THE USE OF MULTIDIMENSIONAL POVERTY TO PROXY CHRONIC POVERTY: AN APPLICATION TO BRAZIL

By

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Introduction

In June 2011, newspapers around the world reported that Brazil had declared war on chronic poverty. "President Dilma Rousseff has launched an ambitious plan…which aims to eradicate dire poverty by 2014", reported *The Guardian Weekly*, quoting the President's historic speech, in which she declared: "We can't forget that the most permanent, challenging and harrowing crisis is having chronic poverty in this country" (Langellier, 2011)

Eradicating chronic poverty has become an important goal in middle and high income countries. It is essential to be able to measure progress in pursuit of this goal. However, the most common methodologies for measuring chronic poverty require panel data. These types of datasets are extremely rare in middle and low income countries. This paper proposes using multidimensional poverty as a proxy for chronic poverty in countries that lack panel data. The paper is structured as follows. First I review issues in the measurement of chronic poverty, second I discuss concepts and the theory of chronic poverty measurement, third I detail a multidimensional poverty measure for Brazil, fourth I provide a validation of the approach, and finally I discuss the implications of its use.

Literature Review

Theoretical Framework for the Measurement of Chronic Poverty

To assess chronic poverty I follow the precedent set by Sen (1976) and separate the measurement of poverty into two steps. First, the identification step identifies who is and who is not poor. In income space, the identification step traditionally involves the selection of the poverty line. Individuals with incomes lower than the poverty line are identified as poor. The aggregation step summarizes overall poverty into an indicator or an “income standard”. In my analysis, I explore how time is incorporated into the identification and aggregation steps.

Components Approach

Yaqub (2000) splits the methodology for the measurement of chronic poverty into two broad classes, the “component approach” and the “spells approach”. Jalan and Ravallion (2000) propose what has become the most common form of the components approach. This approach is grounded in the theoretical notion that consumption (and utility) is based on long term expected earnings. The poor can at least partly insure against temporary income shocks; therefore, a measure of chronic poverty should be based on the long-term expected component of income. Income is separated into two components. The chronic component is defined as the expected income (or consumption) over time and is represented by the arithmetic mean of income over time. The transient component consists of the difference between total poverty and the chronic component of poverty. An individual is identified as poor if the average income over time lies below the poverty line. In order to satisfy the additivity and convexity properties, chronic poverty is aggregated with the squared gap index from Foster-Greer-Thorbecke class of poverty measures. Notice that chronicity in this case refers to a component of an individual’s income, not the state of poverty for an individual. Therefore, when using Jalan and Ravallion’s (2000) approach strictly, it is not possible to identify people as chronically poor; it is only possible to identify components of income that contribute to chronic poverty.

The implicit assumption of this model is that income is perfectly transferrable across periods. Under this assumption, the identification of the chronically poor is not very sensitive to the amount of time an individual actually spends in poverty. In an extreme case, an individual can be non-poor in all but one period and still be considered chronically poor if their mean income is below the poverty line. If it is assumed that income is perfectly transferable across periods then it would be safe to presume that an individual who is appropriately identified as poor in a given period is chronically poor. As a result, the concepts of chronic poverty and poverty become conflated.

Foster and Santos (2006) introduce a measure based on the components approach that relaxes the assumption of perfectly substitutable incomes across time. Foster and Santos (2006) calculate poverty in each period with the Clark, Hemming and Ulph (1981) poverty index and aggregate poverty over time by taking the general mean[1] of poverty from each period. The use of a general mean, based on Atkinson's (1970) equally distributed equivalent, allows the researcher to choose the level of substitutability of incomes across periods.

Spells Approach

In the spells approach, the number of periods in which an individual is poor is fundamental to their identification as chronically poor. Typically, an individual is identified as chronically poor if they are poor in a certain number of periods. The spells approach is particularly useful for identifying transitions in and out of poverty (Hulme &

[1] For a detailed discussion on general means see Foster and Szekely (2008).

Shepherd, 2003). In their classic paper, Bane and Ellwood (1984) define a spell as a set of contiguous periods in which an individual earns an income below the poverty line.

A basic flaw of using the spells approach with the typical data collection methodology is that it is impossible to determine if an individual is poor before, between and after waves of a panel. In order to calculate chronic poverty it is essential to make assumptions or imputations about poverty for individuals during the unobserved periods. In order to mitigate bias in chronic poverty estimates, techniques such as exit probabilities, hazard models (Bane & Ellwood, 1986) and survival analysis (Ruggles & Williams, 1989) have been used to estimate the duration of poverty for truncated datasets. An additional drawback of the spells approach is that time is only incorporated into the identification step, not the aggregation step. Therefore, the length someone spends in poverty does not affect the magnitude of the poverty measurement. This approach also has the implicit assumption that income cannot be smoothed over periods.

Foster (2009)[2] introduces a class of chronic poverty measures based on the FGT class that improves the properties of the aggregation step in the spells approach. This measure employs a dual cutoff to the identification of the chronically poor. The first cutoff, the traditional poverty line, identifies if individuals are poor within a given period. The second cutoff, the duration cutoff, establishes the proportion of periods in which an individual must be identified as poor to be considered chronically poor. This dual cutoff formalizes an identification strategy for chronic poverty that was previously commonly employed (for example Herrera (2001)). The measure introduces the duration monotonicity axiom that states, all else equal, if the number of periods in which a poor

[2] It is interesting to note that the functional form of Foster (2009) is identical to the functional form of the Multi-Dimensional Poverty Index described in Alkire and Foster (2011).

individual is poor increases, then poverty cannot go down. Once the chronically poor have been identified, the measure censors periods in which non-chronically poor individuals are poor. This step ensures that the measurement focuses on the chronically poor so that transient poverty does not affect the level of chronic poverty in a society. The chronic poverty index can then be aggregated using the FGT class of measures. The duration adjusted headcount ratio represents the ratio of the number of periods in which a chronically poor individual is poor in relation to the overall number of periods. The duration adjusted poverty gap index and duration adjusted squared gap index are analogous to the Foster-Greer-Thorbecke-1 and Foster-Greer-Thorbecke-2 index for the censored chronic poverty distribution.

Foster (2009) introduces the time anonymity axiom that implies, "…the ordering of the incomes does not affect the value of the chronic poverty measurement." Foster (2009) justifies this axiom by stating, "It is not entirely clear weather and how the time-ordering of incomes should impact the aggregation (or identification) of chronic poverty." Many subsequent papers have introduced properties in which the overall measure of chronic poverty depends on the specific periods in which the individual is poor. Gradín, Río and Cantó (2011) propose two axioms to create what they call a "path dependent" chronic poverty measure. The *intertemporal poverty spell duration sensitivity axiom* states that, all else equal, when comparing two individuals with two spells of poverty, poverty must be higher if an individual experiences poverty in consecutive spells. The *intertemporal regressive transfer axiom* states that if an individual experiences a regressive transfer between two periods in which she is poor, and the transfer occurs from a period in a long spell to a period in a shorter spell, then poverty must increase. Gradín et. al. (2011) then proposes an intertemporal poverty index, based on Bossert, Chakravarty and D'Ambrosio (2012), with properties that abide by the newly proposed axioms. They achieve these axioms by weighting the periods in the Foster (2009) index with a weight that increases as the number of consecutive periods in which an individual is poor increases. Other papers including Porter and Quinn (2008), Calvo and Dercon (2009) and Mendola, Busetta and Milito (2011) have proposed methodologies for including duration and consecutiveness in the aggregation step of chronic poverty.

Hoy and Zheng (2011) unite the spells approach and the components approach in a measurement of lifetime poverty. To calculate lifetime poverty, the authors aggregate two components. First, spells of poverty in each period of an individual's life are identified and aggregated. Second, a "lifetime" poverty line is identified that represents permanent consumption over time in a way that is similar to the components approach proposed by Jalan and Ravallion (2000). The most obvious drawback of this approach is that there is no dataset that tracks a representative sample over their entire lifetime.

The empirical study of chronic poverty has been limited due to the paucity of nationally representative longitudinal panel datasets. For example, in the Latin American and Caribbean region, only Chile and Peru have panel datasets that allow for the calculation of traditional measures of chronic poverty. Even when panel datasets are available high rates of attrition, ranging anywhere from 0% to 35% (Dercon and Shapiro, 2007), confound the ability to interpret changes in welfare for an entire population. Attrition occurs for a number of reasons including non-response, migration, death, violence and change in household circumstances. The characteristics that cause an individual to drop out of a survey are often concentrated among a few persons, leading to bias in the remaining sample. Many studies test to see if the observable characteristics, ex ante, are similar for those who drop out and those who remain (Alderman, Behrman, Kohler, Maluccio & Watkins, 2001). However, even if initial characteristics are similar for those who remain in the survey and those who leave, shocks may have occurred between waves that changed the welfare status of individuals and caused an individual to drop out. To mitigate the effects of attrition, some studies have used instrumental variables estimation (Fields, Cichello, Freije, Menéndez & Newhouse, 2003), probit models to calculate probability of attrition before and after attrition to re-weight the dataset (Baulch & Quisumbing, 2011) or use of pseudo-panels (Antman & McKenzie, 2007). Other studies have compared multiple datasets (Dragoset & Fields, 2008). In the end, the quality of the tools employed to correct attrition bias depends on the plausibility of the necessary assumptions.

Previous Reviews of Chronic Poverty

There have been a number of review articles that provide a framework for understanding the concepts of poverty over time. Baulch and Hoddinott (2000) point out that individuals in a society can be split into the never poor, the sometimes poor and the always poor. The authors analyze studies of chronic poverty with 13 panel datasets from a variety of countries and find that the proportion of individuals who are sometimes poor is generally greater than the number of individuals who are always poor. The authors attribute this finding to two sources: measurement error and real changes in welfare. Baulch and Hoddinott (2000), along with many who follow, assume that measurement error leads to a positive bias in transitory poverty and a downward bias in chronic poverty. It is important to note that this assumption is correct only when the density around of distribution above the poverty line is greater than the density of the distribution below the poverty line. Only in this case would random errors lead to more non-poor erroneously identified as poor than poor identified as not poor. Even if welfare status is accurately measured, the transitions in and out of poverty may not represent any real changes in welfare. Transitions calculated with the headcount index utilize an absolute poverty line and may represent insignificant fluctuations around a poverty line (Foster, Greer & Thorbecke, 1984; Ravallion, 1996). Later studies found that probability of exit from poverty is higher for incomes close to the poverty line, yet changes in welfare are relatively consistent throughout the distribution (Perge & McKay, 2011; Okidi & McKay, 2003). In contrast to the notion that accumulation of assets is the key to escaping poverty, Baulch and Hoddinott (2000) suggest that change in returns on assets can be a key factor in escaping chronic poverty. The authors cite the Green Revolution in India and the end of Apartheid in South Africa as examples of key events that can change returns to assets.

Hulme and Shepherd (2003) present the concepts underlying chronic poverty. The authors suggest that the durational cutoff for chronic poverty be set at five years for three reasons: most panels have waves less than five years apart; empirical studies of exit probabilities find that if an individual is poor for five years the probability of escape significantly diminishes; and five years is a significant period of time in an individual's life. The authors extend Baulch and Hoddinott's (2000) classification and separate the chronic poor into the always poor and the usually poor. They split the transient poor into those who frequently "churn" in and out of poverty and those who are occasionally poor.

Hulme and Shepherd (2003) push to extend the analysis of chronic poverty beyond monetary indicators to capture the many dimensions that lead an individual into poverty and keep an individual from escaping poverty over time.

Empirical Studies of Chronic Poverty

The most basic empirical exercise in chronic poverty is the production of a transition matrix. For a two wave panel, individuals are identified as poor or non-poor in each period. Individuals are then separated into the always poor (chronically poor), sometime poor (transiently poor), and never poor. Studies often look at the traits of individuals in each of the categories but often cannot determine the causes of chronic poverty due to endogeneity problems. Many studies employ a probit or logistic regression to find the determinants of being in each category. A probit or logistic regression requires a useful continuous variable (income) to be transformed into a dichotomous variable (poverty status) (Ravallion, 2006). In the process, a great deal of interesting information is lost. In order to take into account all of the available information, it would be preferable to run a regression and investigate the determinants of income; from the regression results one could identify who is poor and non-poor.

Poverty Traps

Many of the individuals identified as poor in any given period are mobile and have the ability to escape poverty. For those who remain poor we must ask, what entraps individuals into persistent poverty? Carter and May (2001) suggest that individuals should be identified as chronically poor if they have an asset base that, typically, is insufficient to provide returns on assets that will allow them to exit from poverty. When individuals lie below the asset poverty line, then they must use all of their assets to provide enough consumption to survive; thus they lack the opportunity to accumulate enough assets to escape poverty. There are divergent equilibrium positions -- a higher equilibrium for those with initial assets that allow individuals to participate in activities that lead to escape from poverty and a low level equilibrium that includes the chronically poor who have insufficient assets (Carter & Barrett, 2006). In a well functioning market, individuals would be able to borrow in order to reach the higher equilibrium. With underdeveloped credit markets, imperfect and extremely low initial conditions limit the chances that the chronically poor can move to the higher equilibrium. The source of divergent returns on assets that leads to multiple equilibria is manifold. Adato, Carter and May (2006) combine qualitative and quantitative information and examine how the legacy of apartheid in South Africa led to a divergence in social capital that destines a large cohort to a low equilibrium. Chantarat and Barrett (2011) present a theoretical model on social exclusion and poverty traps that identifies the beneficial yet limited role that social networks can play when exiting poverty. The authors emphasize that social connections are not costless. Some of the poor may choose not to enter social connections because the additional social capital is not sufficient to reach the upper equilibrium; the social transaction is costly and provides zero return. Jalan and Ravallion (2002) employ a new methodology for isolating geographic determinants of return on assets. Using this methodology, they find that divergent returns to skills in certain geographic locations can lead to geographic poverty traps. Sampson and Morenoff (2006) find that initial conditions of neighborhood characteristics, particularly race and income, are very good predictors of future poverty rates in Chicago. Moreover, once a neighborhood becomes "stigmatized" as a poor or minority neighborhood, that area never reverts to a thriving or non-minority area.

Measuring Chronic Poverty without Panel Data

It is impossible to employ the techniques described above to measure chronic poverty without panel data. I discuss three strategies to estimate chronic poverty without panel data: i) utilizing proxies from cross section data that attempt to capture poverty over time, ii) employing pseudo-panels to impute panel data over time, and iii) aggregating monetary and non-monetary indicators into a multi-dimensional measurement.

