Chronic Poverty
Research Centre

Working Paper

December 2010 No. 170

Vulnerability to poverty in Latin America

Empirical evidence from cross-sectional data and robustness analysis with panel data

Marcelo Bérgolo
Guillermo Cruces
Leonardo Gasparini
Andrés Ham

Center for Distributional, Labor and Social Studies (CEDLAS), Universidad Nacional de La Plata
and
National Scientific and Technical Research Council (CONICET)

What is Chronic Poverty?

The distinguishing feature of chronic poverty is extended duration in absolute poverty.

Therefore, chronically poor people always, or usually, live below a poverty line, which is normally defined in terms of a money indicator (e.g. consumption, income, etc.), but could also be defined in terms of wider or subjective aspects of deprivation.

This is different from the transitorily poor, who move in and out of poverty, or only occasionally fall below the poverty line.

www.chronicpoverty.or

Chronic Poverty Research Centre
ISBN: 978-1-906433-83-3

Abstract

This document presents a discussion of vulnerability estimates – defined as the risk of being poor in the future – in Latin American countries from both a conceptual and an empirical perspective, based on recent developments in the distributive literature. The document develops two main contributions. First, it presents cross-sectional vulnerability estimates (and their evolution over time) for 18 countries in the region, and compares their evolution with that of aggregate poverty rates. Second, based on longitudinal data for Argentina and Chile, the document carries out a validation exercise to assess how vulnerability measures fare as predictors of poverty at the aggregate and the micro levels, and compares their performance to that of other deprivation indicators. The main findings indicate substantial cross-country differences in vulnerability levels. Moreover, vulnerability measures provide good estimates of aggregate poverty trends. However, the validation exercise indicates that at the micro level there are sizeable misclassifications of households in terms of expected poverty. These results imply that vulnerability estimates should be complemented with information on shocks and aggregate trends for guiding focalised policy interventions.

Keywords: Poverty, Vulnerability, Latin America

Acknowledgements

The authors wish to thank Armando Barrientos for encouraging this work, and CPRC reviewers who provided valuable comments to earlier versions of this document, as well as participants at the 2010 CPRC Conference '10 Years of War against Poverty'.

Leonardo Gasparini is the director of the 'Centro de Estudios Distributivos, Laborales y Sociales, based at the Universidad Nacional de La Plata (UNLP), Argentina. Guillermo Cruces is CEDLAS' deputy director and a researcher at the National Scientific and Technical Research Council (CONICET). Marcelo Bérgolo and Andrés Ham are researchers based at CEDLAS and graduate students at the UNLP, both funded by CONICET scholarships.

Email: gcruces@cedlas.org

This document is an output from Chronic Poverty Research Centre (CPRC) which is funded by UKaid from the UK Department for International Development (DFID) for the benefit of developing countries. The views expressed are not necessarily those of DFID. The CPRC gratefully acknowledges DFID's support.

Contents

1 Introduction

A wide range of policy interventions in the developing world are guided by the fundamental objective of reducing poverty. These programs and policies are designed to tackle the different aspects, causes and manifestations of this multi-faceted and multi-dimensional problem. Some of the larger initiatives in Latin America consist of income safety nets, emergency and conditional cash transfer programs, aimed at reducing present deprivation and preventing its intergenerational transmission. While these dimensions of poverty are clearly inter-temporal, most of the distributive analysis and policy design processes in Latin America are based on cross sectional data and estimates. For instance, poverty profiles are routinely employed to target households considered to be in a precarious or vulnerable state. The reliance on ex-post outcomes, however, has been subject to an in depth analysis in the context of recent developments in the vulnerability literature (see, for instance, Chaudhuri, 2003, and the references at the end of this document). These studies have analysed the validity of mechanisms based on realised outcomes, the extent to which they account for the threat of future deprivation, and the viability of obtaining vulnerability estimates from cross-sectional data.

This line of research suggests that the risk of being poor and the actual state of poverty are two related but separate phenomena. At any given time, a number of non-poor households may be at high risk of falling into poverty in the next period; these households would be non-poor but vulnerable. On the contrary, there may also be households below the poverty line which are not vulnerable in this sense – their observed current poverty status reflects only a transient deprivation spell. Policy design and distributive analysis in general, should be able to distinguish both a household’s vulnerability to poverty and its current state of deprivation. These two related but distinct aspects of well-being prompt for different palliative measures. For instance, a two-tiered approach would reduce current poverty via income transfers targeted at poor households, and would direct social safety nets to minimise the risk of future poverty to those most vulnerable. This analysis is most relevant in the light of recent policy developments: a number of countries in the region have established poverty alleviation strategies and conditional cash transfer programs, whose design would greatly benefit (for instance, in terms of targeting) from effective vulnerability estimates.

