Who Remained in Poverty, Who Moved Up, and Who Fell Down?

An Investigation of Poverty Dynamics in Senegal
in the Late 2000s

Hai-Anh H. Dang

Peter F. Lanjouw

Rob Swinkels

WORLD BANK GROUP

Development Research Group

Poverty and Inequality Team

&

Urban, Rural, and Social Development Global Practice

December 2014

Abstract

Poverty estimates based on cross-section data provide static snapshots of poverty rates. Although a time series of cross-section data can offer some insights into poverty trends, it does not allow for an assessment of dynamics at the household level. Such a dynamic perspective on poverty generally calls for panel data and this kind of analysis can usefully inform poverty reduction policy, notably the design of social protection interventions. Absent actual panel data for Senegal, this paper applies new statistical methods to construct synthetic panel data from two rounds of cross-section household surveys in 2005 and 2011. These data are used to study poverty transitions. The results suggest

that, in marked contrast to the picture obtained from cross-section data, there exists a great deal of mobility in and out of poverty during this period. More than half the population experiences changes in its poverty status and more than two-thirds of the extreme (food) poor move up one or two welfare categories. Factors such as rural residence, disability, exposure to some kind of natural disaster, and informality in the labor market are associated with a heightened risk of falling into poverty. Belonging to certain ethnicities and factors such as migration, working in the non-agriculture sector, and having access to social capital are associated with a lower risk of falling into poverty.

This paper is a joint product of the Poverty and Inequality Team, Development Research Group; and the Urban, Rural, and Social Development Global Practice. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at <http://econ.worldbank.org>. The authors may be contacted at hdang@worldbank.org.

The Policy Research Working Paper Series disseminates the findings of work in progress to encourage the exchange of ideas about development issues. An objective of the series is to get the findings out quickly, even if the presentations are less than fully polished. The papers carry the names of the authors and should be cited accordingly. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

**Who Remained in Poverty, Who Moved Up, and Who Fell Down?
An Investigation of Poverty Dynamics in Senegal in the Late 2000s**

Hai-Anh H. Dang, Peter F. Lanjouw, and Rob Swinkels*

JEL: C15, I32, O15

Key words: chronic poverty, poverty dynamics, mobility, transition, synthetic panel, Senegal

*Dang (hdang@worldbank.org), Lanjouw (planjouw@worldbank.org), and Swinkels (rswinkels@worldbank.org) are respectively Economist and Research Manager with the Poverty and Inequality Group, Development Research Group, and Senior Social Scientist, Europe and Central Asia Region, World Bank. We would like to thank Philip English, Erik Thorbecke, and participants at the 2013 Spring Symposium on “*Growth Poverty and Inequality Confronting the Challenges of a Better Life for All in Africa*” organized by the Institute for African Development, Cornell University, and the African Economic Research Consortium for useful comments. We would like to thank Latif Dramani and Djibril Ndoeye for helpful support with the data. We would also like to thank Bonsuk Koo for capable research assistance. We are grateful to the UK Department of International Development for funding assistance through its Knowledge for Change and Strategic Research Programs.

I. Introduction

Analyzing dynamic aspects of poverty is important for the design of poverty reduction policies. Without specific insights into the dynamics of poverty, the same poverty rate of, say, 20 percent in two periods could well mask dynamic processes ranging from complete stagnation (i.e., zero mobility where all households see no change in their welfare) to extreme volatility (i.e., perfect mobility where all poor households in the first period escaped poverty and were all replaced by households that had previously been non-poor in the first period). Policies to deal with these situations are clearly very different. If poverty is mostly transitory, attention should perhaps be focused on designing safety net programs to prevent non-poor but vulnerable households from falling into poverty. On the other hand, if poverty is mostly chronic, attention could perhaps better be directed to structural and longer-term interventions such as investment in human capital and building infrastructure. Transitory and chronic poverty typically require different policy instruments and no single policy is likely to successfully address both.

Senegal's annual GDP per capita growth rate averaged 1.6 percent and 0.8 percent between the periods 2001-2006 and 2007-2011, respectively, which translates into an overall annual growth rate of 1.2 percent for the 2000s—around half of the corresponding figure of 2.3 percent for Sub-Saharan African developing countries (World Bank, 2014a). This aggregate performance has been accompanied by poverty rates falling steadily from around 55 percent in 2001-02 to 48 percent in 2005-06 and 47 percent in 2010-11.¹ While its growth trajectory has hardly been dizzying, Senegal appears to be progressing ahead with poverty reduction objectives; consistent with the “slow-growth/high stability economy” characterization frequently used to describe the country (Azam and Dia, 2004). However, while much is known about poverty figures at single

¹ Unless otherwise noted, all numbers shown are our estimates using the household survey data for Senegal or the World Development Indicators database provided by the World Bank.

snapshots in time for Senegal, little research has been done on the dynamics of poverty in this country.

Dissecting poverty dynamics is relevant in the Senegalese context for additional reasons. First, we are interested in identifying the types of households that are most likely to fall into, remain in, or move out of poverty over time for the purpose of designing effective interventions. There have been various shocks (including food and fuel price increases and natural disasters) in the country recently, and these may have affected different households differently, as well as having contributed to the recent economic slump. Indeed, as poverty reduction has slowed in recent years, it is all the more important that we better understand the dynamic mechanisms behind poverty reduction such that more effective interventions can be designed and implemented. Policy makers are likely to be interested in knowing answers to such questions as: what are the profiles of households that remained in poverty? Which households escaped poverty? Who fell back into poverty? As we will illustrate and discuss further below, poverty rates have remained rather stable in Senegal during the latter half of the 2000s. The question arises as to whether this masks any specific poverty dynamics occurring below the surface of the relatively stable poverty estimates deriving from cross section data? If so, how significant were these dynamics?

At first glance, the absence of panel household survey data would suggest that there is little scope to pursue such questions in Senegal—or indeed, in many other developing countries. In an effort to make progress, researchers have pursued second-best options. One estimation strategy is to collect retrospective data on household poverty status over the recent past (Neubourg et al., 2010; Fall et al., 2011), another is to use a household asset index to measure household wealth transitions (Sahn and Stifel, 2000; Booysen et al., 2008). While both of these approaches are

clearly useful in studying poverty transitions, recent studies point to several unsettled issues. For example, with respect to the former approach based on retrospective data, recent research indicates that accurate recall data can be quite difficult to collect (see, for example, Beegle et al., 2012). With respect to asset indices, there are concerns that these are not easily interpreted for the purpose of drawing policy conclusions.

In this paper we pursue an alternative estimation strategy to measure poverty mobility in Senegal. We construct synthetic panel data using two rounds of cross sections in 2005/06 and 2011 based on the methods proposed by Dang, Lanjouw, Luoto, and McKenzie (2014) and Dang and Lanjouw (2013). The key idea behind these methods is that we can exploit the relationship between a household's time-varying poverty status and time-invariant individual and household characteristics (with appropriate adjustments for the error terms), in order to predict, for each household, a past consumption level that can be compared to directly observed current consumption levels. These comparisons then permit an examination of transitions in poverty status over time at the household level. Under reasonably standard assumptions, the time-invariant household characteristics in the two cross sections can function as the panel connectors that are employed to construct synthetic panel households. Dang et al. (2014) and Dang and Lanjouw (2013) report on a number of validation studies and illustrate that estimates based on these constructed synthetic panel data closely match those based on true panel data for a number of countries, such as Bosnia-Herzegovina, Indonesia, Lao People's Democratic Republic, Peru, United States, and Vietnam, spanning different regions and widely varying income levels.²

² One major concern with panel data is that these data may not provide representative estimates of the population over time due to issues including attrition bias or measurement errors. These countries were selected for validation because of their panel data are generally considered to be of high quality. Another validation study of the Dang et al. (2014)'s method using data from Latin American countries is by Cruces et al. (2014).