Proxies

Perge and McKay (2011) use panel datasets from 12 countries to investigate whether the depth of poverty is a good proxy for the duration of poverty. They find that the quality of the proxy depends on the distance between the poverty line and the extreme poverty line. The discussion in this paper relates closely to the discussion in Bourguignon (2004) about the poverty, growth, inequality triangle, where changes in poverty depend on the original spread of the distribution, changes in the spread, economic growth and the selection of the original poverty line. This study elucidates how investigating transitions across an absolute poverty line may not capture real changes in welfare. In fact many individuals who started below the poverty line, but were not severely poor, remained in poverty. Many of the individuals who have zero incomes are identified as extremely poor simply have no income in a given period due to seasonal fluctuations, misreporting or transient shocks. As a result, it would be wise to avoid using severe poverty, particularly the headcount of severe poverty, as a representation of poverty over time.

Chaudhur and Ravallion (1994) examine how well a selection of cross-sectional indicators predicts chronic poverty. Similar to Jalan and Ravallion (2000), an individual is identified as chronically poor if they are “typically poor”. The arithmetic mean of the income standard is taken to be the typical level of income over time. The following indicators are examined: income, consumption, share of income devoted to food, food consumption per capita, and land holding. The paper examines how well cross section levels of each dimension predict mean levels of income and consumption over time. The paper finds that income is the best predictor of the mean level of income, and the food share in the budget is a very poor predictor of mean income. While this paper cautions against using non-monetary indicators to predict chronic poverty, an alternative interpretation may provide more insight. Perhaps this study shows that income is not highly correlated with other intrinsically important variables such as food share and consumption. Therefore, income may be a poor indicator of the command over resources over a period of time (Sen 1981, 1999).

Baulch and Masset (2003) use transition matrices to investigate how persistence of deprivations in non-monetary variables relates to the persistence of income poverty in Vietnam. The non-monetary indicators include nutrition, height z-score for children, BMI for adults, and school enrollment. There is a positive but mild correlation between persistent deprivation of non-monetary indicators and chronic poverty. Non-monetary indicators improve with development but change at a slower rate than income. This may represent a lag in investment in health and education after increases in income or a delay in the non-monetary variables in capturing changes in changes of welfare. Günther and Klasen (2007) use the same dataset and find that while static non-monetary and monetary variables paint very different pictures of poverty, the dynamics of these types of variables are fairly similar.

Another approach to dealing with the lack of panel data is to ask respondents about their poverty and welfare over time. Davis and Baulch (2011) supplemented quantitative panel data in Bangladesh with qualitative “life histories” that asked a sample from the quantitative study to recall their welfare status during previous significant life events. The quantitative data corresponded with the qualitative assessments for only two thirds of the individuals. However, only 5.5% of mismatches were identified as recall error; the majority of mismatches were due to the fact that monetary variables did not align with the individuals’ conception of welfare and discontinuities due to an absolute poverty line. One could argue that retrospective qualitative studies generate a stronger argument for identifying an individual as chronically poor and help paint a better picture of poverty status over time. However, these promising results conflict with the findings, reported in Dercon and Shapiro (2007), of a massive divergence between previous poverty status and self-reported retrospective poverty status in Ethiopia.

Howe and McKay (2007) examine a participatory poverty assessment. The poverty assessment asked the respondents to describe classes of individuals. Six main classes arose from the discussion, four poor classes and two non-poor classes. While four of the classes were poor, the two poorest classes were characterized by the persistence of their deprivation. The researchers used the descriptions of the poor individuals from the participatory assessment to identify variables that characterized the chronically poor. The participatory approach allows for a less paternalistic method of calculating poverty over time without panel data. This approach is much more adept at capturing latent traits that are central to impoverishment such as social exclusion and emotional well-being.

Pseudo and Synthetic Panels

Although most developing countries, particularly in Latin America, do not have panel data, many have fairly high-quality repeated cross section datasets. The central problem with measuring chronic poverty with repeated cross sections is that it is impossible to track how individuals change between periods. However, if the cross sections are representative samples, it is possible to investigate the transition of groups (or cohorts) across waves of the survey. Cohorts are selected based on characteristics such as gender, ethnicity and birth year that do not change over time. The pseudo panel approach makes assumptions about the dynamics of the relationship between cohorts (or individuals) in different waves of a cross section. A set of observable variables is selected to predict income or poverty status for a set of cross sections. The coefficients from the original prediction are used to estimate the incomes or poverty status of cohorts in the most recent period. The literature on pseudo panels is based on Deaton (1985) who estimated a fixed effect among cohorts to capture the dynamics of variables for given cohorts. However, in chronic poverty analysis we are interested in within-group heterogeneity. Deaton's model can only provide group-level measurements and is insufficient for the study of chronic poverty. Bourguignon and Goh (2004) estimate individual level dynamics by making assumptions about the autoregressive process of the error term for cohorts. Lanjouw, Luoto and McKenzie (2011) propose "synthetic panels" based on the small area estimation technique (poverty mapping) from Elbers, Lanjouw and Lanjouw (2003). Synthetic panels relax the distributional assumptions required in pseudo-panel analysis to provide a less biased and more accurate estimate of changes in poverty. Cruces et al. (2011) attempt to validate the synthetic panel approach using panel data from three Latin American countries. They find that the true rates of mobility lie between their proposed bounds; however the gap between the bounds is often so large that it limits the usefulness of results.

There are two key flaws to the pseudo and synthetic panel approach. First, instead of providing an estimate of mobility and chronic poverty, pseudo and synthetic panels can only place upper and lower bounds, which are often very wide, on estimates of chronic poverty. Therefore, we are unable to identify individuals as poor. Moreover, this approach requires that we make assumptions about the dynamics of certain variables. The variables that we are forced to make assumptions about often are the very indicators whose dynamics we are most interested in capturing. Instead, it may be interesting to create a measure that is the aggregation of many variables we have intrinsic reason to value. This is a key motivation underlying multidimensional poverty indices that capture poverty over time.

Multidimensional Poverty

It has long been understood that poverty is a multidimensional concept. Only recently measurements have been created that can identify and aggregate many dimensions of poverty (Bourguignon & Chakravarty, 2003; Alkire & Foster, 2011). Before multidimensional measurement was popularized, Hulme and McKay (2005) lamented how the discussion of chronic poverty is dominated by economists working solely in income space. This is in large part due to the data limitation; developing countries lack panel data, and even when panels are available the quantity and quality of non-monetary variables is very limited. Yet income and consumption are merely instrumental to an individual's well-being and to focus solely on income ignores the many aspects of welfare that are intrinsically important (Sen, 1999). Additionally, income and consumption data are captured at the household level and do not reflect the intra-household heterogeneity of well-being (Haddad & Kanbur, 1990).

Hulme and McKay (2005) suggest a list of requirements for Human Flourishing and Their Relation to Chronic Poverty; the requirements include: bodily well-being, material well-being, mental development/health, work, security, social relations, spiritual well-being, empowerment political freedom, and respect for other species. The authors present a number of potential approaches to the measurement of non-monetary chronic poverty. They suggest that measuring assets is desirable because the stochastic shifts in assets are more stable than income or consumption in the short or medium term. Income fluctuations may represent superfluous short-term changes while assets represent a more stable component of well-being.

The "Needs and Human Development Approaches" view poverty as the deprivation of universal human needs. The focus on universalism attempts to sidestep controversy about cultural relativism and paternalism in poverty discussions.

Apablaza and Yalonetzky (2012) combine Foster (2009) and Alkire and Foster (2011) to propose two measures that capture many dimensions of poverty over time. In measuring *Multidimensional Chronic Deprivation*, first chronic poverty is calculated within each dimension using Foster (2009) methodology. Once chronic poverty within each dimension has been captured, the joint distribution of chronic deprivations is calculated using Alkire and Foster (2011). The second measure is *Chronic Multidimensional Poverty* which first measures multidimensional poverty in each period with Alkire and Foster (2011) then uses Foster (2009) to capture chronic multidimensional poverty. These measures are equivalent when the intersection approach to the deprivation and/or time cutoff is employed. The authors have not yet explored the unique properties derived from the integration of these two measures; however, it is presumed that the properties from the original measures are maintained.

Calvo (2011) utilized pseudo-panels to allow for the measurement of multidimensional chronic poverty without panel data. While previous discussion of pseudo-panels involved the estimation of consumption or income, Calvo (2011) uses the synthetic panel technique discussed above (Lanjouw, Luoto & McKenzie, 2011) to estimate chronicity for three dimensions: schooling, consumption and leisure time. Chronic poverty is then calculated using the components approach to identify individuals as chronically poor; then the Alkire and Foster (2011) methodology is used to identify and aggregate multidimensional chronic poverty. The methodology is validated using panel data from Peru, and he finds that the estimates from synthetic panels are very similar to estimates calculated with actual panel data. The most important drawback of this approach is that dimensions of multidimensional poverty must be cardinal.

Conceptually, it is possible to understand the combination of time and dimensions into the analysis of poverty in many ways. The joint distribution in multidimensional indices can illustrate the accumulation of many deprivations over time. Nandy (2008) creates a multidimensional measurement from variables in the Demographic and Health

Survey (DHS) that represent deprivation over time. The study exploits the fact that the DHS asks how long the respondent has been living in their current place of residence, and it is implicitly assumed that household physical immobility proxies stagnant welfare. The following variables were chosen: the individual has never been to school, the dwelling has a mud floor, the household does not have any sanitation facility, and the household uses an unimproved source of drinking water. Since the DHS collects information on the length of time a person has lived in their current place of residence, it is possible to use this information to represent chronicity or duration of poverty.

A challenge with this approach is that some variables, such as height or education status for adults, are so stagnant that no policy could possibly bring the individual out of poverty. Günther and Klasen (2007) address this challenge by suggesting that if individuals are persistently deprived of capabilities, they should be captured in chronic poverty measurements regardless of the potential for policy.

Kwak and Smith (2011) present a model that unites multidimensional poverty measurement with the poverty trap literature. They posit that when one dimension of wellbeing or type of asset (both pecuniary and non-pecuniary) is deprived, an individual can substitute this dimension with other skills or resources. However, when deprivations accumulate, individuals cannot rely on other resources to accumulate assets and thus are stuck in a poverty trap.

My Thesis combines the “static proxy” and “multidimensional” approaches to capture chronic poverty without a panel dataset. The next section describes multidimensional poverty measurement in detail.

Multidimensional Poverty in Brazil

According to Amartya Sen, the analysis of well-being requires the choice of information in order to measure and subsequently make value judgments about the construct (Sen 1985). When measuring poverty or deprivation, we are concerned with identifying *who is poor* and aggregating the amount of poverty, or *how poor*. Traditional poverty measurement restricts the information that is utilized for these two steps exclusively to monetary indicators, typically income or consumption at the household level. Equally important to the information that is utilized in the measurement of poverty is the information that is excluded from analysis. In my analysis, I will view poverty as the deprivation of basic human functionings. Functionings refer to the "beings" and "doings" that an individual is able to do and has reason to value. Although there is no consensus on the required set of basic functionings, it is widely acknowledged that there is a plurality of intrinsically valuable functionings of which an individual can be deprived. My motivation and choice of functionings is discussed in the "Dimensions and Indicators" section.

My aim is to provide a measurement that captures chronic deprivation. I argue that utilizing exclusively pecuniary information in the analysis of chronic deprivation, and thus actively ignoring all other types of information in the value-judgment, is overly constraining. Monetary indicators of well-being fluctuate substantially over time (Chaudhuri & Ravallion, 1994; Perge and McKay, 2011; Ribas & Machado, 2007). It is very likely that income is a weak proxy for long-term well-being because data on income only provide a limited portion of the vector of information that constitutes well-being. Non-monetary indicators of well-being, such as education, health, nutrition and household assets, do not fluctuate over time as rapidly as monetary indicators (McKay & Lawson, 2003). Many of these non-monetary indicators capture a great deal of information about historical deprivations. For example, once an individual reaches adulthood, the probability of attaining an additional year of education rapidly diminishes. If an individual was deprived of education during childhood, this deprivation can be identified through indicators of years of education throughout the individual's lifetime. When we relax the information constraints in a way that allows us to capture many dimensions of deprivation, we are able to paint a more detailed picture of the deprivation that an individual experiences over time.

The tremendous progress Brazil has made in increasing income for the poor has been well documented (Lopez-Calva & Rocha, 2012). However, it is likely that an individual's ability to transform an increase in income into an increase in functionings is not uniform throughout the Brazilian population. It may be impossible for an individual to increase his/her well-being in some dimensions, due to market imperfections or complete lack of markets. For example, if a rural area does not have a sewage system, then it is impossible for an individual to achieve a basic level of sanitation regardless of improvements in income. If an individual lives in a favela where land rights are not defined, then it is difficult to improve housing conditions and accumulate basic household assets. Through the proposed methodology, I will break down, or "decompose", the gains made in each dimension by region, ethnic group and initial income level. This allows me to identify in which areas gains in income have led to gains in functionings and pinpoint where economic gain has not led to improvements in non-monetary indicators. This information helps the government pinpoint areas and populations that have not expanded human development as a result of economic growth.

The possibility of utilizing a plurality of information in the measurement of poverty has been limited in previous research because there has been no obvious way to aggregate across dimensions. In the past decade there have been new insights in theoretical research on the measurement of poverty that have attempted to capture many dimensions in the aggregation of poverty. Bourguignon and Chakravarty (2003) provide the first measurement of multidimensional poverty that identifies poverty within each dimension. Their measure identifies whether an individual is poor based on a union approach. In their approach, if an individual is poor in one dimension, they may be identified as multidimensionally poor. Alkire and Foster (2011) incorporate dimensionality into the identification step by using dual-cutoff[3] based on the counting approach proposed by Atkinson (2003). The first cutoff, the traditional poverty line, z, identifies if individuals are poor within a given dimension. The second cutoff, the dimensional cutoff, establishes the proportion of dimensions, k, in which an individual must be identified as poor to be multi-dimensionally poor.