This document presents an analysis aimed at distinguishing the risk of future poverty from actual outcomes in Latin America, based on the cross-sectional household data available to analysts. The discussion includes a critical assessment of recent methodological developments in the vulnerability literature, and covers conceptual, methodological and empirical aspects. The empirical evidence presented below is based on a comparative study of 18 countries from Latin America, a region of relatively high poverty and inequality levels.

The analysis also uses short term panel data from Argentina and longer term panels from Chile to evaluate and validate the predictive power of vulnerability estimates obtained from cross-sectional data. In this setting, it is possible to compute vulnerability in one period, and compare those estimates to the actual realised poverty states in future periods. Moreover, it is also possible to compare the performance of vulnerability measures to that of other deprivation indicators. The exercise has a clear policy motivation: good predictive power at the micro level would make vulnerability estimates an ideal targeting tool, separating the transiently from the chronic poor. This has indeed been an important motivation of vulnerability measures in the recent literature (Chaudhuri, 2003).

This document is organised as follows: Section 2 presents a conceptual and methodological discussion of vulnerability measures based on recent developments in the literature, and establishes the empirical strategy adopted throughout the remainder of the document. Section 3 describes the data sources. Section 4 presents the main empirical results, consisting of estimates of vulnerability to poverty for 18 Latin American countries since the early 1990s. Section 5 develops the validation exercise and compares vulnerability estimates with other deprivation indicators. Section 6 concludes.

2 Measuring vulnerability

2.1 Approaches to vulnerability measurement

In abstract terms, vulnerability may be conceived as the threat that welfare may be compromised at a future date. This threat may be derived from two factors: first, high levels of welfare variability, and second, systematically low levels of welfare. Applications of vulnerability methods are closely linked to the way welfare is measured, with three relevant approaches in the context of this study. The first is to assess vulnerability as expected poverty (VEP). This strand of studies seeks to estimate the probability that welfare may fall below some norm or minimum expected standard of living in the future (Chaudhuri *et al.*, 2002). The second is quantifying vulnerability as low expected utility (VEU). Researchers in this area argue that using the VEP methodology is inconsistent with the expected utility framework, and proposes a measure of vulnerability to address these concerns (Ligon and Schechter, 2003). Finally, the last approach is vulnerability as uninsured exposure to risk (VER). This setting, contrary to the previous ones, stems from an ex-post, backward looking perspective, which concentrates on observed past outcomes rather than on an aggregate measure of vulnerability (Tesliuc and Lindert, 2002; Cruces, 2005; Cruces and Wodon, 2007). It is also related to the literature on measurement of chronic and transient poverty (Jalan and Ravallion, 1998).

This paper follows the first approach, defining vulnerability as the threat of future deprivation. While the VEU approach has some attractive features in terms of its interpretation, it requires imposing common utility and risk preferences (Just and Pope, 2003). Finally, the third approach requires longitudinal data on households, and for the majority of countries in Latin America only cross sectional data is available.

2.2 Vulnerability and distributive analysis

As stated in the introduction, vulnerability and poverty are two distinct but related phenomena. Accounting for their significant overlap and identifying them separately is a challenging task. The main motivation for this break down is policy-oriented, since the tools to alleviate poverty are not necessarily the same as those required to prevent it, and these two dimensions must be addressed by social protection systems (Barrientos and Shepherd, 2003). Moreover, as suggested by Barrientos (2007), the concept of vulnerability can be linked to the presence of poverty traps.

Until recently, the relationship between poverty and risk had been mostly unaccounted for in distributive analysis – for instance, in widely used tools for characterising the poor, such as poverty assessments and profiles. While these provide cross-sectional views of deprivation, they fail to account for its dynamic characteristics. A series of recent studies have tried to fill this gap by developing measures of vulnerability.[1] The basic premise of this line of research is that households may be poor at a certain point in time, yet they face different risks of either remaining or becoming poor. By definition, all those who are poor are usually considered vulnerable; however, the converse is not necessarily true (Suryahadi *et al.*, 2000). This is the origin of the overlap between poverty and the threat of poverty, and these recent studies have found substantial differences between the two.

