous section we employ a difference GMM model and carry out some robustness checks.[11] For three of the four specifications, the lag of household expenditure is positive but insignificant. Apparently, for Senegalese rural households past spending is not a good predictor for current spending.

Across specifications, the coefficient associated with household size is negative, but insignificant. This is in line with the poverty dynamics specification. In the poverty dynamics specifications we found that the coefficient on household size is positive and significant for the fixed effects and the Tobit model. Yet, considering all three specifications jointly, we find no effect. Thus, throughout the specifications household size reduces per capita disposable expenditure and simultaneously increases poverty. Yet, the effect is never significant. As indicated in the analysis of the poverty dynamics, household demographics represented by the proportion of infants and children in the household do not have a significant impact on expenditure per capita. However, the proportion of adolescents

[11] We present one step and two step estimates where the latter are derived using the efficient variance-covariance matrix. As a robustness check we also show system GMM results in Columns 3 and 4 of Table 2 because one might credibly argue that household expenditure is sticky and past levels do not suffice to predict current expenditure shocks. As the second column of each pair of results shows, the use of the efficient variance-covariance matrix does not alter our results statistically; one step and two step coefficients are similar in terms of size and significance level. Among the different GMM models the usual overidentification tests suggest that the difference-model is to be preferred. The Sargan test rejects the system GMM specification. For all specification tests presented at the bottom of Table 2 we fail to reject the difference GMM model. As our time series dimension is limited, namely $T = 3$, we can only test for the AR(1) in first differences. It is correctly rejected across all specifications and thus giving back up for our choice of econometric model.

between 15 and 24 do significantly increase per capita expenditure. It seems reasonable to assume that they contribute to the work force of the household and therefore increase household revenues. In contrast, the age (and age squared) of the household head is shown to have no effect on expenditure per capita.

The central determinant in the expenditure regression is per capita land holdings. Across specifications the effect is positive and significant. These findings confirm the intuition that strengthening land rights and land markets may spur household income and expenditure. These result are also consistent with insights from poverty dynamics, which suggest a dominant effect of land holdings on escaping from overall and chronic poverty. The coefficient estimate in the expenditure regression has almost twice the size of the coefficient estimate in the analysis of poverty dynamics. We attribute this increase in size to the efforts of reducing endogeneity bias through lagged variables. The confirmation of the positive income effect of landholdings is not surprising, as we argue that poverty dynamics are nothing but cross-sectional income/expenditure regressions. Yet, we consider our expenditure regressions more credible as these make full use of the panel dimension by employing fixed effects at the household level and lagged variables for identification.

Moving on to Table 3, the growth regressions confirm the insights from the level regressions.[12] Again, land holdings lead to significantly more growth in expenditure, while demographic determinants of growth are not significant with the exception of the proportion of adolescents. Compared to the level regressions, lagged expenditures per capita are a highly significant and negative determinant of growth. The negative coefficient and the statistical unit root relationship suggest strong conditional convergence in rural Senegal. Clearly, convergence does not ensure a world free of poverty, as convergence could lead households to a low equilibrium income. However, it shows that the poorest are catching up among each other controlling for household fixed effects, endogeneity and a series of covariates.

GMM results and the results from the analysis of poverty dynamics point in the same direction and reaffirm each other. Nevertheless we consider our GMM results more credible in the sense that they are more efficient: Firstly, efficiency is increased through a bigger sample (1,076 observations). Secondly, GMM allows to reduce the sources of endogeneity by using lagged variables as instruments for current observations. Thirdly, coefficient size (per capita land) and significance (proportion of adolescents) are improved.

[12] As for the expenditure regressions, based on the over-identification tests our preferred model is the difference GMM model.

9 Conclusion

The results in this paper shed some doubt on the meaning of binary poverty indices. Although poverty lines help to convey simple political messages, they provide limited information about the roots of underdevelopment nor do they help to design policy interventions to raise household income and hedge against income shocks. Our results suggest that variations in the poverty line have little effects on the impact of the determinants of poverty. This in turn implies that poverty lines have only a very limited message to convey. In addition, we have demonstrated that the commonly implemented empirical models by and large overlap. Yet, there is some room for spurious results if an analysis of poverty dynamics only relies on one model and one poverty line. Last but not least the analysis of poverty dynamics only establishes correlations, rather than causation due to the endogeneity of explanatory variables.