This dual cutoff formalizes an identification strategy for chronic poverty that has been commonly employed. The measure introduces the dimensional monotonicity axiom that states, all else equal, if the number of dimensions in which a multidimensionally poor individual is poor increases, then poverty cannot go down. Once the multidimensionally poor have been identified, the measure censors dimensions in which non-multidimensionally poor individuals are deprived. This step ensures that measurement

[3] Note that the identification and aggregation strategy employed by Alkire and Foster (2011) is identical to the methodology in the chronic poverty paper by Foster (2007).

focuses on the poor, and deprivations of non-poor people do not affect the amount of poverty in a society. The multidimensional poverty index can then be aggregated using the FGT class of measures. The adjusted headcount index, M_0, represents the ratio of the number of dimensions in which a chronically poor individual is poor to the overall number of dimensions. M_0 can also be written as HA, where H refers to the headcount ratio and A represents the average deprivation share among the poor, or the number of deprivations experienced by the poor divided by the total number of dimensions for the poor. This provides information on how many people are poor and the breadth of deprivation among the poor. The adjusted poverty gap index, M_1, multiplies M_0 by G, the average poverty gap. The general class of AF measures can be written as $M_a = \mu\big(g^a(k)\big) for\ a \geq 0$. Due to the ordinal nature of many of the variables in the index, I constrain our measurement to the headcount and adjusted headcount ratio.

I use the Alkire-Foster methodology (referred to as AF) for a number of reasons. First, since the 2010 United Nations Human Development Report, the AF methodology has been the most common and widely recognized multi-dimensional poverty measurement. Its wide use makes my study comparable to a number of other studies that have utilized a similar methodology. There are a number of properties unique to the AF methodology that are particularly useful for my measurement. The AF is decomposable both by subgroups and dimensions. As a result, I can make comparisons of poverty between regions, across ethnic groups and by employment sector. This property is particularly useful since the main goal of my investigation is to pinpoint the individuals who have not received benefit from Brazil's rapid development. The dimensional decomposability allows me to compare deprivations within specific dimensions across subgroups of different individuals. Additionally, the AF identification strategy that is based on the joint deprivation allows me to target my analysis only on individuals who are multiply deprived. If an individual is deprived in just one dimension, it can be for a number of reasons including lack of access to a specific service or even the choice of the individual. The AF methodology allows for the use of ordinal, or even categorical, data in the measurement of poverty. This is important because many important indicators of well-being, including health and education, contain a great deal of information that cannot be conveyed with a cardinal variable.

Data

The data utilized in this study is from the Brazilian National Household Survey (PNAD). PNAD is carried out by the Brazilian Institute of Geography and Statistics (IBGE) on a yearly basis, except during census years. The survey investigates characteristics such as education, labor, income, and housing. It is representative for urban and rural areas, macro-regions and at the state level. In 2004 some rural areas from the North region were added to the sample frame.

I estimate poverty using three rounds of the survey: 1999, 2001 and 2009. I analyze the evolution of poverty in Brazil, comparing the income and multidimensional approaches.

Dimensions and Indicators

One of the criticisms of multidimensional poverty indexes is that the choice of dimensions and indicators is subjective. I am aware that the selection of indicators can be crucial to the determination of the magnitude and evolution of multidimensional poverty. My goal is not to capture the ideal or most accurate indicator of multidimensional poverty in Brazil. Instead I hope to show how a standard index of multidimensional poverty can be a good proxy for chronic poverty. In order to make the index as standard as possible, I choose common dimensions of poverty, and I assign equal weights to each dimension in the multidimensional poverty index. The indicators selected are those linked to important health, education and labor outcomes that are associated with poverty.

A total of seven indicators are used to measure poverty. These measures and associated deprivation criteria are given in Table 1.

Table 1 – Selected indicators and deprivation criteria

Indicator	**The household is considered deprived on that dimension if:**
Child School Attendance	if any school-aged (7-17) children is out of school
Years of schooling	if none of the household members has 8 years of schooling or more
Improved sanitation	if the dwelling has no access to the general sanitation network or septic tank
Safe water	if the dwelling has no access to piped water provided by the general network of distribution, well or spring
Electricity	if the dwelling has no access to electricity
Shelter	if living in a shelter not constructed with masonry materials (like bricks and stones)
Assets	if the household does not own at least two of: i) refrigerator/freezer; ii) telephone/mobile; iii) clean cooking fuel stove (gas or electric cooker)

Many of these dimensions have direct policy relevance in Brazil. For example, the main Brazilian social program (*Bolsa-Família*) supports poor families under the condition that school-aged children are actually enrolled in school. In its current design, children 6 to 17 years old are eligible for the program. This means that poor families who are deprived on the child school attendance indicator are also likely excluded from the main social programs or, at least these programs are not being effectively targeted to all children. I chose a cutoff of eight years for years of education because this has been the mandatory schooling level in Brazil since 1971. The program "*Luz para Todos"* aims to provide free access to the electric network to all households in Brazil. If a household is deprived on this indicator, it means that the family lives in a region where very few public services are offered. The water variable tracks how Brazil is progressing in the *Água para Todos* program which aims to bring clean drinking water to all households in Brazil. Good health is fundamental to the *Bolsa-Família* program. Unfortunately, the PNAD dataset does not contain any variables that directly track health. Therefore, we include sanitation and access to clean drinking water as proxies for good health.

Results

In this section, I present the main estimates of the multidimensional poverty index in Brazil. First, I investigate the share of the population deprived on each dimension and evaluate the major challenges facing Brazil to reduce the structural components of poverty. I show the multidimensional headcount and adjusted multidimensional headcount for different values of k and compare these measures across time. I analyze the relationship between multidimensional and income poverty in order to separate chronically and transiently poor and the vulnerable. Finally, I investigate the evolution and characteristics of poverty by state.

Deprivation Rates by Dimension

Figure 1 shows the share of the population deprived on each dimension for the years 1999, 2001 and 2009. First, it is clear that the most common deprivations are sanitation and years of education in all three years. People without adequate sanitation constituted 38.0% of the population in 1999 and 29.6% in 2009. In 2001, 43.2% of the population lived in a household where no resident had completed primary school; this number shrank to 24.8% in 2009. Although the deprivation rate in education level is one of the highest, it had the most significant drop across the period, diminishing 18.4 percentage points, followed by the deprivation rate in assets which decreased 13.5 percentage points. Reductions in deprivations in shelter and child attendance were the most modest, dropping 4.6 and 4.7 percentage points, respectively. Finally, the temporal trends are encouraging. The percentage of people deprived on years of education is expected to keep decreasing while child attendance had one the lowest deprivation rates. Access to electricity is almost universal, and asset ownership is steadily progressing. The high levels of deprivation in sanitation and the relatively steady pattern in shelter remain concerns.

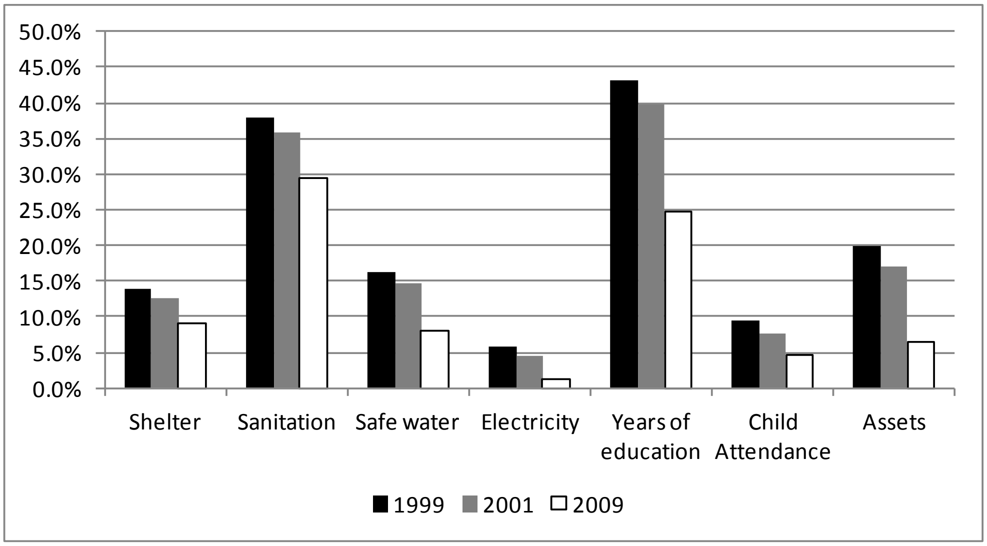


Figure 1 – Share of population deprived for each dimension, by year

The urban and rural patterns are shown in Figure 2. As expected rural regions exhibited much higher deprivation rates for all indicators, with the exceptions of electricity access and child school attendance. Sanitation remained the greatest concern even in the urban areas. The large divergence between rural and urban deprivation rates suggests that geographic location is a strong determinant of poverty. The order of the frequency of deprivations was the same for rural and urban areas and suggests that urban and rural areas experience the same pattern of deprivations, even though deprivation was more common in rural areas.

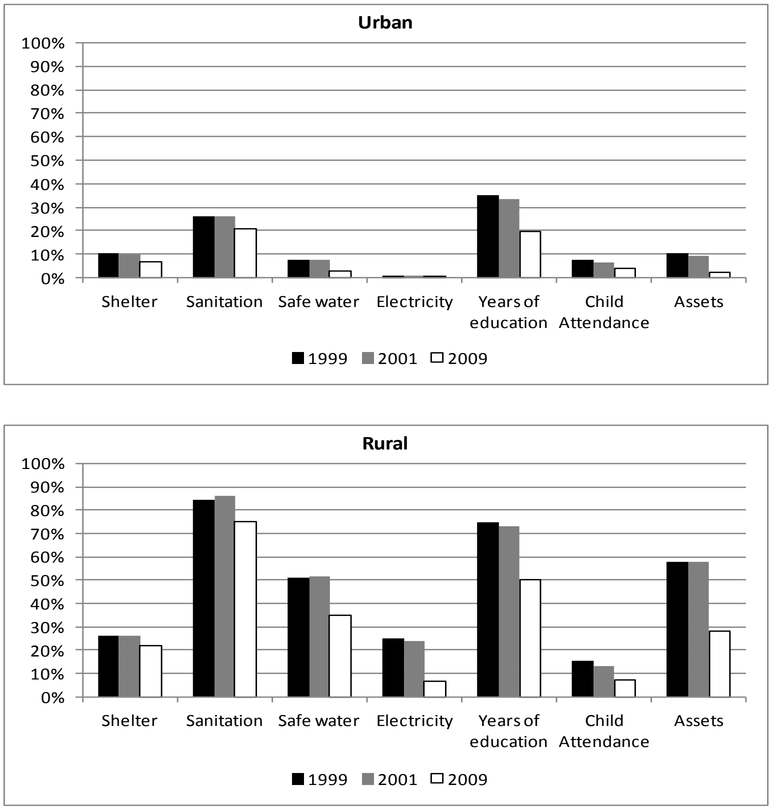
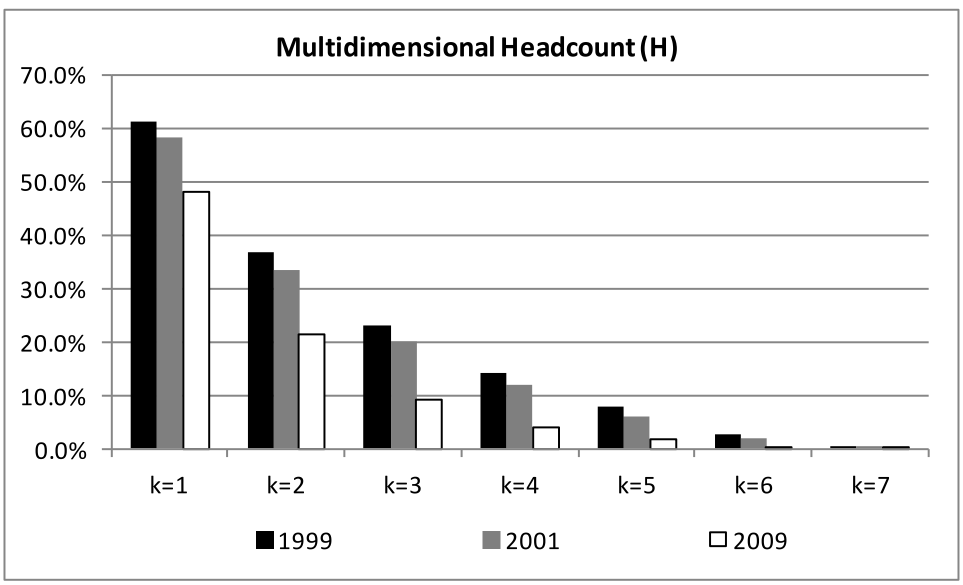


Figure 2 – Share of population deprived for each dimension, by year – Urban *versus* Rural

Multidimensional Poverty

I estimate the Multidimensional Headcount (H) and Adjusted Multidimensional Headcount (M_0) using equal weights for 1999, 2001 and 2009 and all *k* values. The H measure indicates the percentage of people who are deprived in *k* or more dimensions. 23% of the population was multi-dimensionally poor for *k*=3 in 1999. Multidimensional poverty shrank to 9.4% in 2009 (Figure 3). For *k*=4, the multidimensional headcount dropped from 14.4% in 1999 to 4.3% in 2009. The multidimensional headcount in Brazil diminished for all *k* values. Progress in reducing poverty especially for higher *k* values was also impressive. Brazil more than halved its headcount for all $k \geq 3$. For $k=5$, 6 and 7, multidimensional headcount shrank by 79%, 82% and 88% respectively.

The adjusted headcount ratio M_0, which is sensitive to frequency and breadth of poverty, fell greatly even for high k values. It is clear that the multi-dimensionally deprived individuals successfully reduced the number of dimensions on which they were poor. Brazil made great progress in reducing the deprivation rate of some indicators like years of education and assets, electricity and child attendance. However, Brazil has not been nearly as successful in improving sanitation and shelter.