It is noteworthy that in certain respects, these synthetic panel data may possess advantages over true panel data. When true panel data are affected by issues such as attrition bias or panel-specific measurement error, they may no longer be representative of the population and can provide biased estimates.³ Cross sectional data may be less exposed to these issues since these data by design comprise fresh and representative samples of the population.⁴ Since our synthetic panel data are constructed from cross sections, this advantage may extend also to our analysis. Thus beyond our contribution to the policy dialogue in Senegal, this paper represents an early application of the synthetic panel methodology to a country in Sub-Saharan Africa. And since the questions on poverty dynamics raised above may apply not just to Senegal but also to other Sub-Saharan African countries, this paper has potential relevance beyond Senegal, and can potentially motivate studies in other contexts where panel data are not readily available or of poor quality.⁵

Our findings indicate that, beneath the relatively stable poverty rates estimated with cross sectional data, there has been much “churning” out of as well as into poverty in Senegal in the period between 2006 and 2011. Poor households were somewhat more likely to escape poverty (45 percent) than non-poor households were likely to fall back into poverty (40 percent), and were more likely to have stronger consumption growth as well. Overall, the population was rather mobile with more than half (53 percent) of the population experiencing either upward or

³ This situation is more common than one might think. For example, between 15 percent and 42 percent of measured mobility in Vietnam in the 1990s may be caused by upward bias due to measurement error (Glewwe, 2012). See also Gottschalk and Huynh (2010) and Lee et al. (2010) for related studies on the effects on measurement errors on earnings inequality and poverty mobility.

⁴ Strictly speaking, cross sectional data can be mis-measured just as with true panel data. However, while measurement errors can be correlated over time for the latter and thus can result in severe bias, these errors are uncorrelated across different rounds of cross sections since data on different households are collected in each round.

⁵ Synthetic panels constructed using the Dang et al. (2014) and Dang and Lanjouw (2013) methods have recently been applied to study poverty dynamics in various settings including multi-country analysis for Latin America (Ferreira et al., 2013; World Bank, forthcoming), South Asia (World Bank, 2014b), and Europe and Central Asia (World Bank, 2014e). Specific country case studies using synthetic panels investigate countries including the Kyrgyz Republic (Bierbaum and Gassmann, 2012) and Bhutan (World Bank, 2014c). We are also applying synthetic panel methods in our ongoing studies of other countries.

downward mobility. In particular, more than two-thirds of the extreme (food) poor (i.e., people living under the food poverty line) moved up one or two welfare categories. Factors such as education achievement, having a female household head, urban residence, and formal work contract are strongly correlated with movement out of poverty. These factors and others such as migration, belonging to other ethnic groups, working in the non-agriculture sector, having access to social capital,⁶ having experienced no disastrous shock, and having no disability are correlated with households being protected from falling into poverty. Distinguishing between those who are chronically poor from those who have recently fallen into poverty yields interesting insights. Notably, factors such as weak social capital, exposure to natural disasters, and limited access to quality community infrastructure are more strongly correlated with downward mobility than with chronic poverty. Out of all the correlates, education appears to be most strongly linked to escape from poverty.

The paper comprises five sections. We provide a brief overview of the country background and data description in the next section, which is then followed by discussion of the synthetic panel method in Section III. Section IV provides estimation results and Section V concludes with policy recommendations.

II. Country Background and Data Description

II.1. Data Description

We analyze two cross sectional rounds of the household Senegal Poverty Monitoring Surveys (Enquete de Suivi de la Pauvreté au Sénégal, or in short, ESPS) in 2005-2006 (ESPS1) and 2011 (ESPS2). Both surveys were implemented by the national statistical agency (ANSD) with

⁶ Access to social capital is defined as the household that receive financial help from family, neighbors or friend in case of need.

financial support from the World Bank, Canadian International Development Agency, and World Food Program. These surveys collect nationally representative data in a two-stage procedure where primary sampling units or enumeration areas (psu) are randomly drawn in the first stage with stratification, and households are randomly selected from each psu in the second stage. The survey questionnaires consist of a variety of modules on household composition and characteristics, education, health, migration, household expenses and consumption, household perception of economic status, unexpected shocks, and community activities. However, for cost-saving reasons, in 2011 only a subsample (around one-third) of the sampled households were administered the full questionnaire with a household consumption module, while the rest were administered a more abbreviated questionnaire. We focus on this subsample of the survey in this round, and the samples available for our analysis thus hover around 13,329 and 5,904 households, respectively, in the first and second survey rounds. After restricting the sample to an appropriate age range for constructing the synthetic panels, our final samples are 8,584 and 4,030 households for the two survey rounds.

One caveat exists on the timing and thus comparability of the surveys. ESPS 1 was implemented between December 2005 and March 2006, while ESPS 2 was implemented between August and November 2011. Since the harvesting season takes place between October and December, the difference in the timing of the surveys may differently affect household reporting of consumption during the preceding 12 months prior to being interviewed. We believe our estimates are thus likely to provide somewhat conservative (downward biased) figures on poverty decline between 2006 and 2011, since ESPS 1 was implemented right after the harvest season.

II.2. Country Background

An overview of poverty numbers in Senegal between 2005/06 (hereafter referred to as 2006) and 2011 is provided by Table 1, where estimates are provided for the whole country as well as for three geographical regions: Dakar (the capital city), other urban areas, and rural areas. Table 1 shows that poverty slightly decreases during this period from 48 percent in 2006 to 47 percent in 2011. However, this change is not statistically significant, falling roughly within one standard error of these estimates, implying that poverty remained largely unchanged over time, with a similar pattern holding for the three geographical regions. Indeed, when the distributions of household consumption for the two years are plotted against each other, they appear rather stable over time, with the distribution in 2006 being almost identical to that in 2011 (see Appendix 1, Figure 1.1).

While the changes in poverty over time do not stand out, estimates from both survey rounds point to a clear spatial ordering of poverty in Senegal. Poverty is highest in rural areas, where more than half (57 percent) of the population are poor, but decreases by around 30 percent in other urban areas, and then by more than half in Dakar. Rural areas are also most populous and account for more than half of the population, while the rest are roughly divided between Dakar (23 percent) and other urban areas (20 percent).

Another way to gauge the change in household welfare is to compare households' own assessments of their economic status in the two survey rounds (Figure 1). While this information is based on households' subjective evaluations, it is also useful at least as a qualitative measure of household welfare over time. Figure 1 shows that slightly more households consider themselves to be less poor and more likely to belong to the "average" economic category in 2011 compared to 2006. Fewer households also think about themselves as less rich in 2011, but the

proportions of households regarding themselves as rich are much smaller than the other categories. On the whole, households appear to think they are somewhat better off in 2011.

In sum, objective measures of household consumption indicate almost no change in poverty rates at two snapshots in time, but subjective measures show a slight, but definitely positive trend.⁷ There can, however, be issues with both sets of results. The former result only reflects the net change in poverty after movement out of poverty is adjusted by that into poverty. In other words, this little change does not necessarily indicate little transition of households into or out of poverty over time but can even mask a large level of churning if the degree of movements into poverty is cancelled out on the average by that out of poverty. For example, a difference of one percentage point between the percentage of households moving into poverty and those that move out of poverty can in theory occur regardless whether the current economic situation is one of low mobility (say, 6 percent and 5 percent, respectively, for the former and the latter) or of very high mobility (say, 52 percent and 51 percent). At the same time, without a specially designed questionnaire to collect data on subjective well-being, the latter approach may provide some useful but not finally conclusive evidence due to inter-personal differences in subjective evaluations (see, e.g., King et al. (2004)). These mixed results highlight the value of acquiring a better understanding of poverty dynamics.

III. Framework of Analysis

III.1. Overview of the Synthetic Panel Method⁸

Let x_{ij} be a vector of household characteristics observed in survey round j ($j = 1$ or 2) that are also observed in the other survey round for household i , $i = 1, \dots, N$. These household

⁷ See also World Bank (2014d) for a recent poverty assessment report on Senegal.

⁸ We provide an overview of the synthetic panel method developed by Dang et al(2014) and Dang and Lanjouw (2013) in this section. For more details, interested readers are encouraged to read the original papers.

characteristics can include such time-invariant variables as ethnicity, religion, language, place of birth, parental education, and others available in the survey. The vector x_{ij} can also include deterministic variables such as age (which given the value in one survey round can then be determined given the time interval between the two survey rounds), or time-varying household characteristics if retrospective questions about the round-1 values of such characteristics are asked in the second round survey. To reduce spurious changes due to changes in household composition over time, we usually restrict the estimation samples to household heads age, say 25 to 55 in the first cross section and adjust this age range accordingly in the second cross section.⁹

Let y_{ij} then represent household consumption or income in survey round j , $j = 1$ or 2 . The linear projection of household consumption (or income) on household characteristics for each survey round is given by

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

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

Let z_j be the poverty line in period j , $j = 1$ or 2 . We are interested in knowing such quantities as

$$P(y_{i1} < z_1 \text{ and } y_{i2} > z_2) \quad (3a)$$

which represents the percentage of households that are poor in the first period but nonpoor in the second period (considered together for two periods), or

$$P(y_{i2} > z_2 \mid y_{i1} < z_1) \quad (3b)$$

which represents the percentage of poor households in the first period that escape poverty in the second period. In other words, for the average household, quantity (3a) provides the joint probabilities of household poverty status in both periods, and quantity (3b) the conditional

⁹ This age range is usually used in traditional pseudo-panel analysis but can vary depending on the cultural and economic factors in each specific setting.

probabilities of household poverty status in the second period given their poverty status in the first period.