Results in this paper suggest to consider income/expenditure dynamics of the bottom quintile of the society when assessing the needs of the economically and socially weakest. Using expenditure variables allows us to exploit the panel dimension of the dataset to the maximum. Furthermore, on can better address endogeneity issues and causal statements can be drawn with more confidence. Analyzing expenditure levels also allows us to consider expenditure growth. We find strong evidence of conditional expenditure convergence. Although this does not imply that overall expenditure levels are rising and poverty is regressing, it suggests that the poorest are conditionally catching up amongst each other.

Nevertheless, the two empirically very different approaches, poverty and expenditure dynamics, convey a common message. The most important determinant of household expenditure in rural Senegal appears to be land holdings and consequently land titles and rights. Land holdings seem to be key to reduce poverty and increase the expenditure levels and growth. As suggested by Schultz (1980) this requires the strengthening of peasant rights and lobbying for the rural poor instead of neglecting them, in particular since a majority of the world's poor live in rural areas.

References

Arcand, J.-L., and L. Bassole (2007): "Does Community Driven Development Work? Evidence from Senegal," Etude et document CERDI, No. 2006-6, CERDI-CNRS, Université d'Auvergne, juin.

Arellano, M., and S. Bond (1991): "Some Tests of Specification of Panel Data: Monte Carlo Evidence and An Application to Employment Equations," *Review of Economic Studies*, 58(2), 277–297.

Bhatta, S., and S. K. Sharma (2006): "The Determinants and Consequences of Chronic and Transient Poverty in Nepal," *CPRC Working Paper*, (66).

Cruces, G., and Q. Wodon (2003): "Transient and chronic poverty in turbulent times: Argentina 1995-2002," *Economics Bulletin*, 9(3), 1–12.

Duclos, J.-Y., A. Araar, and J. Giles (2010): "Chronic and transient poverty: Measurement and estimation, with evidence from China," *Journal of Development Economics*, 91(2), 266–277.

IFAD (1999): "Report and Recommendation of the President to the Executive Board on a Proposed Loan to the Republic of Senegal for the National Rural Infrastructure Project," Document No. 67493, International Fund for Agricultural Development, Executive Board, Sixty-Eighth Session, Rome, Italy, 8-9 December.

Koenker, R. (2008): "Censored Quantile Regression Redux," *Journal of Statistical Software*, 27(6).

Koenker, R., and K. Hallock (2001): "Quantile Regression," *Journal of Economic Perspectives*, 15(4), 143–156.

Kurosaki, T. (2006): "The measurement of transient poverty: Theory and application to Pakistan," *Journal of Economic Inequality*, 4(3), 325–345.

McCulloch, N., and M. Calandrino (2003): "Vulnerability and Chronic Poverty in Rural Sichuan," *World Development*, 31(3), 611–628.

Muller, C. (1997): "Transient Seasonal and Chronic Poverty of Peasants: Evidence from Rwanda," *CSAE WPS*, (8).

Ravallion, M., and J. Jalan (2000): "Is transient poverty different? Evidence for rural China," *Journal of Development Studies*, 36(6), 82 – 99.

Ribas, R. P., and A. F. Machado (2007): "Distinguishing Chronic Poverty from Transient Poverty in Brazil: Developing a Model for Pseudo-Panel Data," Working Papers 36, International Policy Centre for Inclusive Growth.

Schultz, T. W. (1980): "Nobel Lecture: The Economics of Being Poor," *Journal of Political Economy*, 88(4), 639–651.

Wooldridge, J. (2001): *Econometric Analysis of Cross-Section and Panel Data*. MIT Press, Cambridge, MA, 1st edn.