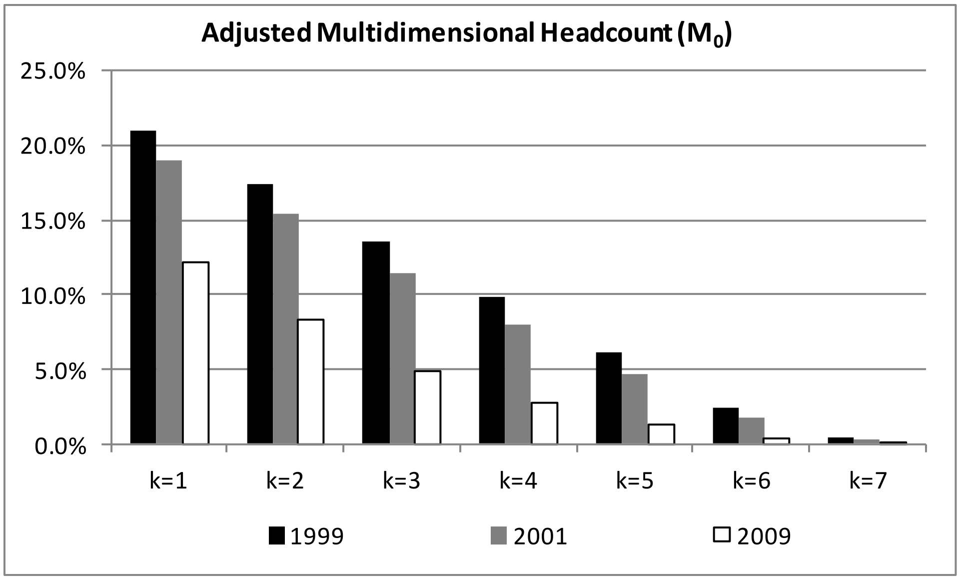


Figure 3 – Multidimensional Poverty for different *k* values

Figure 4 shows the evolution of the Multidimensional Headcount and Adjusted multidimensional headcount for urban and rural regions. It is clear that in rural areas the multidimensional headcount decreased for higher *k* values but changed little for *k*=1. Indeed, 84.4% (75%) of rural population was deprived in sanitation in 1999 (2009). Thus while Brazil was successful at reducing multiple deprivations, there was less success in eliminating all deprivations. It is possible to interpret this finding in many ways. First, some deprivations, such as household education, are sticky. It may take a long period of enhance policies to see improvement in education data. Second, the marginal effort required to reduce deprivations may increase as the breadth of deprivations decrease. Also, it can be noticed that both urban and rural areas made progress in reducing multidimensional poverty, but rural regions still have a significant share of population facing a sizable number of deprivations. The adjusted multidimensional ratio, however, shows a significant reduction in the breadth of poverty especially in rural areas.

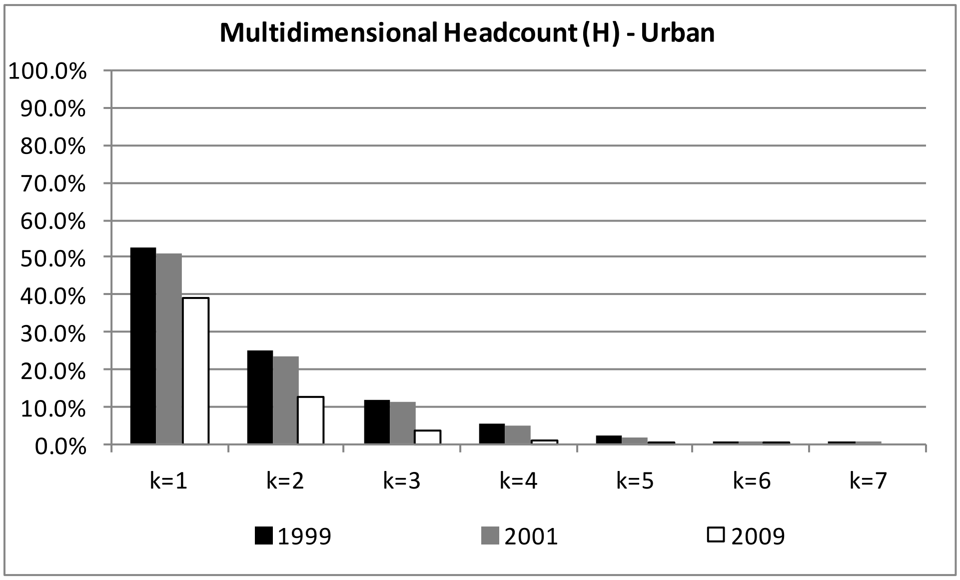
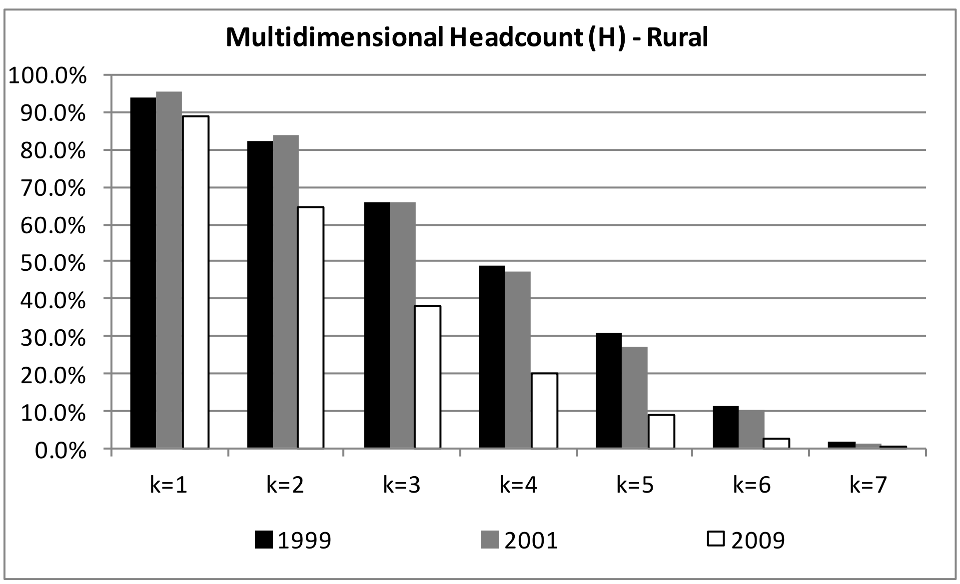
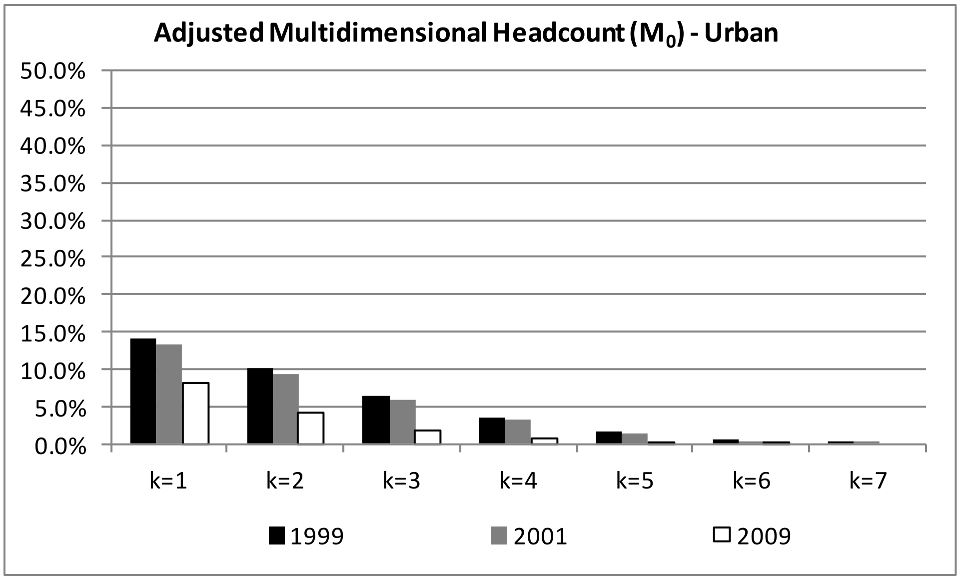


Figure 4 – Multidimensional Poverty for different *k* values – Urban *versus* Rural





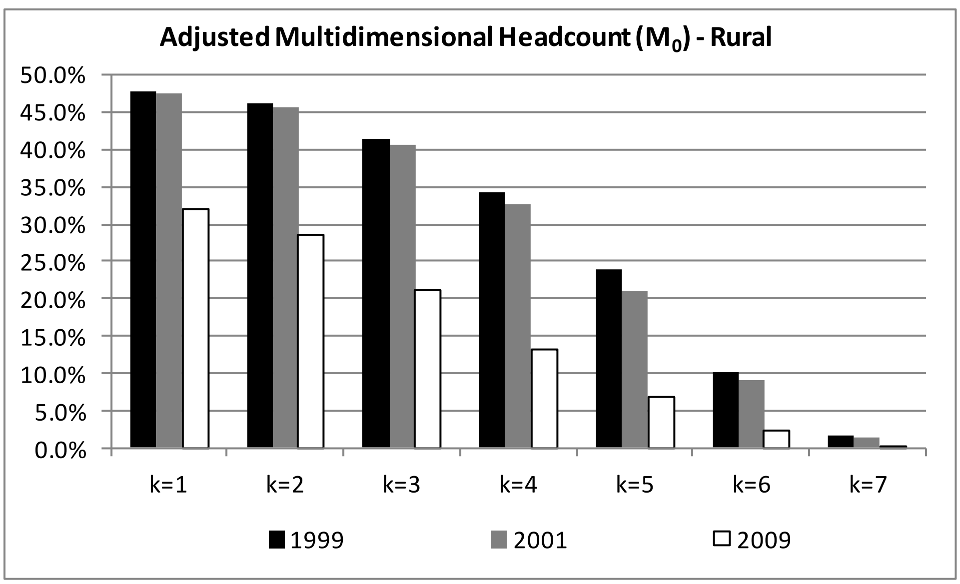
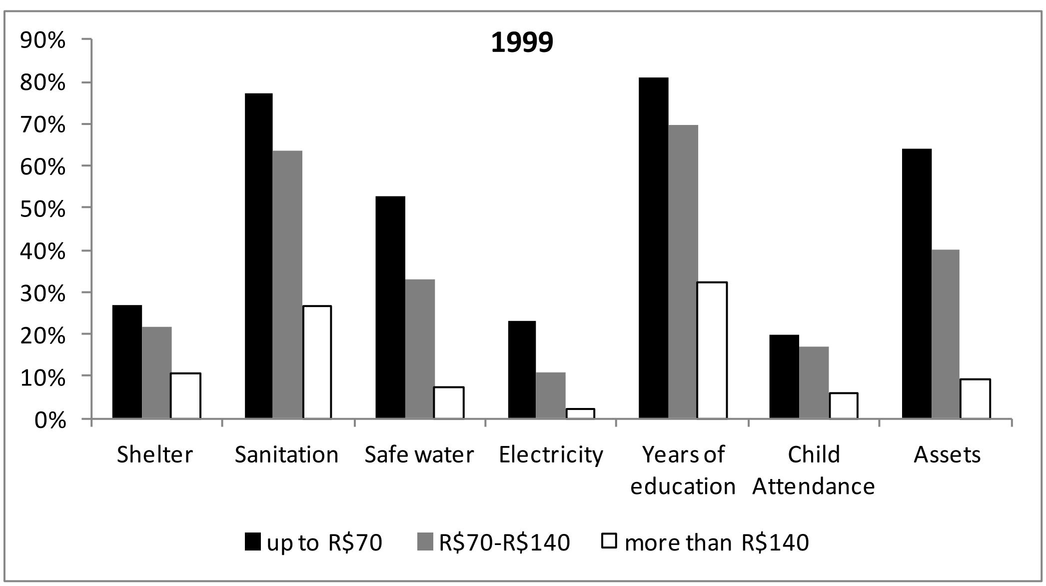


Figure 4 continued

Multidimensional and Income Poverty

Next, I analyze the relationship between multidimensional and income poverty. In order to be consistent with policies in Brazil, I use three income brackets: i) people living in households with less than R$ 70 per capita[4], which is the official extreme poverty line established by the Brazilian Government and also determines the target of the main and ambitious program to eradicate extreme poverty named *Brasil sem Miséria*; ii) people living in households earning between R$ 70 and R$ 140 per capita, which can be interpreted as the official moderate poverty line (for instance, households in this bracket are eligible for the main Conditional Cash Transfer program in Brazil - *Bolsa Família* - if they have children regularly attending school); and finally, iii) people living in households with more than R$ 140 per capita.

Figure 5 shows the deprivation rates for each dimension by different income groups. The deprivation rates for all dimensions dropped in all income groups from 1999 to 2009. Access to adequate sanitation and safe water increased more for the less income wealthy.



[4] They are 2010 values. INPC (National Consumer Price Index) was used as the deflator.