If true panel data are available, we can straightforwardly estimate the quantities in (3a) and (3b); but in the absence of such data, we can use synthetic panels to study mobility. To operationalize the framework, we make two standard assumptions. First, we assume that the underlying population being sampled in survey rounds 1 and 2 are identical such that their time-invariant characteristics remain the same over time. More specifically, this implies the conditional distribution of expenditure in a given period is identical whether it is conditional on the given household characteristics in period 1 or period 2 (i.e., $x_{i1} = x_{i2}$ implies $y_{i1}|x_{i1}$ and $y_{i1}|x_{i2}$ have identical distributions). Second, we assume that ε_{i1} and ε_{i2} have a bivariate normal distribution with correlation coefficient ρ and standard deviations σ_{ε_1} and σ_{ε_2} respectively.¹⁰ If ρ is known, quantity (3a) can be estimated by

$$P(y_{i1} < z_1 \text{ and } y_{i2} > z_2) = \Phi_2\left(\frac{z_1 - \beta_1' x_{i2}}{\sigma_{\varepsilon_1}}, -\frac{z_2 - \beta_2' x_{i2}}{\sigma_{\varepsilon_2}}, -\rho\right) \quad (4)$$

where $\Phi_2(\cdot)$ stands for the bivariate normal cumulative distribution function (cdf) (and $\phi_2(\cdot)$ stands for the bivariate normal probability density function (pdf)). Note that in equality (4), the estimated parameters obtained from data in both survey rounds are applied to data from the second survey round (x_2) (or the base year) for prediction.¹¹

Since ρ is usually unknown in most contexts, Dang and Lanjouw (2013) propose that we can first approximate the simple correlation coefficient $\rho_{y_{i1}y_{i2}}$ between birth cohort-aggregated household consumption between the two surveys, then estimate ρ using the following formula

¹⁰ In other words, this assumption implies that households in period 2 that have similar characteristics to those of households in period 1 would have achieved the same consumption levels in period 1 or vice versa.

¹¹ We can use data from the first survey round as the base year as well. See the cited studies for more detailed discussion.

$$\rho = \frac{\rho_{y_{i1}y_{i2}} \sqrt{\text{var}(y_{i1}) \text{var}(y_{i2})} - \beta_1' \text{var}(x_i) \beta_2}{\sigma_{\varepsilon_1} \sigma_{\varepsilon_2}} \quad (5)$$

It is then straightforward to estimate quantity (3b) by dividing quantity (4) by $\Phi\left(\frac{z_1 - \beta_1' x_{i2}}{\sigma_{\varepsilon_1}}\right)$,

where $\Phi(\cdot)$ stands for the univariate normal cumulative distribution function (cdf). Further asymptotic results and formulae for the standard errors are also provided in Dang and Lanjouw (2013).

It is also useful to note that, we have by definition

$$P(y_{i2} < z_2 \mid y_{i1} < z_1) + P(y_{i2} > z_2 \mid y_{i1} < z_1) = 1 \quad (6)$$

or equivalently, for the poor population in period 1, they can fall into either one of two poverty categories in period 2: poor or non-poor. Consequently, the characteristics that are positively associated with the former type of poverty dynamics (i.e., remaining in poverty in both periods or chronic poverty) would be negatively associated with the latter type (i.e., poor in the first period but escaping poverty in the second period or upward mobility). A similar result holds for the dynamics of the non-poor population in period 1. We will come back to more discussion using this result in a later section.

If there is an interest in further disaggregating the poor population into those that are in extreme (food) poverty and those with a consumption level higher than the food poverty line but still lower than the general poverty line, we can extend equation (3a) to investigate poverty mobility over the two periods using these different poverty lines. Let m_j represent the extreme

poverty line in period j , $j = 1$ or 2 , the percentage of extreme poor households in the first period that escape extreme poverty but still remain poor in the second period is¹²

$$P(y_{i1} < m_1 \text{ and } m_2 < y_{i2} < z_2) = \Phi_2\left(\frac{m_1 - \beta_1'x_{i2}}{\sigma_{\varepsilon_1}}, \frac{z_2 - \beta_2'x_{i2}}{\sigma_{\varepsilon_2}}, \rho\right) - \Phi_2\left(\frac{m_1 - \beta_1'x_{i2}}{\sigma_{\varepsilon_1}}, \frac{m_2 - \beta_2'x_{i2}}{\sigma_{\varepsilon_2}}, \rho\right) \quad (7)$$

Put differently, while equation (3a) (or 3b) offers the framework of analysis for a two by two transition matrix of poverty mobility, equation (7) provides a corresponding framework for a three by three transition matrix. The former considers two outcome categories for poverty dynamics (i.e., poor and non-poor), and the latter three outcome categories (i.e., extreme poor, poor, and non-poor).

III.2. Selection of Estimation Models

We apply the framework discussed above to data from ESPSs 1 and 2 to construct synthetic panel data. We begin by identifying the potential time-invariant variables available in the two surveys, which include household heads' gender, age, years of schooling, marital status, disability status, and residence area (i.e., urban or rural). These variables can usually be assumed to be time-invariant if the underlying population remains unchanged over time. One way to test this assumption is to use a t-test for the equality of the means of the same variables in the two survey rounds. We provide test results that take into account the complex survey design of two-stage sampling with stratification in Appendix 1, Table 1.1.¹³ The assumption of equality of means is satisfied for heads' years of schooling and residence area but is not satisfied for heads'

¹² See Dang and Lanjouw (2014) for the full derivations and a related investigation that disaggregates the non-poor population into two groups: those that are vulnerable (but not poor) and those that can be classified as belonging to the middle class.

¹³ This can be straightforwardly done in Stata by first setting the data to incorporate sampling design (use "svy" command), and then use a combination of this "svy" command and "lincom" to obtain estimation results.

gender, marital status, and disability status.¹⁴ The last two variables, however, have very similar means thus these may not practically make much difference to the final estimates.

As a result, we will consider three estimation models where the first model includes all these time-invariant variables except for marital status and disability status, and two other models where these two variables are added sequentially. If estimation results are similar across the three models, it indicates that inclusion of these variables in the regression models is optional. Furthermore, for additional comparison, we also consider another model that controls for regional dummy variables. While adding such variables would usually increase the model's goodness-of-fit (R^2 value), imposing these variables as time-invariant necessarily entails an additional assumption that the distributions of these regional dummy variables remain stable over time. Put differently, this assumption is equivalent to no or very little household migration over time among these different regions. In the specific context of Senegal, three new regions were administratively created between 2006 and 2011 (ANSD, 2010), which may have resulted in some spatial churning of the population during this period and consequently, this additional assumption is likely to be violated.

As discussed in Dang and Lanjouw (2013), equations (1) and (2) can be estimated either with or without survey weights depending on the specific context. Ultimately, the yardstick to decide on using weighted regressions or unweighted regression—or selecting the final regression model—is whether the estimated poverty rates for each period based on the synthetic panels are reasonably close to those that can be directly estimated from each cross section. More formally, this means good estimated poverty rates based on the synthetic panels should fall within the 95

¹⁴ We do not test for the difference of the distributions of the age variable in the two survey rounds since it is a deterministic variable.

percent confidence interval of those directly based on the cross sections. Gauging how close the former are to the latter can thus help us select the model with the best fit.