	Min	Max	Mean	Median	Std.
Household Size	1	31.571	10.926	10	4.909
Variation in Household Size	0	7.118	0.744	0.503	0.856
Proportion of Infants	0	0.525	0.176	0.165	0.122
Proportion of Children	0	0.615	0.249	0.250	0.128
Proportion oc Adolescents	0	0.681	0.216	0.218	0.132
Female Head Dummy	0	1	0.106	0	0.308
Age	28	106	61.991	62	13.118
Land pc (log)	-3.025	1.778	-0.802	-0.776	0.733
Variation in Land pc (log)	0	1.409	0.324	0.275	0.234
3 Min. to School	0	1	0.011	0	0.103
3-10 Min. to School	0	1	0.051	0	0.221
10-30 Min. to School	0	1	0.062	0	0.241

Table 1: Summary Statistics.

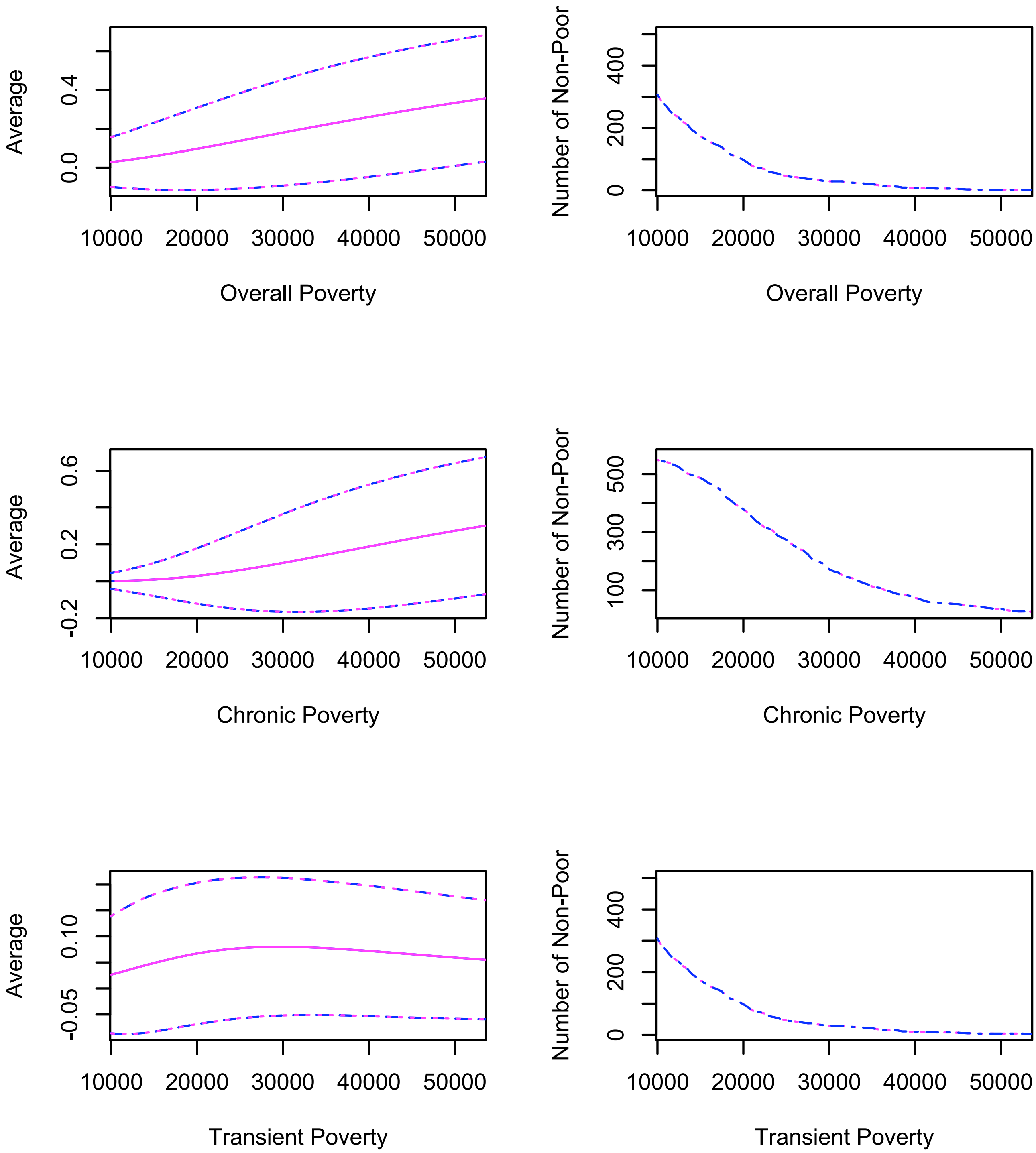

Figure 1: The evolution of the average level of poverty (Column 1) and the number of non-poor households (Column 2) across a continuum of 100 poverty lines. Results are shown for overall poverty and its decomposition into chronic and transient poverty.