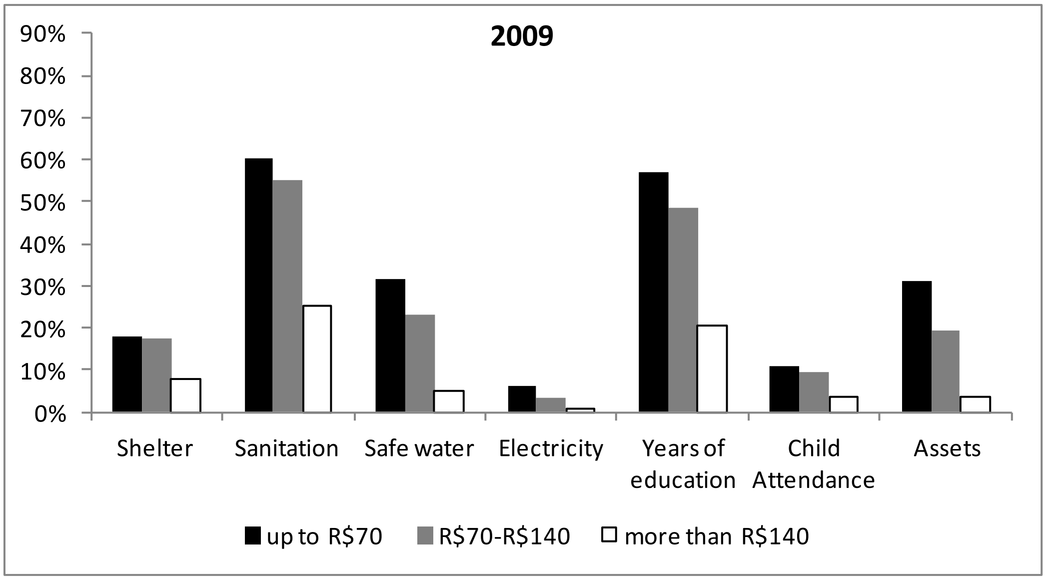


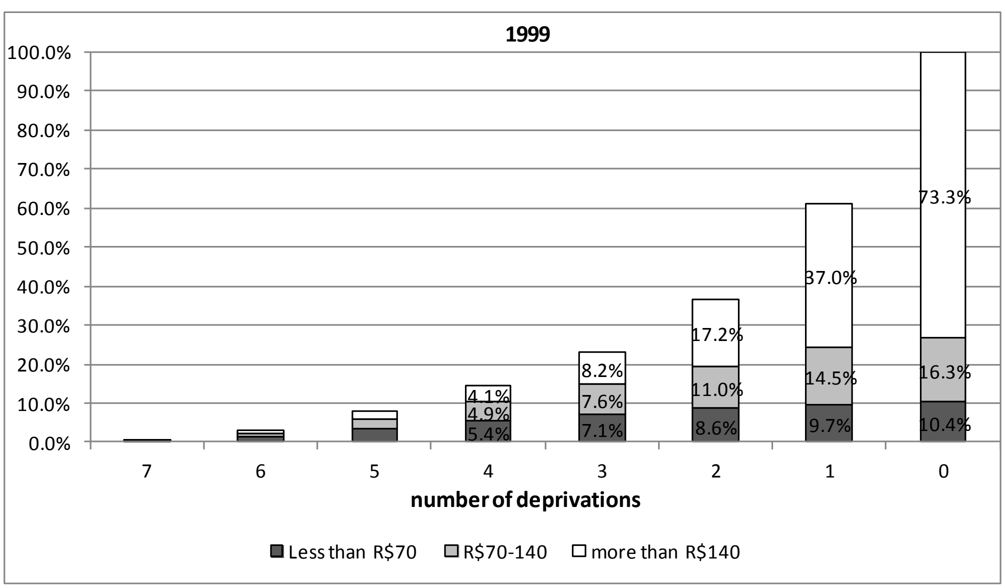
Figure 5 – Deprivation rates by income brackets

Income poverty decreased over the decade in Brazil. Before 2004, multidimensional poverty was decreasing more rapidly than income poverty. Since then, income poverty reduction picked up. While the multidimensional headcount changed from 14.4% in 1999 to 11.9% in 2001 and 4.3% in 2009, extreme income poverty remained constant from 10.4% in 1999 to 10.5% in 2001 then decreased to 5.1% in 2009.

I investigate the composition of multidimensional poverty and income poverty for each *k*. In Figure 6, each bar represents the multidimensional headcount poverty for a specific *k*. I split the multi-dimensionally poor into: income extreme poor (less than R$ 70 per capita), income moderate poor (R$70 to R$ 140 per capita) and income non-poor (more than R$ 140 per capita). In 1999, 14.4% were multi-dimensionally poor using *k*=4. Out of this group, 5.4% were income extreme poor, 4.9% were income moderate poor and 4.1% were not considered income poor. That means that 37.5% of the multi-dimensionally poor were considered extreme income poor. Using *k*=3, 30.8% of the 23%

of individuals who were considered multi-dimensionally poor were extremely income poor.

Figure 6 shows that multidimensional and income poverty decreased simultaneously over the decade. As a result the composition of multidimensional and income poverty changed. Using k=3, I observe that 31% of those who were multi-dimensionally poor in 1999 were also extreme income poor. In 2009, 20.2% of the multi-dimensional poor were also extreme income poor (Figure 7). The trend is similar when I analyze the composition of those who were extreme income poor; 69% of extreme poor were considered multi-dimensionally poor in 1999, while this number was only 37.1% in 2009. Figure 7 describes this evolution in a matrix format. The percentage of people who simultaneously lived with less than R$70 per capita and were deprived in at least three dimensions dropped significantly due to both reduction in deprivation rates and income extreme poverty.



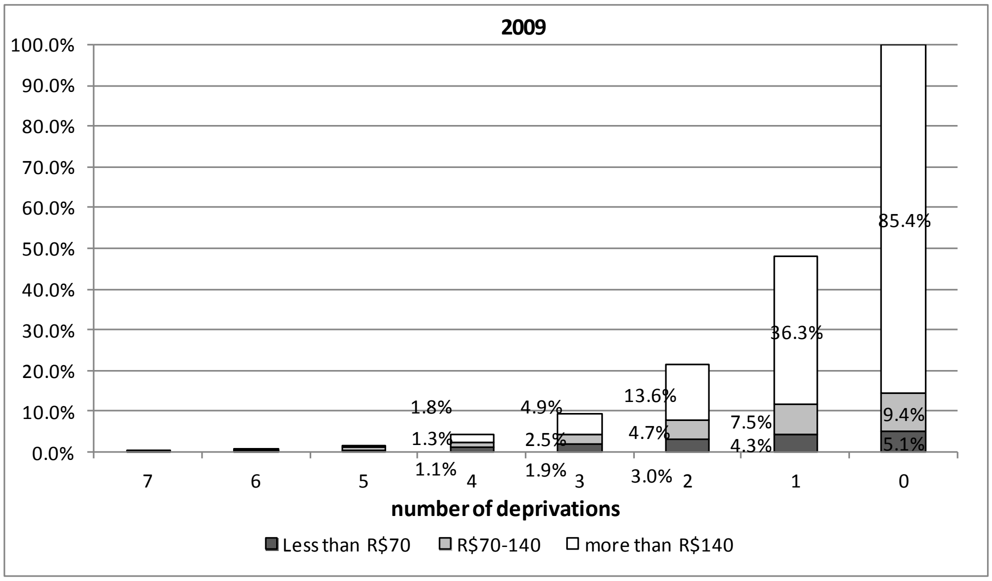


Figure 6 – Cumulative distribution of population by number of deprivations and household per capita income

1999	Equal or more than 3 deprivations	Less than 3 deprivations
More than R$ 140	8.2%	65.1%
R$70-140	7.6%	8.7%
Less than R$ 70	7.1%	3.2%

2009	Equal or more than 3 deprivations	Less than 3 deprivations
More than R$ 140	4.9%	80.5%
R$70-140	2.5%	6.9%
Less than R$ 70	1.9%	3.2%

Figure 7 – Matrix Multidimensional poverty *versus* household per capita income brackets

Figure 7 illustrates the usefulness of multidimensional poverty in providing additional information. In 2009, over half of the individuals experiencing multidimensional poverty were not identified as income poor. If social programs were targeted only using information provided by income, the government would neglect a large part of the population that is deprived of the goods and services that the social programs are attempting to provide. Additionally, more than half of the individuals identified as extreme poor are not multi-dimensionally poor. Many of these individuals likely have low incomes in 2009 for reasons that may have little to do with underlying deprivations. They may have experienced a seasonal income shock, have misreported income, or be on vacation during the month in which income was reported. It would be inappropriate to target social assistance programs to individuals who are not truly deprived.

To investigate the changing composition of poverty—and assuming *k*=3 as a reasonable cutoff to define people who are multi-dimensionally poor[5]–the population is categorized as follows. *Severe poor* are those who are simultaneously multi-dimensionally poor and extreme income poor. People who face extreme income poverty are less likely to leave this condition the higher the number of dimensions on which they are deprived. Many of those dimensions like assets, education and child attendance, have been shown to be determinants of poverty traps (Carter & Barrett, 2006). This class of poverty is both broad in terms of dimensions and deep in terms in lowness of welfare. *Moderate poor* are individuals who are multi-dimensionally poor but located between the moderate and extreme income poverty line. The *vulnerable by deprivation* are those who live above the poverty line but are still deprived on several dimensions. The *transiently poor* are not multi-dimensionally poor in spite of living below the moderate poverty line.

[5] Although the selection of k is discretionary and can potentially change the share of population categorized in each group, choosing different k values does not change the overall pattern of poverty evolution and composition or the key messages derived from it.

This group is more affluent in social indicators and has a higher probability to escape poverty; its current status is likely to be just transitory. Finally, the *better off* are those who are neither income poor nor multi-dimensionally poor.

Figure 8 illustrates how these groups evolved over time. *Severe* poverty experienced a sizeable reduction of 79 percent in the period, from 7.1 percent in 1999 to 1.5 percent in 2011. *Moderate* poverty also decreased significantly, from 7.6 percent to 1.8 percent, over the period. The *vulnerable* by *deprivation* dropped by a relatively small amount, from 8.2 percent to 4.1 percent. Although deprivation rates have been falling, some income poverty leavers are still multi-dimensionally poor; this explains the lower variation in this group. Finally, the proportion of *transiently* poor dropped only slightly from 11.9% to 10.1% over the decade. Once again, this population likely does not have latent well-being that should be characterized as poor. Their incomes may be low due to seasonal variation, short-term income losses, under-reporting or measurement error. If social programs are targeted based on income alone, the transiently poor population represents “errors of inclusion” while the vulnerable population represents “errors of exclusion”. The overall evidence suggests that individuals at the lower end of the distribution in Brazil experienced significant improvements in well-being.

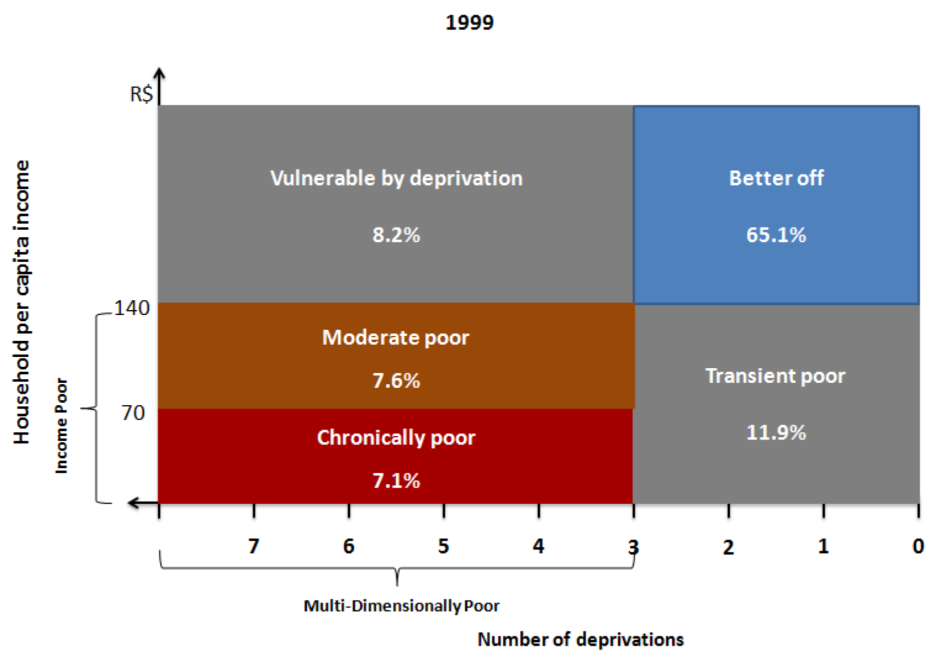
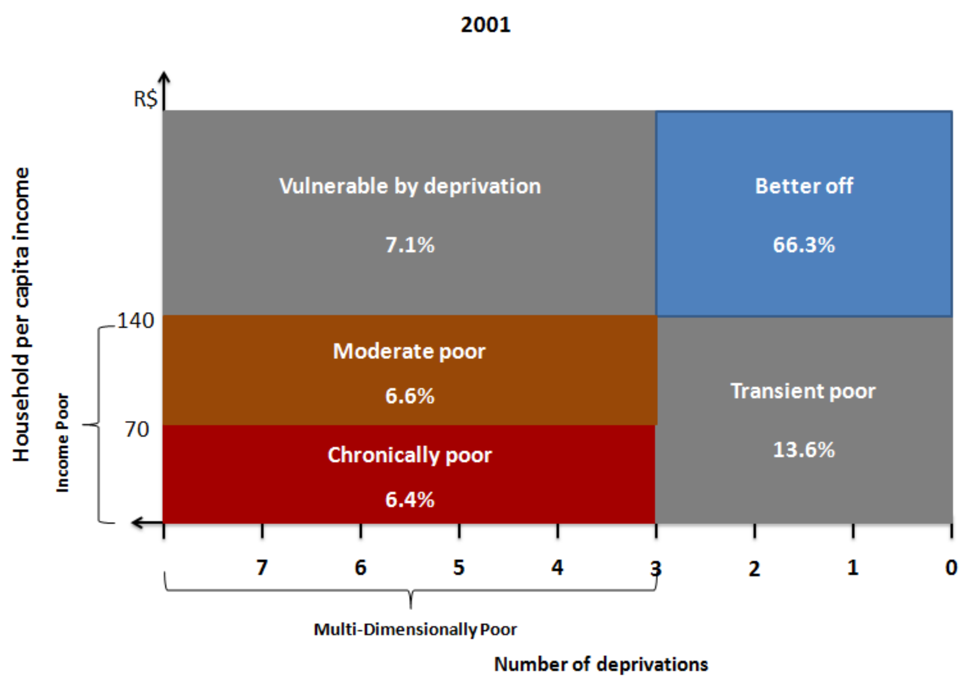