One way to evaluate the prediction fit of the synthetic panels is to compare the poverty rates for each period using the synthetic panels against those using the cross sectional data. This holds since by construction, the poverty rate, say, in period 1 is equal to the sum of the percentage of the population that are poor in both periods and the percentage of the population that are poor in the first period but non-poor in the second period. This idea can be expressed mathematically as follows

$$P(y_{i1} < z_1) = P(y_{i1} < z_1 \text{ and } y_{i2} < z_2) + P(y_{i1} < z_1 \text{ and } y_{i2} > z_2) \quad (8)$$

The (population weighted) regressions for four models using data from the two cross sections are shown in Appendix 1, Table 1.2, where Model 1 controls for heads' gender, age, years of schooling, and a dummy variable indicating whether the residence area is urban or rural. Model 2 then adds to Model 1 a dummy variable indicating heads' marital status, Model 3 adds to Model 2 a dummy variable indicating disability status. Finally, Model 4 adds to Model 3 the regional dummy variables. The control variables are mostly significant at the 5 percent level or lower, suggesting that these variables can help predict household consumption.¹⁵

Estimation results for poverty dynamics using the estimated parameters from these different models and the second survey year as the base year are then provided in Appendix 1, Table 1.3. Estimates are rather stable across the different models, and are in fact almost identical for

¹⁵ Note that testing the assumption of bivariate normality of the error terms requires true panel data (that have two data points for the error terms). This assumption, however, can be partially tested by testing the predicted error terms in each cross section for univariate normality. But note that most of the existing normality tests are rather stringent and may provide only supporting evidence. As discussed above, the validity of estimates based on the synthetic panels (for poverty in each period) should better be evaluated against their comparison with estimates based on the cross sections. We use weighted regressions in subsequent estimates since they provide better results than unweighted regressions.

Models 1 to 3. Model 4 provides the most different estimates, even though these differences fall in a tight range of between 0.3 and 1.5 percentage points.

We thus compare next the estimates for the poverty rate in each period with those based on the cross sections (Table 1), and find the former lie well within one standard error of the latter. For example, the estimated poverty rate for 2011 based on the synthetic panels is between 46.7 percent (i.e., adding the first and third rows under Model 1 in Table 1.3, such that $26.4 + 20.8 = 47.2$) and 47.2 percent; the corresponding figure based on the cross section for 2011 is 46.9 percent with a standard error of 1.3 percent (Table 1). These encouraging results indicate that we can use any of the four models for our estimation of poverty dynamics. However, Model 3 is our preferred model for all subsequent estimates for the reasons discussed above.

IV. Poverty Dynamics Estimation

IV.1. All Population

Estimation results on poverty dynamics are provided in Table 2, where column 2 shows the joint probabilities of household poverty status in both periods, and column 4 shows the conditional probabilities of household poverty status in the second period conditional on their poverty status in the first period. Estimation results show that there is a considerable level of transition into and out of poverty in Senegal during 2006-2011. For both survey years considered together, 26 percent of the population remained in poverty in both periods, 21 percent were poor in the first period but escaped poverty in the second period, and about the same proportion of the population (21 percent) were not poor in the first period but fell back into poverty in the second period.

Judging from the similar movements into and out of poverty for the joint probabilities, it may be simplistic to conclude that there is hardly any progress with poverty reduction over these two

periods. Indeed, while the transitions into and out of poverty almost balance out in the total—which is already reflected in the net poverty reduction of 1 percent from the cross sectional estimates shown in Table 1—the conditional probabilities (column 4) tell a different and more positive story where poor households have a larger chance of escaping poverty (45 percent) than that of non-poor households falling back into poverty (40 percent). This result is due to the fact that the proportion of the population that was poor in 2006 was smaller than the proportion that was not poor in the same year; consequently, the same level of transition out of or into poverty in absolute terms would translate into a higher figure in relative terms for the former population group (i.e., the average household that was poor in 2006 would have a higher chance of escaping poverty five years later).

For a comparative analysis, this probability of moving out of poverty is comparable to that of another developing country at a different time interval, Lao PDR during 2002/03-2007/08 (Dang and Lanjouw, 2013), and less than that of Bhutan around a similar time interval during 2007-2012 (World Bank, 2014c).¹⁶ The corresponding figures for these countries are respectively 50 percent and 56 percent. However, both Bhutan and Lao PDR enjoyed a faster economic growth during these time intervals (approximately 7 percent and 5 percent annual per capita growth, respectively), thus the probability of falling back into poverty for these countries was much lower at respectively 5 percent and 16 percent. But regardless of the comparison, the seemingly unchanged poverty figures estimated from the cross sections for Senegal have clearly masked a high degree of poverty mobility in this country as revealed by the synthetic panels.

IV.2. Poverty Profiling for Population Groups

¹⁶ The average GDP per capita in US dollars in constant prices in 2005 is \$1,734, \$465, and \$789 respectively for Bhutan (during 2007-2012), Lao PDR (during 2002-2007), and Senegal (during 2006-2011) (World Bank, 2014a).

We next turn to examining the profiling of poverty transitions, or the different poverty dynamics for population groups. We start first with a brief review of recent studies on poverty dynamics for other developing countries before showing estimation results for Senegal.

IV.2.1. Brief Literature Review

A large and fast-growing literature exists on the factors that are associated with poverty reduction. The techniques as well as data employed in this literature are diverse, ranging from examination of bivariate relationship to multivariate regression analysis, and from a single cross section to both small-scale and large-scale panel data sets. The topic focus also varies and can reflect context-specific issues as well as different research questions that can be supported by the available data. A brief, but not exhaustive, overview of recent studies suggests that the major correlates of poverty status and/ or welfare dynamics can include the following (set of) characteristics¹⁷

- education achievement (see, e.g., Behrman (2010) for a review)
- ethnicity (see, e.g., Hall and Patrinos (2012) for a multi-country study)
- residence location (see, e.g., Kedir and McKay (2005) for Ethiopia)
- household demographics (see, e.g., Haddad and Ahmed (2003) for the Arab Republic of Egypt)
- work sector and/ or skill levels (see, e.g., Fields et al. (2003) for Indonesia, South Africa, Spain and República Bolivariana de Venezuela; Himanshu, Lanjouw, Murgai, and Stern (2013) for India)

¹⁷ These studies often share a common finding on the association with welfare mobility for several correlates but we only highlight one correlate from each study for lack of space.

- disability status (see, e.g., Mont and Nguyen (2011) for Vietnam; Mitra, Posarac, and Vick (2013) for a multi-country study)
- unexpected shocks (see, e.g., Dercon (2004) for Ethiopia), and
- geographical isolation/ remoteness or lack of community infrastructure (see, e.g., Bloom, Canning, and Sevilla (2003) and Sachs et al. (2004) for multi-country studies), and
- migration (see, e.g., Christiaensen and Todo (2014) for a multi-country study).

These characteristics are also generally consistent with the findings in recent review studies on poverty mobility by Dercon and Shapiro (2007) and Baulch (2011). We examine separately the bivariate relationship between some major correlates and poverty dynamics before considering them all together in an attempt to provide some rough ordering of the importance of these correlates on poverty mobility in the next section.

IV.2.2. Poverty Profiling

Residence Area

The relationship between residence area and poverty mobility is graphically illustrated in Figure 2, where Panel A and Panel B show poverty movements conditional on households being poor in the first period and non-poor in the second period, respectively. The bar charts then indicate the breakdown of the transitions that are separately categorized by urban areas and rural areas. Figure 2 thus shows a much larger proportion (around 56 percent) of households moving out of poverty in urban areas than in rural areas, which is around 16 percent more as indicated by the yellow bars in Panel A. Equivalently, as earlier discussed with equation (6), the factors that are positively associated with upward mobility are by definition negatively associated with chronic poverty, and vice versa. Thus an alternative way to interpret the same result that is also borne out graphically is that a much smaller proportion of households remained in poverty in

urban areas (as indicated by the dark blue bars, Panel A). For brevity, we will discuss one or the other type of dynamics but not both.

Considering households that fell back into poverty given that they were non-poor in the first period, households residing in urban areas were particularly unlikely to experience this undesirable change. While rural households had slightly more than a 50 percent chance of falling back into poverty, the corresponding figure for urban households was roughly two-fifths lower at 30 percent (as represented by the brown bars, Panel B).

Residence Area Combined with Gender of Household Head

We can then combine residence areas with the gender of household heads to study the interactive effects of these two characteristics. We show in Figure 3 a similar transition as in Figure 2, Panel A but break this transition first by heads' gender, then by residence areas. Interestingly enough, several observations are in order for this figure. First, female-headed households had a higher chance of escaping poverty compared to male-headed households, and this difference was more pronounced in rural areas than in urban areas. Second, urban households had a higher chance of escaping poverty than their rural counterparts, regardless of the gender of household heads. Third, the effects associated with residence areas appeared somewhat stronger for male-headed households than female-headed households. This was shown by a difference of around 10 percentage points between female-headed households residing in rural and urban areas, and the corresponding figure for male-headed households is around 12 percentage points.

Finally, the combined effects of residence areas and heads' gender were most brought out by comparing the chance of escaping poverty for rural female-headed households and urban male-

headed households and rural male-headed households and urban female-headed households. The difference between the former types of households is 9 percent, amounting to two-thirds of the corresponding number between the latter types of households.