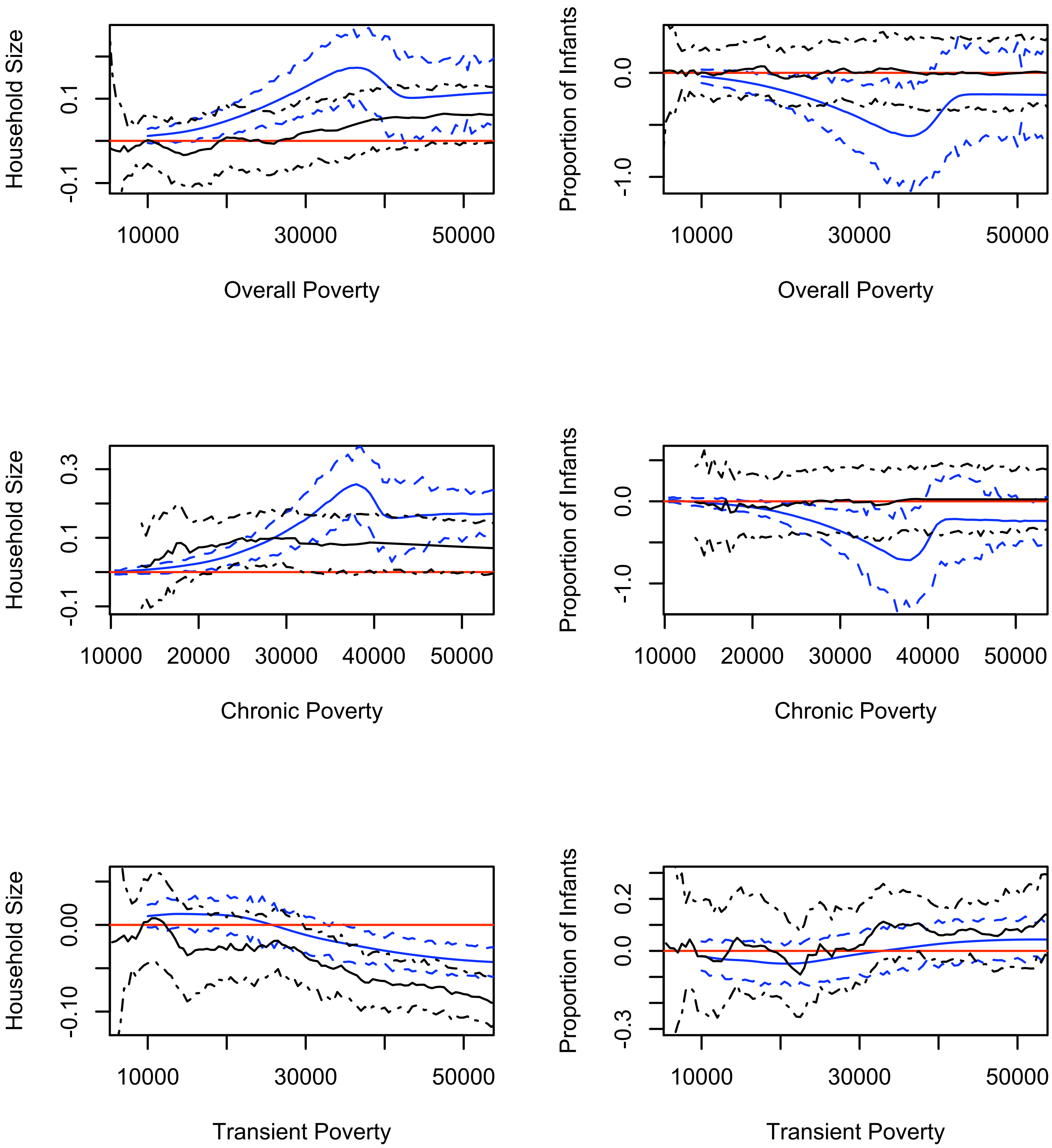

Figure 2: The evolution of the estimated coefficients associated with household size (Column 1) and the proportion of infants (Column 2) across a continuum of 100 poverty lines. Results are shown for overall poverty and its decomposition into chronic and transient poverty.