Figure 8 – Matrix multidimensional and income poverty



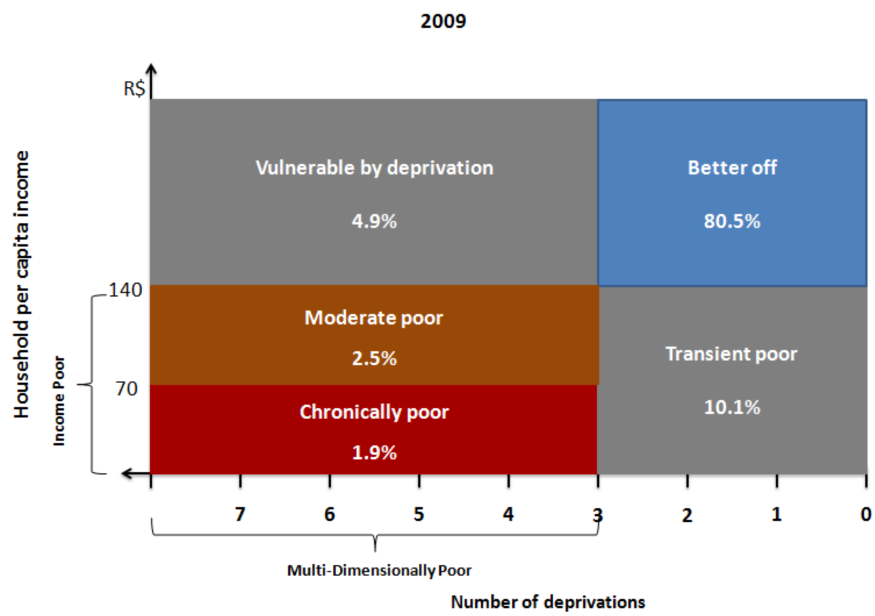
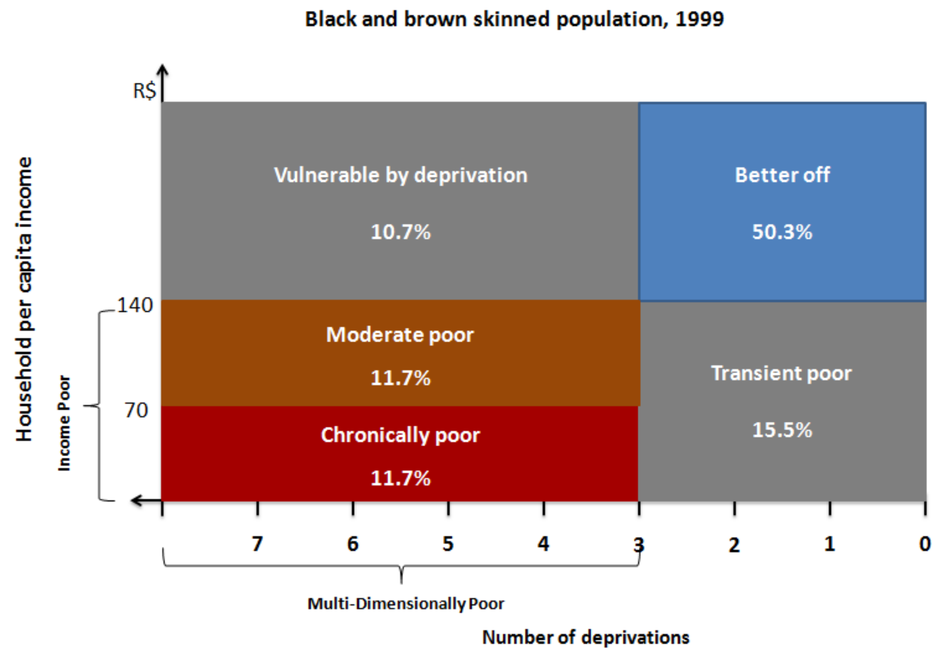


Figure 8 – continued

Another important issue is to analyze the poverty patterns of different groups of society. The black and brown skinned population experience significantly higher poverty and vulnerability rates (Figure 9). The good news is that chronic and moderate poverty dropped dramatically. The share of population under poverty and vulnerability was converging to the overall average.

Figure 10 shows poverty and vulnerability profiles for people below the age of 18. Younger people also had higher income and multidimensional poverty than the rest of the population. This may be explained by lifecycle effects and because Brazil has a generous pension system and intergenerational transfers that benefit most of the older people. In Brazil, the payouts from the social assistance program are linked to the minimum wage. Over the period of this study the minimum wage increased 5.8% annually, in real terms. As a result, many of the social assistance programs increased their payouts. The majority of these beneficiaries were older individuals. Meanwhile, social programs and transfers that directly benefited children had a much lower budget share compared to those eligible for old people.



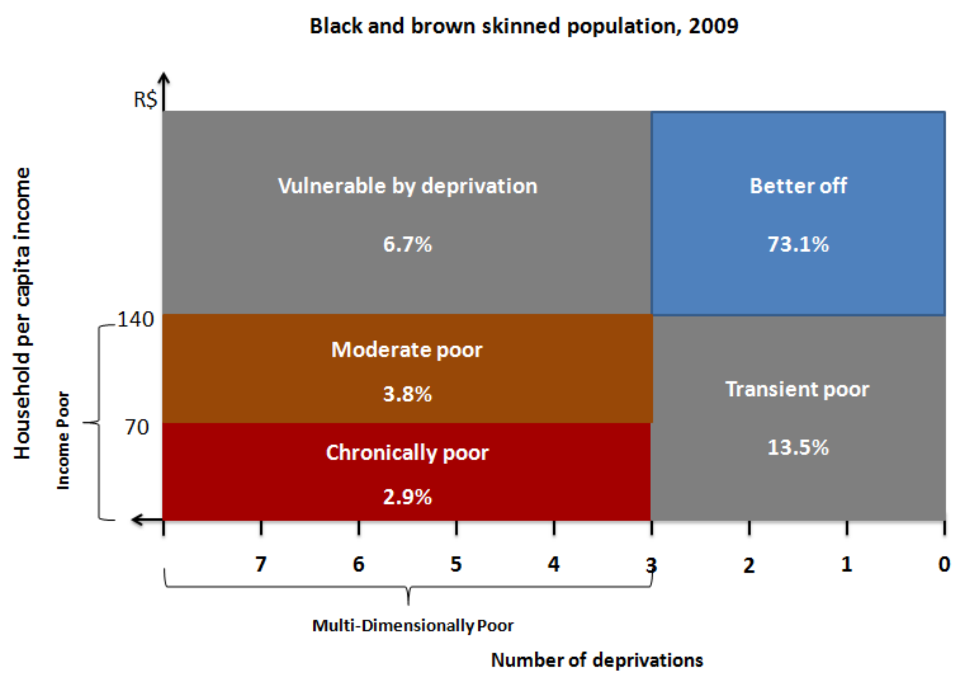
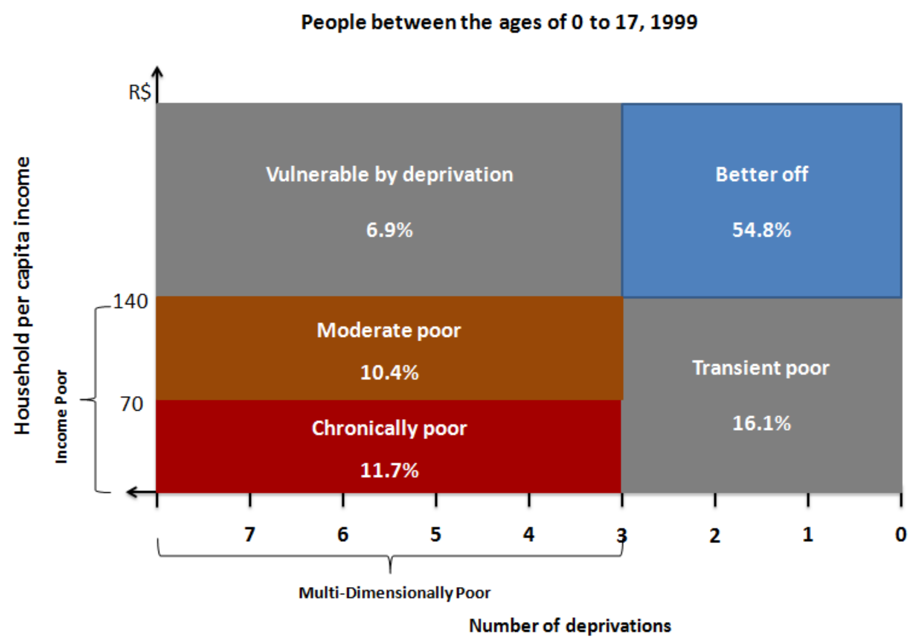


Figure 9 – Matrix Multidimensional and income poverty - Black and Brown skinned population



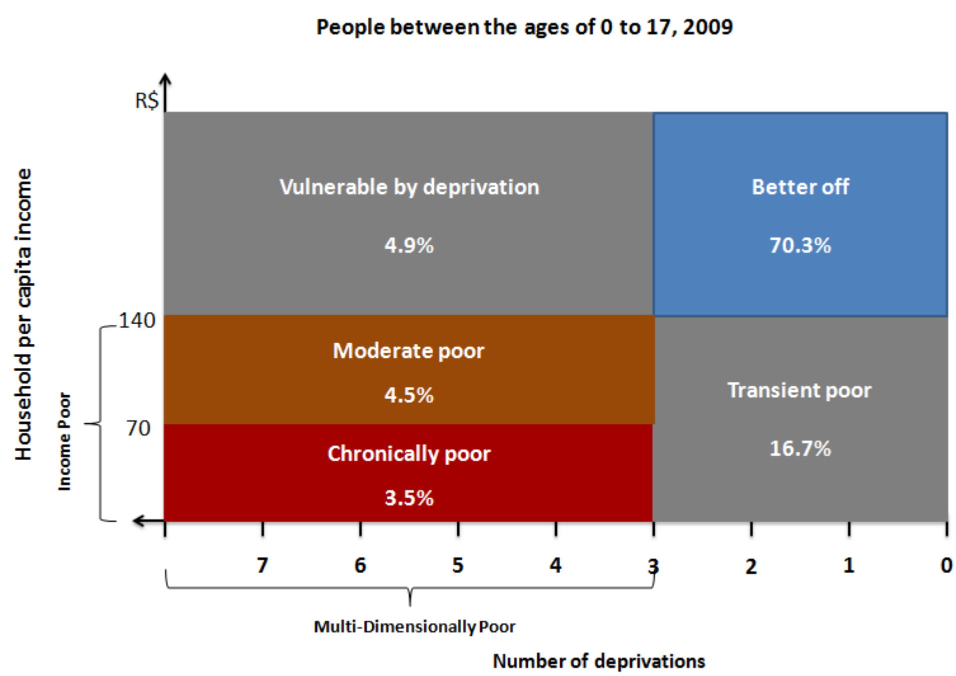


Figure 10 – Matrix Multidimensional and income poverty – people between the ages of 0 to 17

It is useful to examine how each of these groups faired dimension by dimension (Figure 11). Households who are multi-dimensionally poor are more likely to be deprived in each of the dimensions. Surprisingly, households who are vulnerable by dimension are more likely to be deprived of shelter than households who are multi-dimensionally poor and income poor. The chronically poor, moderate poor and the vulnerable all had very high frequencies of deprivation in sanitation and years of education. Among the multi-dimensionally poor, higher income does not lead to substantially lower rates of deprivation in sanitation, years of education and shelter. The transiently poor are much less likely to be deprived in every dimension than the multi-dimensionally poor.

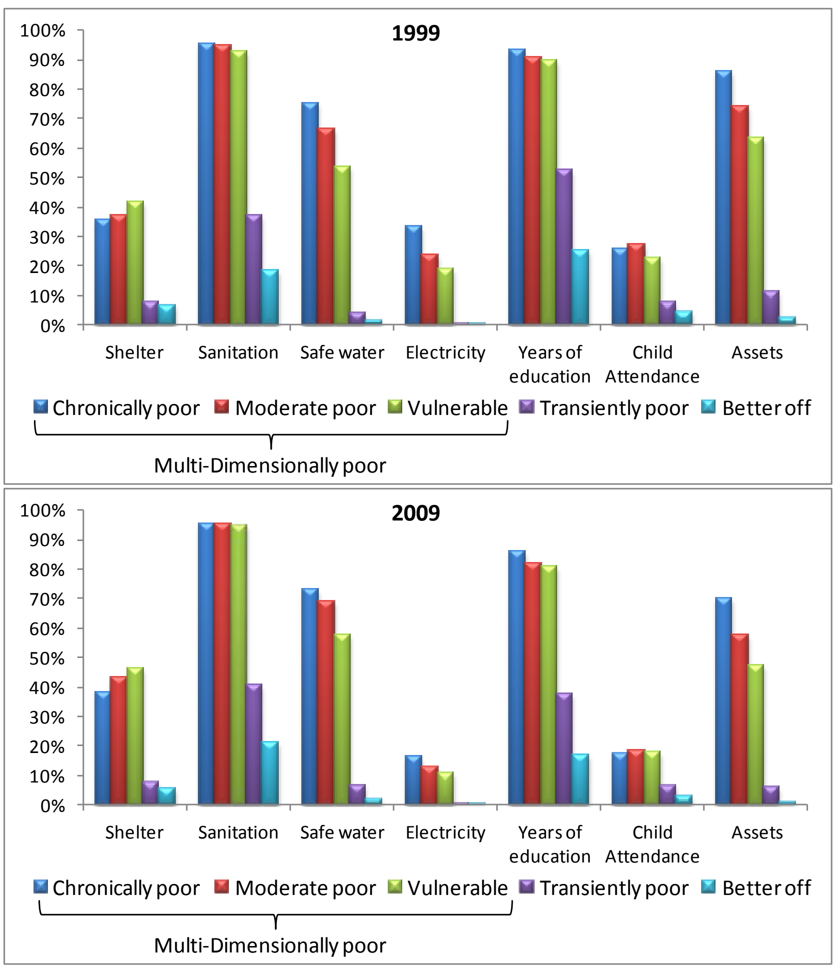


Figure 11 – Deprivation rates by groups

Income Poverty and Multidimensional Poverty by States

While Brazil is a country with a federalist government, it is also important to analyze differences between the states and the major challenges for each of them. Figure 12 shows income and multidimensional poverty headcounts for 1999 and 2009. I note a high correlation between income and multidimensional poverty in both years. Also, there was a high correlation between income and multidimensional poverty reduction (Figure 13). The states with the highest initial poverty level were those with the highest reduction during the decade.