Education Achievement

Perhaps it comes as no surprise that education attainment was strongly associated with poverty mobility, which is clearly indicated by the steady and almost linear increase (decrease) for transition out of (into) poverty in Figure 4, Panel A. For example, moving from an education level of less than primary school to primary school (i.e., completing between 6 and 9 years of schooling) was associated with increasing the chance of escaping poverty by almost 20 percentage points. There appeared, however, some diminishing returns to scale at higher education levels: achievement of a middle school education (i.e., completing between 10 and 12 years of schooling) or a high school education or more (i.e., completing 13 years of schooling or more) was associated with raising this chance up by less than half as much at respectively 8 percentage points and 6 percentage points. Panel B in Figure 4 similarly shows a negative association between education levels and the chance of falling back into poverty.

Ethnicity

The relationship between ethnicity and poverty mobility is depicted in Figure 5, where the percentage bars (i.e., similar as in Figure 2) are stacked on top of each other instead to save space. The three major ethnic groups Wolof, Serere, and Poular together make up 83 percent of the population, with the other ethnic groups accounting for the remaining 17 percent. There was

not much difference for poverty transitions between the different ethnic groups, even though the three major ethnic groups did slightly worse than the other ethnic groups.

Work Sector and Employment Status

Employing a similar graphical format as with Figure 5, Figure 6 illustrates the combined relationship between work sector (i.e., agriculture work versus non-agriculture work) and employment status (i.e., being employed with work contract and without work contract) and poverty mobility. Two main results stand out in this figure: non-agriculture work was associated with a higher chance of moving out of poverty (or not falling back into poverty), as was being employed with a formal work contract. Furthermore, there was an interactive effect between work sector and employment status, those who had a formal work contract in the non-agriculture sector would be in the best welfare position. For example, the chance for these workers to move out of poverty in the second period given that they were poor in the first period would be almost 20 percentage points higher than their peers who were employed without a formal work contract in the agriculture sector. The corresponding figure for not falling back into poverty climbed up even higher to almost a 30 percentage point difference between these two types of workers.

Migration

We turn next to the relationship between migration and poverty mobility. Figure 7 plots in Panel A and Panel B respectively the distributions of the conditional probabilities that households moved out of and into poverty by three migration categories identified by the number of years households lived in the current location: 5 years or less, between 6 and 10 years, and 11 years or longer. As with other density plots, a larger concentration of households at a certain

level of the conditional probabilities is represented by a larger horizontal bar (or longer dot). For better illustration of the trends, we also mark the median of the distributions in each migration category with a red bar. Two observations stand out with Figure 7. First, the distributions of the conditional probabilities for the least migrant households (i.e., those having lived in the current location for 11 years or more) are heavier toward the lower probabilities in Panel A (i.e., less likely to escape poverty) and the larger probabilities in Panel B (i.e., more likely to fall into poverty). Second, the medians of the distributions show a noticeable downward sloping trend and upward sloping trend in Panel A and Panel B respectively. Figure 7 thus reveals a clear pattern that more recently migrated households were more likely to move out of poverty as well as being less likely to fall into poverty.

Putting It All Together

While it is useful to separately consider each correlate of poverty to identify better its impact, we may run into the familiar “counting” issue where the list of such correlates may go on and on.¹⁸ We thus bring all these correlates together in Figure 8 and Figure 9, which respectively look at the movements out of and into poverty. There is certainly a caveat with doing so, since there can be overlap between different population groups (e.g., those with higher education levels may also have better employment status). However, subject to careful interpretation of the results, useful insights may still be obtained from this exercise. Furthermore, plotting all the different correlates together on the same graph can help provide some rough ordering of their

¹⁸ Using our synthetic panels framework, the probabilities of belonging to each of the four welfare status as indicated in quantity 3a (e.g., being poor in the first period but nonpoor in the second period) are predicted for each household based on the linear projection of household consumption on time-invariant household characteristics, with the appropriate adjustment for the error terms. Since these predicted probabilities are derived this way, it is not straightforward to use regression models to regress these probabilities on household characteristics again. We leave this area for future research.

importance, potentially assisting within the prioritization of policy recommendations in resource-scarce environments. Thus in addition to the correlates studied above, we also add in Figures 8 and 9 several more variables including disability status, social capital, natural disaster, and the distance from the household's home to the nearest paved road. As briefly reviewed in the previous section, these variables have been found to be strongly associated with poverty mobility for other developing countries.

Figure 8 depicts factors that have a stronger-than-average correlation with poverty reduction as golden circles and factors associated with a less-than-average correlation with poverty reduction as dark blue triangles, which are respectively above and below the dotted red line (i.e., the national average). Among all the correlates considered, the former group of factors include education achievement, having a female household head, non-agricultural work, formal work contract, social capital, no disability, urban residence, belonging to Wolof or other ethnic groups, living two kilometers or less from the nearest paved road and in the current location for 10 years or less, and suffering no natural disasters. Out of these factors, higher levels of education achievement, having urban residence, a female household head, and a formal work contract are noticeably more strongly associated with poverty reduction than the remaining factors.

Education attainment also has the strongest association with preventing households from falling into poverty (Figure 9), which is then followed in an approximate order by a formal work contract, urban residence, having a female head, migration, belonging to other ethnic groups, working in the non-agriculture sector, social capital, having no disaster, and having no disability. These factors are depicted as bright red dots under the dotted red line, while the factors associated with households being more likely than average to fall into poverty depicted as the brown triangles above the dotted red line.

These results broadly concur with the existing literature reviewed in the previous section. But one important finding is that education appears to be the strongest correlate of poverty reduction for Senegal. Another is that having disability is strongly correlated with both chronic poverty and downward mobility - clearly indicated by the dark blue triangle and the brown triangle standing respectively far below and above the dotted red line in Figure 8 and Figure 9.

IV.3. Further Analysis with Extreme Poverty

Given a considerable level of poverty transition underneath the relatively stable cross sectional poverty rates for Senegal, it may also be useful to further investigate the dynamics with regards to extreme poverty for a couple of reasons. First, a poverty rate of 47 percent is rather large and can be broken down for more finely tuned analysis; and second, one can argue that it may even be more important to understand the dynamics of extreme poverty as a more severe form of poverty for any effective policy on poverty reduction.

Using equation (7), Table 3 further disaggregates the poor households in Table 2 into two groups: those that are extreme (food) poor and those that are poor (i.e., have consumption levels higher than those in the extreme poverty group but still below the poverty line). Over the period 2006-2011, the Extreme Poor group enjoyed the strongest growth where as many as 68 percent ($= (5.7 + 6.6) / 18$) of this group moved up to either the Poor category or Non-poor category. The Poor group also had healthy growth with almost half (48 percent) of this group escaping poverty; however, this group also suffered much downward mobility movement, with 19 percent of the Poor group falling back into extreme poverty. For the Non-poor group, 12 percent and 27 percent slid back into extreme poverty and poverty respectively. The population was thus rather mobile with more than half (53 percent, or the sum of the off-diagonal cells) of the population

experiencing either upward or downward mobility, while the rest remain in the same welfare status. These results are consistent with earlier results for the two by two transition matrix (Table 2).

A more general method to study welfare dynamics is to employ the growth incidence curve (GIC) (Ravallion and Chen, 2003), which traces out the growth rate over time for the different percentiles along the whole consumption distribution instead of discretized poverty categories. Consumption growth is then naturally considered to be pro-poor if the poorer part of the consumption distribution, which can be delineated by the poverty line, grows faster than the richer part. Figure 12 plots two GICs, one for the cross sectional data and the other for the synthetic panel data; these two GICs are also known respectively as the anonymous curve and the non-anonymous curve due to their different treatments of the longitudinal nature of the data. The non-anonymous curve is constructed based on the upper bound approach in Dang et al. (2014) and thus provides an upper bound estimate of consumption mobility. Both curves are graphed based on the changes of the median consumption of consumption deciles.