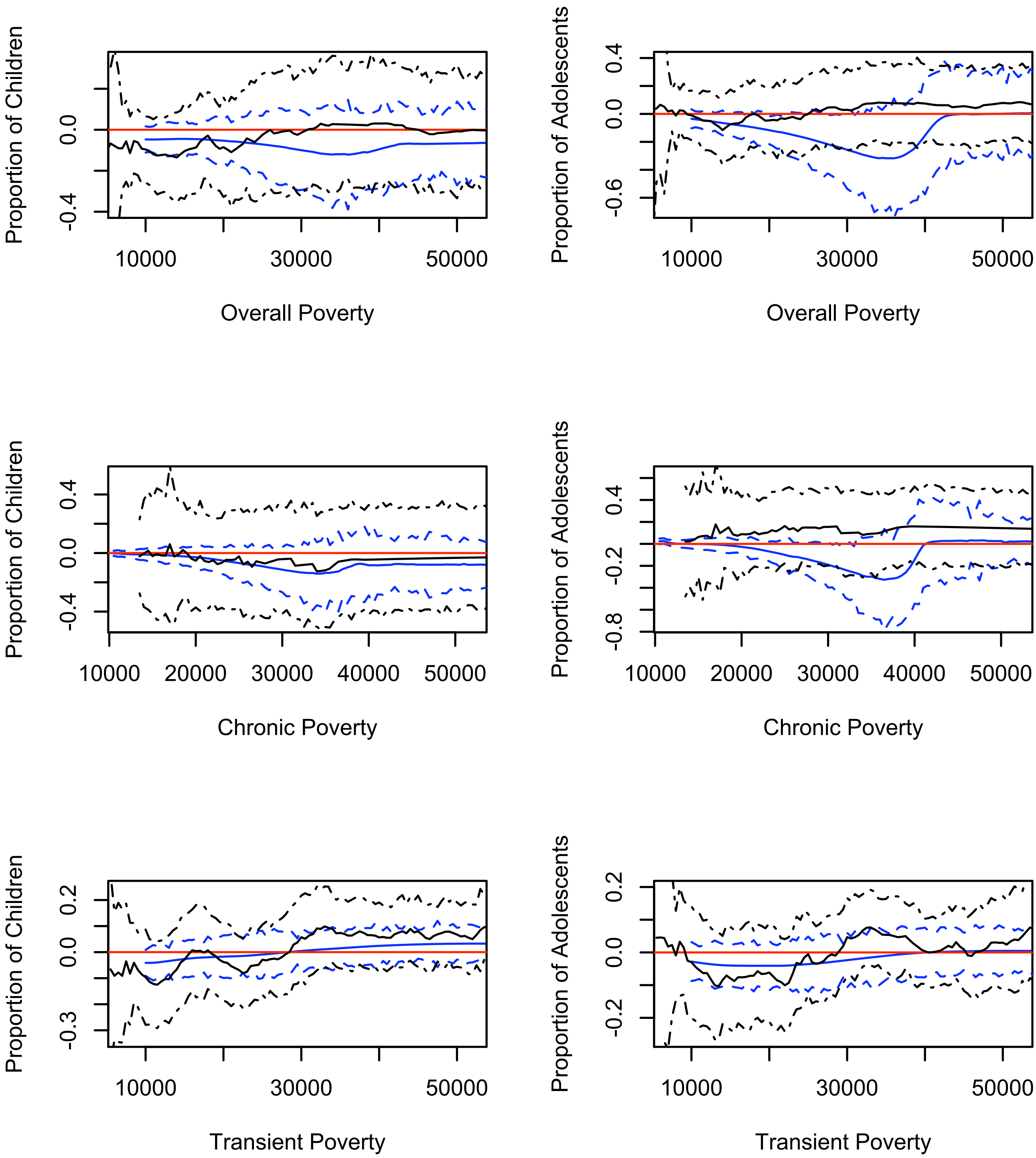

Figure 3: The evolution of the estimated coefficients associated with the proportion of children (Column 1) and the proportion of adolescents (Column 2) across a continuum of 100 poverty lines. Results are shown for overall poverty and its decomposition into chronic and transient poverty.