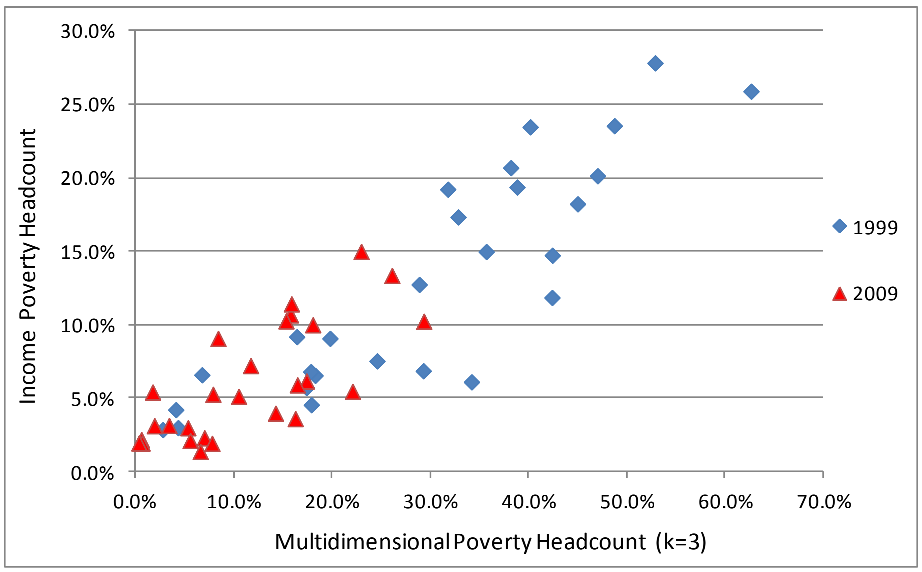


Figure 12 – Income and Multidimensional Poverty – 1999-2009

Figure 13 illustrates the multidimensional poverty convergence between states over the 1999-2009 period. It is clear that the states with the highest initial poverty rates experienced the most rapid poverty reductions. Ceará (in the Northeast region) and Amapá in the (North region) made relatively sizable progress in multidimensional poverty reduction. On the other hand, Alagoas, Piauí (in the Northeast), Acre and Roraima (in the North) had multidimensional poverty headcount rates that decreased less than expected, compared to similar states.

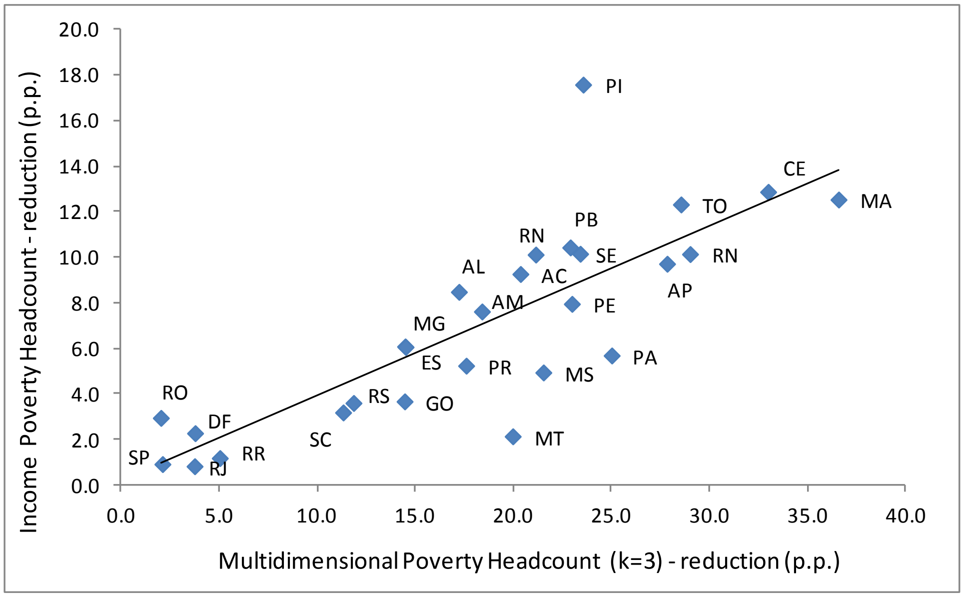
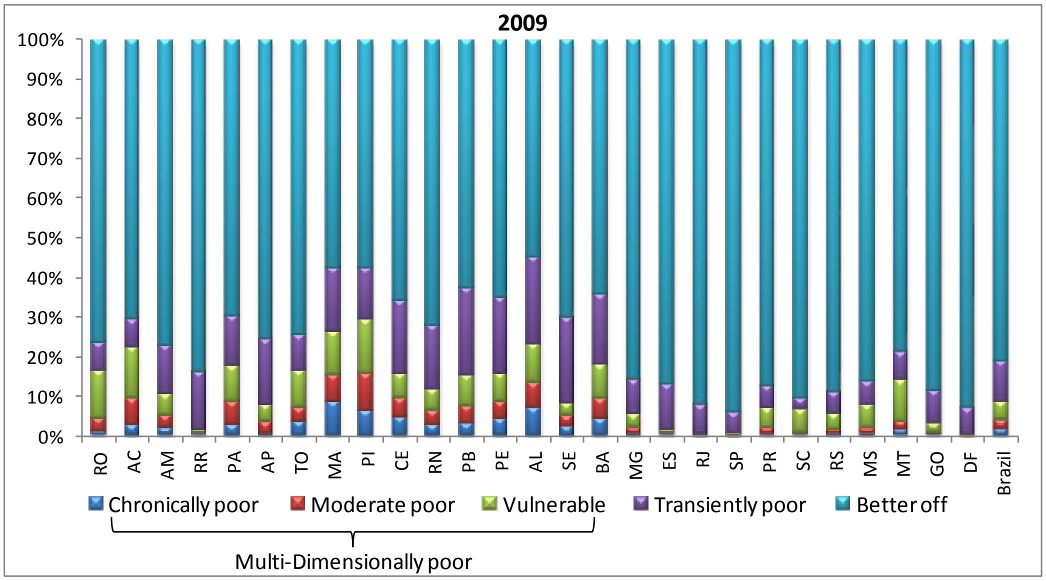


Figure 13 – Income and Multidimensional Poverty reduction (p.p.) – 1999-2009

Figure 14 shows the distribution of the defined groups of poverty for each state. Poverty fell during the period in all states, particularly the poorest ones. While chronic and moderate poverty significantly decreased in all states, the specific type of poverty that was most common varied by region. In rich states like São Paulo, Rio de Janeiro and Distrito Federal multidimensional poverty was practically zero. These states should focus on reducing transient poverty. States from North, South and Center-West regions should focus on reducing vulnerability. In the Northeast chronic, moderate and transient poverty all remain of great concern.



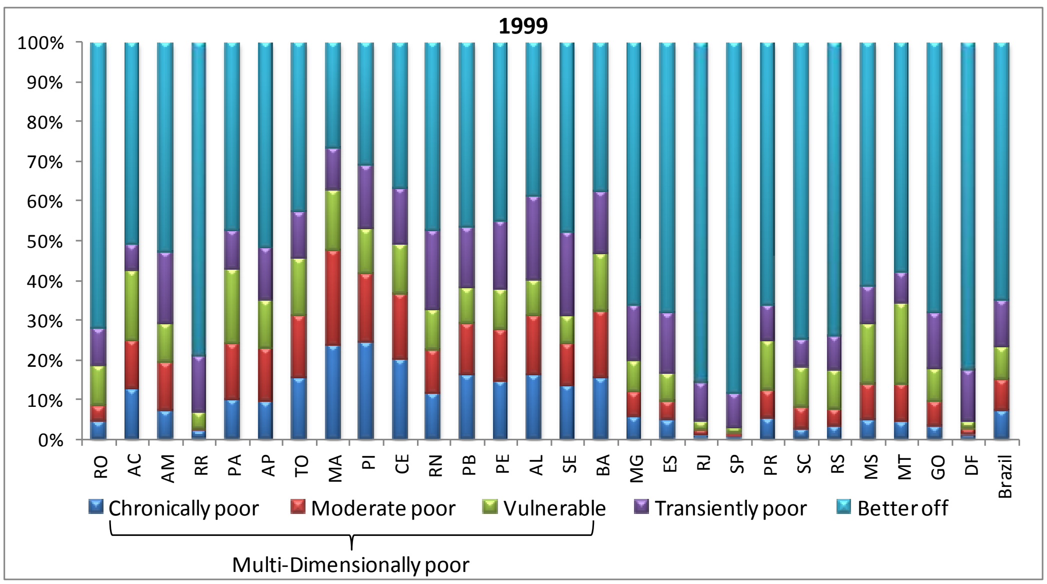


Figure 14 – Distribution of population by States

Figure 15 shows the contribution of each social dimension to the intensity of multidimensional poverty (using k=3) by states. Again, it is clear that sanitation and years of schooling are the major challenges. However, deprivation in shelter seems to be an issue in North, South and Southeast regions.

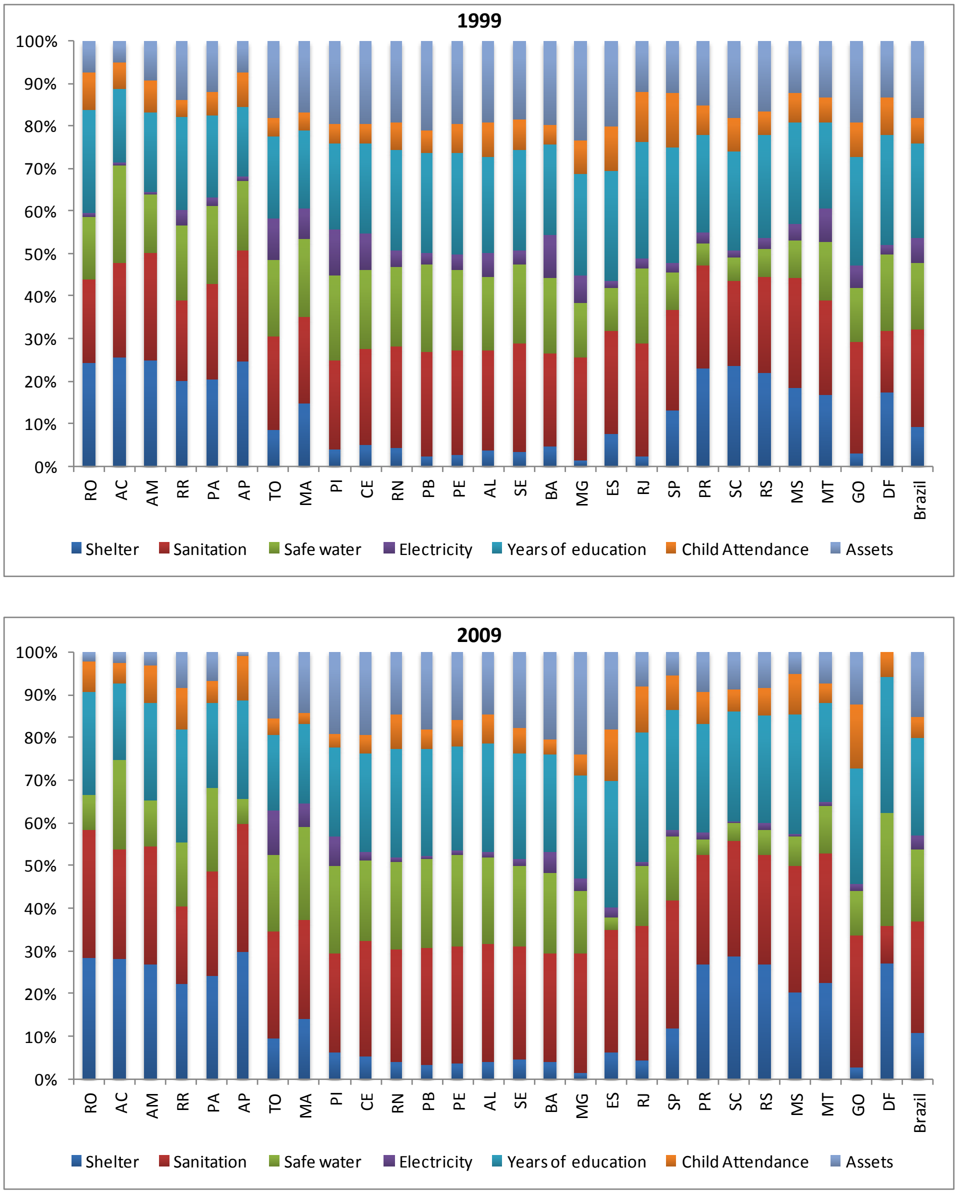


Figure 15 – Contribution of each dimension to the intensity of multidimensional poverty by States

Checking Robustness of Chronic and Multidimensional Poverty using Synthetic Panels

In the introduction to this paper, I asserted that the incorporation of many dimensions into the identification step of poverty measurement would provide a better proxy for long term well being and hence be a more accurate predictor of chronic poverty. In this section, I attempt to validate this approach by investigating how well multidimensional poverty proxies chronic income poverty. To do this, I compare the probability that poor persons remains in poverty given that they are multi-dimensionally poor or not multi-dimensionally poor. If a multi-dimensionally poor individual is more likely to remain in poverty over two periods, then multi-dimensional poverty provides a more informed proxy of chronic poverty than static monetary measures.

Ideally, I would utilize panel datasets to compare transition matrices for individuals who are multi-dimensionally poor vs. multi-dimensionally non-poor. Unfortunately, there are no Brazilian panel datasets that contain the variables necessary to accurately measure poverty. Instead, I use the methodology suggested by Lanjouw et al. (2011) and validated by Cruces et al. (2012) to construct a synthetic panel from a series of cross sections. I construct a synthetic panel with two periods, from 2003 to 2009, when Brazil experienced a sizeable reduction in moderate and extreme poverty[6]. I use the round of 2003 as the baseline and calculate the predicted income for 2009. Because I need to estimate the panel on the individual level, I only rely on estimating the *lower bound* on mobility by assuming perfect correlation between error terms[7]. Once people in 2003 are classified by multidimensional poverty status (MPI) and their predicted income in 2009, I can calculate how multidimensional poverty is associated with the probability of remaining in poverty.

For individuals in the synthetic panel, I calculate the probability they are income poor in 2009 given they are income poor in 2003. Then, I examine the probability an

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[6] The synthetic panels in this paper are based on the synthetic panels calculated in Fruttero, Castaneda, Lopez-Calva & Lugo (2012). Many thanks to Andres Casteneda for sharing his synethic panels.
[7] The *upper bound* only gives us estimates of movements in and out of poverty by fraction of people. I cannot obtain the predicted income for each individual.

individual remains poor for individuals who are MPI poor and MPI not-poor in 2003. My hypothesis is:

$$P(Poor\ 2009 = 1 | Poor\ 2003 = 1, MPI\ 2003 = 1)$$
$$> P(Poor\ 2009 = 1 | Poor\ 2003 = 1, MPI\ 2003 = 0)$$

The null hypothesis is:

$$P(Poor\ 2009 = 1 | Poor\ 2003 = 1, MPI\ 2003 = 1)$$
$$= P(Poor\ 2009 = 1 | Poor\ 2003 = 1, MPI\ 2003 = 0)$$

Table 2 shows the probability of remaining in poverty from 2003 to 2009 for those who were poor in the initial period given the individual was or not MPI (k=3) poor in 2003. My hypothesis is confirmed and is significant at the 95% confidence level. I check the robustness of my estimates using probit, logit and linear probability models. All models generate the similar results. The results remain robust to all specifications and poverty levels.