The anonymous curve is rather flat along the consumption distribution, which is consistent with our earlier finding that poverty rates remain stable over time. However, since by construction, the anonymous curve tends to underestimate growth for the poorer part of the consumption distribution while it overestimates that of the richer part,¹⁹ our non-anonymous curve can provide upper bound and lower bound estimates for consumption growth. Thus taking these two curves together, the true growth for the poorer part of the consumption distribution

¹⁹ A simple example can help illustrate this. Given some upward mobility, some households in the poorest consumption decile in the first year moved to other richer deciles in the second year. Thus the cross sectional growth (underlying the anonymous curve) in the median consumption of the poorest decile in the two survey rounds would not capture these upward mobile households and would underestimate consumption growth for this decile. A similar reasoning results in this cross sectional growth of the richest overestimating consumption growth since some households moved down instead. The (synthetic) panel growth (underlying the non-anonymous curve) can capture these households and can provide better estimates for their consumption growth over time. See, e.g., Glewwe and Dang (2011) for a related discussion in the context of consumption growth for Vietnam.

would lie in the area above the green line and below the orange lines in Figure 12; similarly, the true growth for the richer part of the consumption distribution would be the area under the green line but above the orange line. Clearly, the former area is much larger than the latter area, suggesting that growth was pro-poor for Senegal during 2005-2011. This result is, again, consistent with our findings discussed above.

The profiling of the transitions with extreme poverty is shown for upward mobility and downward mobility respectively in Figure 10 and Figure 11.²⁰ Estimation results are rather similar to the poverty transitions presented in Figure 9 and Figure 10. For example, education attainment comes out again as being strongly associated with boosting households' transition out of poverty and preventing their movement into poverty. But consistent with our discussion above, the average probabilities of escaping and falling back into extreme poverty as represented by the dotted red lines are remarkably different from those associated with poverty; the former probabilities are approximately 70 percent and 15 percent, compared with the corresponding figures of 45 percent and 40 percent for the latter.

Table 4 illustrates more clearly the magnitude of the correlation by presenting the percentage of the population in each group of characteristics relative to the national average that either remained in (extreme) poverty in both periods or fell into poverty in 2011 despite being non-poor in 2005. Put differently, Table 4 categorizes the poor in 2011 by their major characteristics into two groups: those that were also poor, and those that were non-poor in 2005. This division would help bring into better focus the factors that are associated with chronic poverty versus downward mobility, both of which are further disaggregated into extreme poverty and poverty.

²⁰ For simplicity, we categorized the population into two poverty groups, Extreme Poor and Non-Extreme Poor, for these figures.

A couple of remarks are in thus in order for Table 4. First, roughly speaking, two groups of factors stand out: one group is more or less equally associated with both reducing chronic poverty and downward mobility, while the other is more strongly associated with reducing either chronic poverty or downward mobility. The first group includes factors such as urban residence, heads' gender, ethnicity, work sector, employment status, migration, and disability. For example, having disability is associated with a 21 or 22 percentage point higher than average of being stuck in poverty or sliding into poverty.

The second group includes the remaining factors (i.e., education, social capital, natural disasters, and community infrastructure). For example, education attainment is associated with lowering chronic poverty more strongly than downward mobility: having completed high school or above is associated with a 25 percentage point lower than the average likelihood of remaining in extreme poverty, but a 13 percentage point lower than the average likelihood of falling into this same category. On the other hand, suffering natural disasters is associated with a 1 percentage point higher than the average likelihood of remaining in extreme poverty but a 9 percentage point higher than the average likelihood of falling into extreme poverty.

Second, within each poverty category, while most factors have a similar association with extreme poverty or poverty, some exceptions exist. For example, urban residence is more strongly associated with decreasing chronic extreme poverty (21 percentage points lower) than chronic poverty (11 percentage points lower).

V. Conclusion

We provide in this paper an investigation of poverty dynamics in Senegal during 2006-2011. Applying the new statistical methods developed by Dang et al. (2014) and Dang and Lanjouw

(2013), we construct synthetic panel data from the two rounds of cross sections ESPS 1 and 2. In the absence of true panel household survey data, these synthetic panel data allow us to profile the population that remained in poverty or moved out of or into poverty in this time period.

Our findings point to considerable movement across the poverty line in Senegal during 2006-2011 - both upwards and downwards. This is in contrast with the relatively stable cross sectional poverty rates. Poor households were somewhat more likely to escape poverty than non-poor households falling back into poverty, and more likely to have enjoyed stronger consumption growth. More than half of the population experienced either upward or downward mobility; in particular, more than two-thirds of the extreme (food) poor moved up one or two welfare categories. Factors such as education achievement, having a female household head, urban residence, and formal work contract are strongly correlated with poverty reduction. The correlates that help prevent households from falling into poverty include education achievement, work contract, urban residence, having a female head, migration, belonging to other ethnic groups, working in the non-agriculture sector, social capital, having no disaster, and having no disability. In particular, compared to all the other correlates, education appears to be most effective in pushing households out of poverty and keeping them from falling into poverty.

It is particularly important to note that these factors can have varying degrees of association with chronic poverty or downward mobility. Policy makers interested in designing social protection programs (e.g., cash transfers) may want to look closely at those factors that are strongly correlated with downward mobility. These may point to instances where the “social safety net” needs to be repaired or strengthened. The evidence suggests that in Senegal efforts to build up social capital, provide insurance against natural disasters, and improve community infrastructure might serve to diminish the vulnerability of the population to falling into poverty.

These factors can be included as elements of targeting programs. In contrast, addressing chronic poverty, especially chronic extreme poverty, might be most effectively achieved via a combination of interventions that lift long-term income prospects —such as measures aimed at assisting the disabled to participate in society—and measures that promote economic growth in sectors where the poor are active, such as agriculture. Measures that promote school attendance by children in these chronically poor families as well as building and maintaining rural roads are also important in this respect.

Of course, the results presented here may be suggestive, but they should be interpreted with the appropriate caution. Our profiling of population groups defined in terms of their poverty trajectories has been entirely descriptive, with little explicit attention to underlying causal mechanisms. For example, our finding that education is associated with escaping poverty or with being counted among the never-poor, could imply that education raises income levels. But it could also reflect the fact that ambitious and dynamic individuals are both likely to earn high incomes and seek to educate themselves. Our analysis has not attempted to dig into such processes. A great deal of additional work and analysis is needed before underlying mechanisms can be well understood. Further research could also usefully exploit the richness of the ESPS 1 and 2 data, and also bring in analysis from the 2001 household survey, thereby offering a longer-term perspective on welfare transitions in Senegal.

In providing an early application of the synthetic panel data method to study poverty dynamics in Sub-Saharan Africa, it is hoped that this paper can serve as a useful template for work elsewhere. Each country with its own specific socio-political economy structure may reveal an entirely different set of issues associated with poverty dynamics. Since one of the strengths of

this method is its relatively light data requirements, there would seem to be ample scope for expanding this line of research more broadly in the Sub-Saharan Africa region.

References

- Agence Nationale de la Statistique et de la Démographie. (ANSD). (2010). “Enquete de Suivi de la Pauvreté au Sénégal: Note d’Orientation Technique de l’ESPS”. Dakar, Senegal.
- Azam, Jean-Paul and Margueye Dia. (2004). “Pro-Poor Growth in Senegal”. Working paper. University of Toulouse.
- Baulch, Bob. (2011). “Overview: Poverty Dynamics and Persistence in Asia and Africa”. In Bob Baulch. (Eds.). *Why Poverty Persists: Poverty Dynamics in Asia and Africa*. UK: Edward Elgar.
- Beegle, Kathleen, Joachim De Weerd, Jed Friedman, and John Gibson. (2012). “Methods of Household Consumption Measurement through Surveys: Experimental Results from Tanzania”. *Journal of Development Economics*, 98(1): 3-18.
- Christiaensen, Luc and Yasuyuki Todo. (2014). “Poverty Reduction during the Rural–Urban Transformation – The Role of the Missing Middle”. *World Development*, 63: 43–58.
- Behrman, Jere R. (2010). “Investment in Education—Inputs and Incentives”. In Dani Rodrik and Mark Rosenzweig. (Eds.). *Handbook of the Development Economics*. Volume 5: 4883–4975. Amsterdam: North-Holland.
- Bloom, David E, David Canning, and Jaypee Sevilla. (2003). “Geography and Poverty Traps.” *Journal of Economic Growth*, 8: 355-378.
- Booyesen, Frikkie, Servaas van der Berg, Ronelle Burger, Michael von Maltitz, and Gideon du Rand. (2008). “Using an Asset Index to Assess Trends in Poverty in Seven Sub-Saharan African Countries”. *World Development*, 36(6): 1113-1130.
- Cruces, Guillermo, Peter Lanjouw, Leonardo Lucchetti, Elizaveta Perova, Renos Vakis, and Mariana Viollaz. (2011). “Estimating Poverty Transitions Repeated Cross-Sections: A Three-country Validation Exercise”. *Journal of Economic Inequality*, DOI 10.1007/s10888-014-9284-9.
- Dang, Hai-Anh, Peter Lanjouw, Jill Luoto, and David McKenzie. (2014). “Using Repeated Cross-Sections to Explore Movements in and out of Poverty”. *Journal of Development Economics*, 107: 112-128.
- Dang, Hai-Anh and Peter Lanjouw. (2013). “Measuring Poverty Dynamics with Synthetic Panels Based on Cross-Sections”. *World Bank Policy Research Working Paper* No. 6504. Washington DC: World Bank.
- . (2014). “Welfare Dynamics Measurement: Two Definitions of a Vulnerability Line and Their Empirical Application”. *World Bank Policy Research Paper* No. 6944.