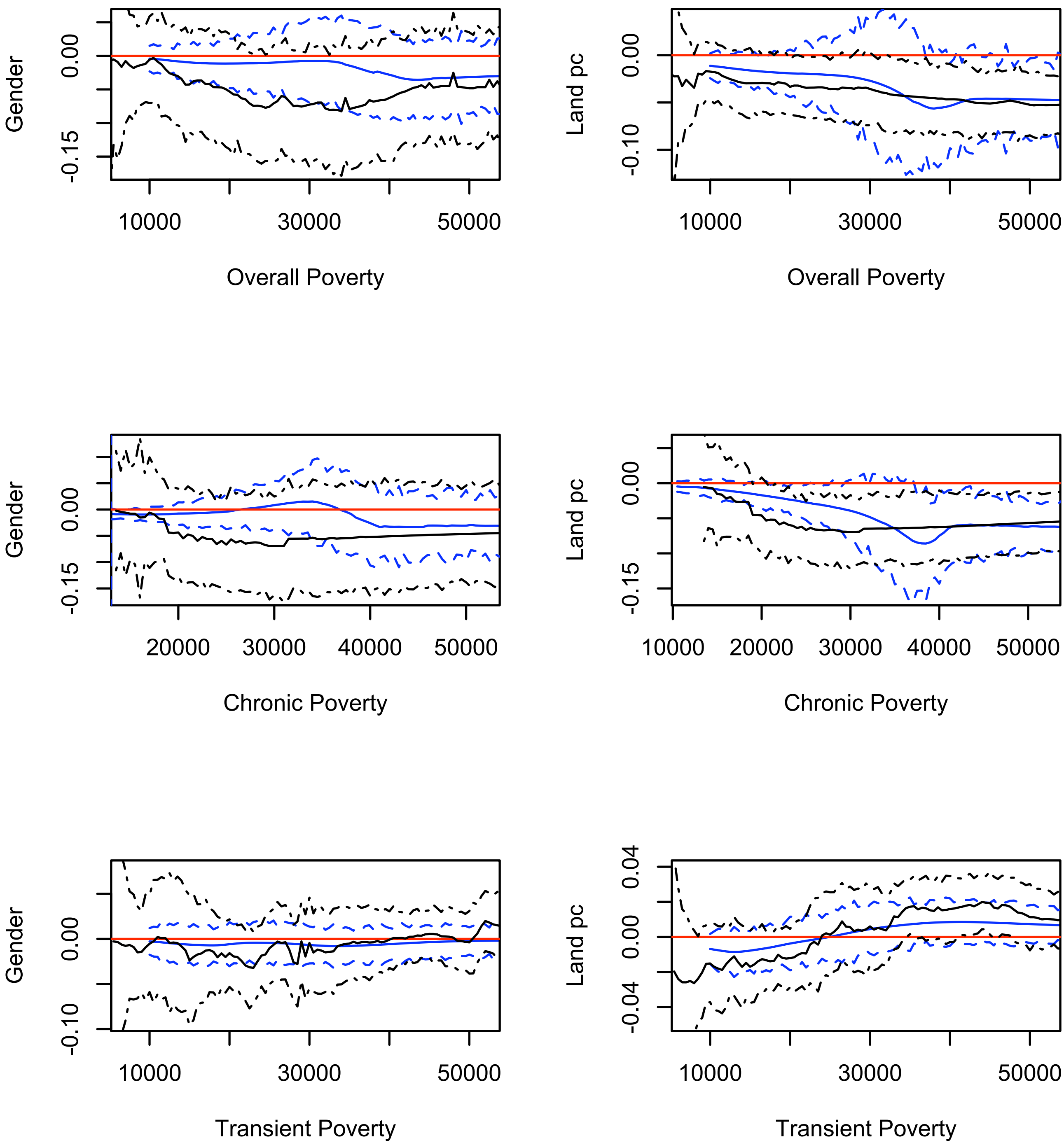

Figure 4: The evolution of the estimated coefficients associated with the gender dummy (Column 1) and land per capita (Column 2) across a continuum of 100 poverty lines. Results are shown for overall poverty and its decomposition into chronic and transient poverty.