Note that the extreme IPEA line provides the least significant result. It is possible that many households with income below the extreme IPEA poverty line have low incomes because of transitory shocks to income or errors in reporting. It is possible that many individuals identified as “extremely poor” do not have extremely low latent well-being. Therefore, a measurement that better captures latent well-being may not improve the identification of poverty in this extreme category.

For example, using a poverty line of R$140 a month, people who were MPI poor (k=3), that is, they were deprived on 3 or more dimensions, had a probability of remaining in poverty 12.2 percent higher than those who were not MPI poor (47.3% versus 35.1%). That means that if an individual was multi-dimensionally poor in the first period, she is over 35% more likely to be chronically poor than if she was not MPI poor. Using international poverty lines, such as the $2.5 a day PPP, the multidimensionally poor were 45% more likely to remain in poverty (16.2 percent higher).

Table 2 - Probability of remaining in income poverty conditional to initial multidimensional poverty status (k=3)

Poverty line	Probability of remaining in poverty if not MPI (1)	Probability of remaining in poverty if MPI (2)	Difference (3) = (2)-(1)	(3)/(1)	(2)/(1)
R$140 a month	35.1%	47.3%	12.2%	34.8%	1.35
R$ 250 a month	42.2%	68.2%	26.0%	61.5%	1.61
Extreme IPEA	39.6%	41.2%	1.7%	4.2%	1.04
Moderate IPEA	39.6%	61.4%	21.8%	55.2%	1.55
$ 2.5 a day	35.8%	52.0%	16.2%	45.3%	1.45
$ 4 a day	42.7%	69.6%	26.9%	63.0%	1.63
$10 a day	68.4%	93.7%	25.3%	37.0%	1.37

Table 3 reports similar results, but in this case I consider MPI poverty as deprivation on at least four dimensions. In general, results are slightly larger than those registered using k=3, with the exception of using a $10 a day poverty line.

Table 3 - Probability of remaining in income poverty conditional to initial multidimensional poverty status (k=4)

Poverty line	Probability of remaining in poverty if not MPI (1)	Probability of remaining in poverty if MPI (2)	Difference (3) = (2)-(1)	(3)/(1)	(2)/(1)
R$140 a month	36.3%	51.0%	14.7%	40.6%	1.41
R$ 250 a month	45.2%	73.0%	27.8%	61.5%	1.62
Extreme IPEA	39.0%	43.5%	4.4%	11.4%	1.11
Moderate IPEA	42.1%	65.4%	23.4%	55.5%	1.55
$ 2.5 a day	37.6%	55.9%	18.3%	48.6%	1.49
$ 4 a day	45.7%	74.7%	29.1%	63.6%	1.64
$10 a day	70.6%	96.1%	25.4%	36.0%	1.36

These results suggest that a multidimensional poverty analysis does indeed add information in the identification of the chronically poor. During a period of sizeable reduction in poverty, people who are income poor and multi-dimensionally poor had a significantly lower probability to leave monetary poverty.

One could ask whether these results were driven by the impact of a single dimension. If a specific dimension is associated with "chronicity" and not the intersection of several dimensions, other uni-dimensional indicators would be able to capture chronicity efficiently. In order to investigate this issue, I ran regressions of the probability of remaining in poverty on MPI status, excluding people who are deprived on each specific dimension. If the result was totally driven by that single dimension, I expect that MPI status would not lead to higher probabilities of being poor in 2009. Table 4 (for k=3) and Table 5 (for k=4) report the impact (in terms of change in percentage points) of MPI status on the probability of remaining below the monetary poverty line. MPI status still explains a significant difference in the probabilities of people remaining in income poverty. The impact of MPI diminished the most in the regression in which people deprived on assets were excluded.

Table 4 – Impact on probability (p.p.) of remaining in income poverty conditional to initial multidimensional poverty status (k=3) and for people not deprived on specific dimensions

Poverty line	MPI (k=3) - All	MPI (k=3) - not deprived on Shelter	MPI (k=3) - not deprived on Sanitation	MPI (k=3) - not deprived on Safe water	MPI (k=3) - not deprived on Electricity	MPI (k=3) - not deprived on Education	MPI (k=3) - not deprived on child	MPI (k=3) - not deprived on Assets
R$140 a month	12.2%	11.4%	7.6%	7.0%	10.6%	5.9%	12.2%	3.5%
R$ 250 a month	26.0%	27.7%	28.0%	18.1%	24.3%	20.8%	26.4%	15.7%
Extreme IPEA	1.7%	0.2%	-0.3%	-0.7%	0.8%	-6.2%	1.5%	-6.5%
Moderate IPEA	21.8%	22.0%	24.6%	15.5%	20.6%	15.2%	22.5%	14.2%
$ 2.5 a day	16.2%	15.9%	16.0%	9.7%	14.6%	8.6%	16.5%	7.7%
$ 4 a day	26.9%	28.8%	28.7%	18.6%	24.9%	21.0%	27.3%	16.5%
$10 a day	25.3%	26.7%	24.4%	22.5%	24.7%	28.4%	25.8%	21.2%

Table 5 – Impact on probability (p.p.) of remaining in income poverty conditional to initial multidimensional poverty status (k=4) and for people not deprived on specific dimensions

Poverty line	MPI (k=4) - All	MPI (k=4) - not deprived on Shelter	MPI (k=4) - not deprived on Sanitation	MPI (k=4) - not deprived on Safe water	MPI (k=4) - not deprived on Electricity	MPI (k=4) - not deprived on Education	MPI (k=4) - not deprived on child attendance	MPI (k=4) - not deprived on Assets
R$140 a month	14.7%	13.3%	16.8%	9.3%	13.5%	9.5%	14.9%	4.9%
R$ 250 a month	27.8%	28.2%	33.8%	17.7%	26.8%	21.8%	29.1%	19.6%
Extreme IPEA	4.4%	2.1%	14.2%	2.5%	4.0%	-9.8%	4.3%	-4.7%
Moderate IPEA	23.4%	22.4%	30.0%	14.8%	22.8%	17.3%	24.6%	20.0%
$ 2.5 a day	18.3%	17.5%	22.2%	10.5%	17.1%	11.3%	19.1%	8.9%
$ 4 a day	29.1%	30.0%	33.5%	18.3%	27.6%	24.6%	30.2%	19.9%
$10 a day	25.4%	26.9%	27.5%	24.2%	25.5%	29.0%	25.7%	23.3%

An alternative exercise is to estimate the impact of deprivation in each dimension on the probability of remaining in poverty for those who are not MPI poor. Under the hypothesis that MPI, and not a single dimension, proxies "chronicity", the impact of each dimension should be small compared to the impact of being MPI poor. Tables 6 and 7 show the results. In general, the impact of being deprived on each individual dimension (and not MPI) is low compared to the impact of being MPI poor[8]. Therefore I conclude that the *intersection* of deprivations provided useful information that could not be gathered by looking at each of the dimensions independently.

Table 6 - Probability of remaining in income poverty conditional to each deprivation, for not M-poor (k=3)

Poverty line	MPI (k=3) - All	Shelter	Sanitation	Safe Water	Electricity	Education	Enrollment	Assets
R$140 a month	12.2%	-2.0%	-3.3%	-3.5%	2.9%	-0.6%	-2.3%	7.5%
R$ 250 a month	26.0%	-1.2%	2.7%	8.7%	19.6%	7.1%	2.7%	22.2%
Extreme IPEA	1.7%	0.6%	-3.9%	-4.4%	28.7%	-3.9%	-8.5%	-1.0%
Moderate IPEA	21.8%	-0.2%	1.3%	5.1%	-8.8%	5.6%	3.7%	17.4%
$ 2.5 a day	16.2%	-1.4%	-1.9%	-0.6%	-0.3%	0.5%	-0.4%	9.8%
$ 4 a day	26.9%	-2.3%	3.3%	9.4%	11.0%	7.3%	3.9%	22.9%
$10 a day	25.3%	-1.0%	10.5%	15.7%	20.7%	14.9%	10.0%	22.5%

[8] Note that assets form consistently the strongest dimension for predicting chronic poverty. This result supports the asset poverty trap argument of Carter and Barrett (2006).

Table 7 – Probability of remaining in income poverty conditional to each deprivation, for not M-poor (k=4)

Poverty line	MPI (k=4) - All	Shelter	Sanitation	Safe Water	Electricity	Education	Enrollment	Assets
R$140 a month	14.7%	-2.2%	-0.4%	1.6%	2.8%	1.1%	-1.8%	8.2%
R$ 250 a month	27.8%	-1.6%	7.4%	15.3%	20.9%	10.1%	4.7%	23.3%
Extreme IPEA	4.4%	-1.5%	-3.8%	-3.9%	11.8%	-3.7%	-8.0%	0.6%
Moderate IPEA	23.4%	0.2%	5.4%	11.0%	6.2%	8.5%	4.2%	18.5%
$ 2.5 a day	18.3%	-1.3%	1.4%	5.7%	2.1%	3.0%	0.6%	11.0%
$ 4 a day	29.1%	-1.9%	7.9%	15.8%	16.8%	10.5%	5.4%	23.6%
$10 a day	25.4%	2.6%	14.1%	19.5%	24.8%	16.7%	10.3%	23.4%

Policy Implications

Income as the Main Targeting Mechanism

Brasil sem Miséria is the main strategy for reducing chronic poverty in Brazil. The targeting mechanism of the strategy focuses on people living with a household income below R$70 per capita. *Brasil sem Miséria* aggregates several social programs in Brazil that can potentially benefit people who are deprived on several dimensions, even if they are not considered extremely poor according to the official criterion. Accordingly, *Bolsa Familia* also benefits individuals living with a household income below R$140 per capita a month. The policies attempt to expand social programs that increase productivity and access to basic services like education, health, electricity, and sanitation.

The main social programs that aim to guarantee a minimum income level, like *Bolsa Família* and *Brasil Carinhoso*, still use a target exclusively based on income. Additionally, within the scope of the *Brasil sem Miséria* program, R$70 is used as an extreme poverty line, and it determines the target for government anti-poverty actions. For instance, the mobilization of “Busca Ativa”, the inclusion of people in *Cadastro Único*, and the selection of people for social programs are basically based on income.

Eligibility for social programs under Bolsa Familia is determined by incomes that are reported by the potential recipient. There are a number of potential concerns to using self-reported income data as the inclusion criterion for social programs. First, there is a risk of moral hazard. Respondents may under-report their income in hope that they become eligible for the program. Second, there are great risks of measurement error when capturing self-reported income. Previous research suggests that poorer individuals have greater difficulty recalling their income over a period of time (Soares, Ribas & Soares, 2010). For example, it may be more difficult to recall income earned in the informal sector versus a regular salary in the formal sector.

Even if respondents provide accurate assessments of self-reported income, it still may be an imprecise criterion for targeting social programs. The decision to be included or excluded from the *Cadastro Único*, the list that determines inclusion in social programs, occurs only once every two years. As a result, it is very important that the criterion for inclusion captures notions of well-being that are persistent in nature. Previous evidence suggests that self-reported income may be a poor representation of long-term well-being. Ribas and Machado (2007) utilize pseudo-panels and estimate that approximately 27% of the urban poor, at any given period of time, are temporarily poor. Ribas and Machado (2008) use a short-term rotating labor force panel and find very high income volatility amongst the poor. They report that in 2005, 31% of individuals who are identified as poor are not poor a month later, and 50% of those identified as poor are not poor a year later. Moreover, within a given period of time, many non-poor individuals fall into poverty. Barros, Mendonça and Neri (1995) find that 15% of the population entered or exited poverty between 1982 and 1992. It is clear that self-reported income is a very unstable measure of well-being. According to Ribas and Machado's results[9], 50% of those who would be selected for *Bolsa Familia* in 2005 would not be included if the selection for the *Cadastro Único* was taken in 2006.

Multidimensional Targeting

In order to mitigate potential problems with targeting arising from self-reported income, Brazil has previously investigated using a multi-dimensional poverty index to validate the beneficiary list for *Cadastro Único*. In 2003, IPEA introduced the *Indice de Desenvolvimento Familiar* (IDF), which is a multi-dimensional index based on the United Nation's Human Development Index (Paes de Barros, de Carvalho, and Franco 2003). The main drawback of the IDF is that it does not identify an individual as poor or not poor. Instead, it aggregates across multiple dimensions in order to say "how poor" every individual is. This limits the use of the IDF as a selection criterion for a social program. Since the IDF was first proposed in 2003, new methodologies to identify *and* aggregate multidimensional poverty have been proposed (Alkire & Foster, 2011). In this paper I show how the advanced properties of the Alkire Foster Multidimensional Poverty Index can help the IDF accomplish the initial goal -- to provide a more accurate and stable picture of poverty in Brazil and better target social programs to deprived individuals.

[9] The poverty lines used in Ribas and Machado (2008) are slightly different than the selection criteria for Bolsa Familia.

Conclusion

In the past few years a lively debate has emerged about the appropriateness and usefulness of multidimensional poverty indices (Alkire & Foster, 2011; Ravallion, 2011). The view that poverty is multi-dimensional is shared by all parties in the debate. Even the strongest critics of multidimensional poverty advocate incorporating many dimensions into the aggregation step of poverty measurement. For example, the approach advocated by Ravallion (2011) aggregates each dimension of poverty into a dashboard where each of the dimensions is independent. The policy question is whether many dimensions of well-being should be incorporated into the identification step of poverty measurement (Alkire & Foster, 2012).

This paper provides strong evidence of the usefulness of incorporating the intersection of many dimensions into the identification of poverty. Like Ravallion (2012) I present a dashboard of many dimensions of poverty. However, a dashboard provides insufficient information for the targeting of social programs. The Ministry of Social Development in Brazil must find a way to identify the chronically poor in order to establish inclusion criteria for social programs. I show that targeting individuals with a multidimensional poverty measure, the targeting mechanism is between 11% and 61% more likely to identify individuals who are poor in two periods, compared to targeting with income alone. Each independent dimension of poverty provides some additional information useful in targeting the chronic poor. Most importantly, it is information embedded in the intersection of multiple deprivations that is most valuable in identifying the chronically poor.

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