- Dercon, Stefan. (2004). "Growth and Shocks: Evidence from Rural Ethiopia." *Journal of Development Economics*, 74: 309–29.
- Dercon, Stefan and Joseph S. Shapiro. (2007). "Moving On, Staying Behind, Getting Lost: Lessons on Poverty Mobility from Longitudinal Data". In Deepa Narayan and Patti Petesch. (Eds.) *Moving out of Poverty: Cross-Disciplinary Perspectives on Mobility*. Washington DC: World Bank and Palgrave Macmillan.
- Fall, Abdou Salam, Philippe Antoine, Rokhaya Cissé, Latif Dramani, Mohamadou Sall, Tidiane Ndoeye, Mody Diop, Bakary Doucouré, Momar Ballé Sylla, Papa Ngom, and Abdoulaye Faye. (2011). "Les Dynamiques de la Pauvreté au Sénégal: Pauvreté Chronique, Pauvreté Transitoire et Vulnérabilités". Chronic Poverty Centre Working paper.
- Ferreira, Francisco H. G. , Julian Messina, Jamele Rigolini, Luis-Felipe López-Calva, Luis Felipe López-Calva and Renos Vakis. (2012). *Economic Mobility and the Rise of the Latin American Middle Class*. Washington DC: World Bank.
- Fields, Gary S., Paul L. Cichello, Samuel Freije, Marta Menéndez, and David Newhouse. (2003). "Household Income Dynamics: A Four-Country Story." *Journal of Development Studies*, 40 (2): 30–54.
- Glewwe, Paul and Hai-Anh Dang. (2011). "Was Vietnam's Economic Growth in the 1990's Pro-Poor? An Analysis of Panel Data from Vietnam". *Economic Development and Cultural Change*, 59(3): 583-608.
- Glewwe, Paul. (2012). "How Much of Observed Economic Mobility is Measurement Error? IV Methods to Reduce Measurement Error Bias, with an Application to Vietnam". *World Bank Economic Review*, 26 (2): 236-264.
- Gottschalk, Peter, and Minh Huynh. 2010. "Are Earnings Inequality and Mobility Overstated? The Impact of Non-Classical Measurement Error." *Review of Economics and Statistics*, 2(2): 302–315.
- Haddad, Lawrence and Akhter Ahmed. (2003). "Chronic and Transitory Poverty: Evidence from Egypt, 1997–99." *World Development*, 31(1): 71–85.
- Hall, Gillette and Harry Patrinos. (2012) (Eds.) *Indigenous Peoples, Poverty and Development*. New York: Cambridge University Press.
- Himanshu, Peter Lanjouw, Rinku Murgai, and Nicholas Stern. (2013). "Nonfarm Diversification, Poverty, Economic Mobility, and Income Inequality: A Case Study in Village India". *Agricultural Economics*, 44: 461–473.
- Kedir, Abbi M., and Andrew McKay. (2005). "Chronic Poverty in Urban Ethiopia: Panel Data Evidence." *International Planning Studies*, 10 (1): 49–67.

- King, Gary, Christopher J. L. Murray, Joshua A. Salomon, and Ajay Tandon. (2004). "Enhancing the Validity and Cross-cultural Comparability of Measurement in Survey Research". *American Political Science Review*, 98: 191–207.
- Lee, Nayoung, Geert Ridder, and John Strauss. (2010). "Estimation of Poverty Transition Matrices with Noisy Data," BREAD Working Paper 270. Available at <http://ipl.econ.duke.edu/bread/papers/working/270.pdf>
- Mitra, Sophie, Aleksandra Posarac, and Brandon Vick. (2013). "Disability and Poverty in Developing Countries: A Multidimensional Study." *World Development*, 41: 1–18.
- Mont, Daniel, and Nguyen Viet Cuong. (2011). "Disability and Poverty in Vietnam." *World Bank Economic Review*, 25(2): 323–359.
- Neubourg, Chris de, Verena Drabing, Anne Hilger, and Richard Bluhm. (2010). "Multidimensional Poverty in Senegal: An Assessment of Multidimensional Poverty, Poverty Dynamics and Patterns of Deprivations". Working paper, Maastricht Graduate School of Governance.
- Ravallion, Martin and Shaohua Chen. (2003). "Measuring Pro-poor Growth". *Economics Letters*, 78: 93–99.
- Sachs, Jeffrey, John W. McArthur, Guido Schmidt-Traub, Margaret Kruk, Chandrika Bahadur, Michael Faye, and Gordon McCord. (2004). "Ending Africa's Poverty Trap". *Brookings Papers on Economic Activity*, 1: 117–240.
- Sahn, David E. and David C. Stifel. (2000). "Poverty Comparison over Time and across Countries in Africa". *World Development*, 28(12): 2123–2155.
- World Bank. (2014a). *World Development Indicators Database*. Washington DC: World Bank.
- . (2014b). *Inequality in South Asia*. Regional Flagship Report. Washington DC: World Bank Group.
- . (2014c). *Bhutan Poverty Assessment Report*. Poverty Reduction and Economic Management, South Asia Region. Washington DC: World Bank Group.
- . (2014d). *Senegal Poverty Assessment Report*. Poverty Reduction and Economic Management, Africa Region. Washington DC: World Bank.
- . (2014e). *Economic Mobility in Europe and Central Asia: Exploring Patterns and Uncovering Puzzles*. Poverty Reduction and Economic Management, Europe and Central Asia Region. Washington DC: World Bank.
- . (forthcoming). *Left Behind: Chronic Poverty in Latin America*. Global Poverty Practice. Washington DC: World Bank.

Table 1: Poverty Estimates Based on Cross Sections, Senegal 2006- 2011 (Percentage)

Regions	2006		2011	
	Poverty Rates	Population Distribution	Poverty Rates	Population Distribution
Dakar	28.3	24.1	26.6	23.0
	(2.3)		(3.1)	
Other urban areas	40.9	17.6	41.4	20.2
	(1.7)		(2.2)	
Rural areas	58.5	58.3	57.0	56.8
	(1.6)		(1.9)	
All population	48.1	100	46.9	100
	(1.2)		(1.3)	
N	13,329		5,904	
Note: Standard errors in parentheses. All numbers are estimated taking into account the two-stage cluster random sampling with stratification.				

Table 2: Poverty Dynamics Based on Synthetic Data, Senegal 2006-2011 (Percentage)

Joint Probabilities		Conditional Probabilities	
Poverty Status	Estimates	Poverty Status	Estimates
Poor, Poor	26.3	Poor--> Poor	55.3
	(0.4)		(0.8)
Poor, Nonpoor	21.3	Poor--> Nonpoor	44.7
	(0.1)		(0.3)
Nonpoor, Poor	20.8	Nonpoor--> Poor	39.6
	(0.1)		(0.3)
Nonpoor, Nonpoor	31.7	Nonpoor-->Nonpoor	60.4
	(0.6)		(1.0)
N	4030		4030

Note: Predictions are obtained based on data in the second survey round. Standard errors are in parentheses. We use 500 bootstraps in calculating standard errors. All numbers are weighted using population weights. Household heads' ages are restricted to between 25 and 55 for the first survey round and adjusted accordingly with the year difference for the second survey round. All numbers are estimated taking into account the complex survey design.

Table 3: Joint Poverty Probabilities Based on Synthetic Data For Different Poverty Categories, Senegal 2006-2011 (Percentage)

		2011			
		Extreme Poor	Poor	Nonpoor	Total
2006	Extreme Poor	5.7	5.7	6.6	18.0
		(0.1)	(0.0)	(0.0)	(0.1)
	Poor	5.7	9.7	14.2	29.6
		(0.0)	(0.1)	(0.0)	(0.1)
	Nonpoor	6.4	13.9	32.1	52.4
		(0.0)	(0.1)	(0.3)	(0.2)
	Total	17.8	29.3	52.9	100
		(0.1)	(0.1)	(0.2)	
Note: Predictions are obtained based on data in the second survey round. Standard errors are in parentheses. We use 500 bootstraps in calculating standard errors. All numbers are weighted using population weights. Household heads' ages are restricted to between 25 and 55 for the first survey round and adjusted accordingly with the year difference for the second survey round. Estimation sample size is 4,030 households. All numbers are estimated taking into account the complex survey design.					