	Difference GMM		System GMM	
	1 step	2 step	1 step	2 step
Lag Household Expenditure pc	0.025	0.036	0.019	-0.012
	[0.533]	[0.373]	[0.710]	[0.824]
Household Size (log)	-0.927	-1.041	-0.253	-0.292
	[0.288]	[0.280]	[0.169]	[0.140]
Proportion of Infants	2.154	1.543	0.092	0.758
	[0.178]	[0.356]	[0.928]	[0.452]
Proportion of Children	1.073	0.004	0.549	0.555
	[0.393]	[0.998]	[0.483]	[0.488]
Proportion of Adolescents	3.010	2.230	0.369	0.817
	[0.014]	[0.080]	[0.588]	[0.249]
Gender			0.022	0.012
			[0.836]	[0.902]
Land pc (log)	0.260	0.251	0.160	0.182
	[0.012]	[0.009]	[0.004]	[0.001]
Age	0.069	0.072	0.013	0.017
	[0.460]	[0.479]	[0.400]	[0.239]
Age squared	-0.001	-0.001	0.000	0.000
	[0.459]	[0.507]	[0.313]	[0.164]
3 Min. to School			3.924	3.581
			[0.113]	[0.165]
3-10 Min. to School			-0.302	-0.111
			[0.791]	[0.941]
10-30 Min. to School			-1.678	-2.077
			[0.138]	[0.028]
Observations	1076	1076	1764	1764
AR(1) in $1^{st}\Delta$	[0.000]	[0.000]	[0.000]	[0.000]
Sargan Test	[0.267]	[0.267]	[0.000]	[0.000]
Hansen Test	[0.338]	[0.338]	[0.375]	[0.375]

Table 2: Expenditure Regressions. The dependent variable is per capita expenditure. Results of the difference GMM specification are in Columns 1 and 2, results of the System GMM specification in Columns 3 and 4. Windmeijer adjusted p-values in brackets.

	Difference GMM		System GMM	
	1 step	2 step	1 step	2 step
Lag Household expenditure pc	-0.963	-0.949	-1.038	-1.035
	[0.000]	[0.000]	[0.000]	[0.000]
Household Size (log)	-0.966	-1.269	-0.215	-0.399
	[0.363]	[0.217]	[0.515]	[0.262]
Proportion of Infants	1.988	1.725	-1.452	-0.435
	[0.235]	[0.315]	[0.430]	[0.795]
Proportion of Children	0.925	0.489	-0.501	-0.554
	[0.495]	[0.728]	[0.718]	[0.722]
Proportion of Adolescents	2.694	2.383	-0.089	0.558
	[0.035]	[0.066]	[0.932]	[0.605]
Gender			-0.057	-0.030
			[0.756]	[0.877]
Land pc (log)	0.265	0.217	0.147	0.147
	[0.016]	[0.031]	[0.033]	[0.036]
Age	0.075	0.086	0.014	0.021
	[0.443]	[0.359]	[0.543]	[0.476]
Age squared	-0.001	-0.001	0.000	0.000
	[0.432]	[0.365]	[0.344]	[0.372]
3 Min. to School			8.547	8.434
			[0.136]	[0.194]
3-10 Min. to School			-2.794	-3.888
			[0.464]	[0.473]
10-30 Min. to School			-0.989	0.702
			[0.804]	[0.877]
Observations	1076	1076	1764	1764
AR(1) in $1^{st}\Delta$	[0.000]	[0.000]	[0.000]	[0.000]
Sargan Test	[0.332]	[0.332]	[0.001]	[0.001]
Hansen Test	[0.688]	[0.688]	[0.540]	[0.540]

Table 3: Growth Regressions. The dependent variable household expenditure growth. Results of the difference GMM specification are in Columns 1 and 2, results of the System GMM specification in Columns 3 and 4. Windmeijer adjusted p-values in brackets.