Table 4: (Heads') Characteristics Associated with Poverty Mobility Relative to the Means and Conditional on Poverty Status in 2006, Senegal 2006- 2011

No	Characteristics	Chronic Poverty		Downward Mobility	
		Remained Extreme Poor in Both 2006 and 2011	Remained Poor in Both 2006 and 2011	Non-Extreme Poor in 2006, but Fell into Extreme Poverty in 2011	Non-Poor in 2006, but Fell into Poverty in 2011
1	Residence area				
	Rural	1.2	4.9	10.0	11.0
	Urban	-21.9	-11.2	-10.1	-10.1
2	Sex of household head				
	Female-headed	-12.0	-11.0	-6.4	-8.4
	Male-headed	0.5	2.8	2.7	3.3
3	Ethnicity				
	Wolof	-2.2	-0.5	-0.4	0.6
	Serere/ Poular	-0.1	1.7	2.5	2.0
	Other ethnic groups	-3.1	-3.7	-3.1	-5.3
4	Educational levels				
	Less than primary education	0.0	3.4	4.7	8.0
	Primary education	-13.4	-12.7	-7.3	-8.0
	Junior high school	-18.8	-21.4	-10.8	-16.0
	High school or above	-24.1	-29.1	-12.8	-22.5
5	Work sector				
	Non-agriculture	-4.7	-3.8	-3.8	-4.2
	Agriculture	1.9	5.6	10.1	11.3
6	Employment status				
	No work contract	-0.4	2.2	3.4	4.9
	Having work contract	-10.8	-11.0	-9.0	-13.8
7	Migration				
	Living in current location for less than 5 years	-5.2	-5.4	-6.3	-7.0
	Living in current location for between 5 and 10 years	-3.1	-3.4	-3.7	-6.5
	Living in current location for 11 years or more	-1.1	0.6	1.2	1.3
8	Disability				
	No handicap	-2.0	-0.5	-0.1	-0.4
	Having handicap	22.0	21.2	19.2	21.9
9	Social capital				
	No social capital	0.6	4.0	6.1	7.9
	Having social capital	-1.8	-0.7	-0.5	-1.0
10	Natural disasters				
	No disaster	-2.3	-1.2	-1.3	-1.5
	Having disaster	1.4	4.6	8.6	8.8
11	Community infrastructure				
	Distance to paved road less than 2km	-4.6	-3.8	-4.0	-4.3
	Distance to paved road more than 2km	1.6	5.2	9.3	10.2
Note: Estimates show the difference between the probability of falling into each category relative to the mean (conditional probabilities) and are calculated based on the same estimation results in Figures 8 to 11.					

Figure 1: Household Perception of Economic Status, Senegal 2006- 2011

Figure 2: Poverty Dynamics by Residence Area, Senegal 2006- 2011

Figure 3: Poverty Dynamics by Gender of Household Heads And Residence Area, Senegal 2006- 2011

Figure 4: Poverty Dynamics by Education Level, Senegal 2006- 2011

Figure 5: Poverty Dynamics by Ethnicity, Senegal 2006- 2011

Figure 6: Poverty Dynamics by Work Sector and Status, Senegal 2006- 2011

Figure 7: Poverty Dynamics by Migration History, Senegal 2006- 2011

Figure 8: Profiling of the Probability of Different Population Groups Escaping Poverty in 2011 Conditional on Being Poor in 2006, Senegal

Figure 9: Profiling of the Probability of Different Population Groups Falling Back into Poverty in 2011 Conditional on Being Non-poor in 2006, Senegal

Figure 10: Profiling of the Probability of Different Population Groups Escaping Extreme Poverty in 2011 Conditional on Being Extreme Poor in 2006, Senegal

Figure 11: Profiling of the Probability of Different Population Groups Falling Back into Extreme Poverty in 2011 Conditional on Being Non-extreme poor in 2006, Senegal

Figure 12: Bound Estimates on Growth Incidence Curve, Senegal 2005-2011

Appendix 1: Additional Tables and Figures

Table 1.1: Summary Statistics, Senegal 2006- 2011

	2006	2011	Differences
Log of per capita consumption	12.54	12.53	0.02
	(0.02)	(0.02)	(0.03)
Head is female (1= yes, 0= no)	0.18	0.24	0.07***
	(0.01)	(0.01)	(0.02)
Head's age	43.81	48.42	4.61
	(0.17)	(0.24)	(0.30)
Head's years of schooling	2.60	2.44	-0.16
	(0.15)	(0.12)	(0.19)
Head is married (1= yes, 0= no)	0.91	0.89	-0.02**
	(0.01)	(0.01)	(0.01)
Head is handicapped (1= yes, 0= no)	0.01	0.02	0.01**
	(0.00)	(0.00)	(0.00)
Urban (1= urban, 0= rural)	0.41	0.42	0.00
	(0.02)	(0.02)	(0.03)
N	8584	4030	
Note: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses and the differences are estimated taking into account the complex survey design. We do not test for the difference of the distributions of the age variable in the two survey rounds since it is a deterministic variable.			

Table 1.2: Estimation Models of Household Consumption, Senegal 2006- 2011

	2006				2011			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Head is female	0.128*** (0.017)	0.160*** (0.018)	0.161*** (0.018)	0.133*** (0.017)	0.195*** (0.022)	0.246*** (0.025)	0.244*** (0.025)	0.226*** (0.024)
Head's age	-0.006*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)	-0.001 (0.001)	-0.000 (0.001)	0.000 (0.001)	-0.001 (0.001)
Head's years of schooling	0.036*** (0.002)	0.036*** (0.002)	0.036*** (0.002)	0.034*** (0.001)	0.038*** (0.002)	0.038*** (0.002)	0.038*** (0.002)	0.042*** (0.002)
Head is married		0.101*** (0.025)	0.101*** (0.025)	0.118*** (0.023)		0.146*** (0.034)	0.137*** (0.034)	0.111*** (0.032)
Head is handicapped			-0.079 (0.058)	-0.057 (0.054)			-0.369*** (0.065)	-0.288*** (0.062)
Urban	0.641*** (0.014)	0.647*** (0.015)	0.647*** (0.015)	0.442*** (0.017)	0.605*** (0.021)	0.614*** (0.021)	0.609*** (0.021)	0.541*** (0.022)
Constant	12.440*** (0.036)	12.338*** (0.044)	12.337*** (0.044)	12.714*** (0.045)	12.188*** (0.055)	12.005*** (0.069)	11.995*** (0.069)	12.241*** (0.068)
Regional dummy variables	No	No	No	Yes	No	No	No	Yes
Adjusted R2	0.356	0.357	0.357	0.443	0.333	0.336	0.341	0.408
N	8584	8584	8584	8584	4030	4030	4030	4030
Note: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in parentheses. Estimates are provided using weighted regressions. All models do not control for regional dummy variables, except for Models 4 and 8. Dependent variable is log of household consumption per capita.								

Table 1.3: Poverty Dynamics Based on Synthetic Data with Different Estimation Models, Senegal 2006-2011 (Percentage)

Poverty Status (Joint Probabilities)	Model 1	Model 2	Model 3	Model 4
Poor, Poor	26.4	26.3	26.3	26.6
	(0.4)	(0.4)	(0.4)	(0.6)
Poor, Nonpoor	21.2	21.2	21.3	20.1
	(0.1)	(0.1)	(0.1)	(0.4)
Nonpoor, Poor	20.8	20.8	20.8	20.1
	(0.1)	(0.1)	(0.1)	(0.4)
Nonpoor, Nonpoor	31.7	31.7	31.7	33.2
	(0.6)	(0.6)	(0.6)	(0.7)
N	4030	4030	4030	4030

Note: Predictions are obtained based on data in the second survey round. Standard errors are in parentheses. We use 500 bootstraps in calculating standard errors. All numbers are weighted using population weights. Estimation model numbers correspond to those for the models shown in Appendix 1, Table 1.1. Household heads' ages are restricted to between 25 and 55 for the first survey round and adjusted accordingly with the year difference for the second survey round. All numbers are estimated taking into account the complex survey design.

Figure 1.1: Distribution Graph for Household Consumption, Senegal 2006- 2011