The inclusion of the vulnerability dimension has a series of potential benefits. On the one hand, it helps identify the household characteristics linked to vulnerability. On the other hand, it also sheds light on households' coping mechanisms towards risk. Findings in these two dimensions could inform the policy design process, for instance by supporting mechanisms which reduce vulnerability (e.g. credit and insurance markets), and by pointing directions for strengthening existing social safety nets for both idiosyncratic and aggregate risk. Finally, the notions of risk and vulnerability rely on finding the determinants of income in the future, and thus provide a starting point for studying the behaviour of permanent income (Zhang and Wan, 2008).

The notion of the threat of deprivation is related to recent efforts in overcoming traditional welfare assessments by classifying the poor into the chronically (or structurally) poor and the transient (or temporary) poor. Jalan and Ravallion (1998, 2000) highlight the importance of this distinction for policies, which require different policy interventions. Evaluation of chronic and transient poverty is generally undertaken by observing income fluctuations for households and comparing to the poverty line (Fields and Ok, 1999). Those who are observed to be always poor have been found different in their characteristics from the sizeable fraction of households experiencing temporary poverty related to specific shocks (see for instance Jalan and Ravallion, 1998 for China, and Cruces and Wodon, 2003 for Argentina).

This dichotomy is similar to the distinction between the poor and vulnerable discussed before, but there is an important conceptual and practical distinction: while the transient/chronic poverty approach is ex-post or backward looking, the vulnerability literature attempts to capture the distribution of future welfare levels. The empirical application of these concepts differs greatly: the transient/chronic distinction requires longitudinal household data, which is relatively scarce in developing countries. This is the main reason for the static nature of most poverty assessments, which remain the primary input for poverty alleviation policies.

[1] See for instance: Chaudhuri *et al.* (2002), Chaudhuri (2003), Elbers and Gunning (2003), Kamanou and Morduch (2003), Christiaensen and Subbarao (2005), Dercon (2001, 2005) and Hoddinott and Quisumbing (2008).

The recent developments in the vulnerability literature have attempted to study expected welfare levels using cross sectional data as an input. Contributions such as Chaudhuri *et al.* (2002), Chaudhuri (2003) and Christiaensen and Subbarao (2005) have dealt explicitly with the measurement of vulnerability from a single survey, or from time series of cross sections, when panel data is unavailable. This is the relevant case for Latin America. These studies and some of their empirical applications are reviewed in the following sub-section.

2.3 Brief review of the recent vulnerability literature

The brief literature review of vulnerability as expected poverty aims to provide a methodological framework and a summary of previous applications. These will frame the empirical evidence for Latin America presented throughout the rest of the study. For a more complete literature review, which includes the VEU and VER approaches to vulnerability, see Hoddinott and Quisumbing (2008), while Prowse (2003) provides a review of the relationship between vulnerability and chronic poverty.

Chaudhuri *et al.* (2002) and Chaudhuri (2003) provide some of the initial contributions to the recent literature on vulnerability as expected poverty. The framework developed in those studies define vulnerability estimates as probabilities of falling into poverty, which are computed as the expected value of a poverty score in the future, conditional on a series of covariates. This poverty score takes the form of the Foster, Greer and Thorbecke (1984) FGT measures, specifically the headcount index (*FGT(0)*) which represents a probability (Kurosaki, 2007). The authors state that panel data of sufficient length would provide a better source for vulnerability estimates – the availability of repeated observations adds a crucial dimension (variability) to measures of household welfare. Given the scarcity of longitudinal data in developing countries, they develop a series of assumptions under which cross-sectional data could form the basis of vulnerability estimates.

Chaudhuri *et al*. (2002) applied their methodology to cross-sectional data from Indonesia.[2] Their results show that the vulnerable population is generally larger than the fraction observed as poor at a given point in time, implying that the true poverty cost of risk is higher than the observed outcome (Dercon, 2005). The authors also found differences between the distribution of vulnerability and poverty across different population characteristics (e.g. regions and educational levels). Chaudhuri (2003) applied these methods to cross-section data from the Philippines and Indonesia, finding similar patterns.

Suryahadi and Sumarto (2003) analysed the effects of the 1997 economic crisis in Indonesia on vulnerability. The results suggest that the proportion of vulnerable households more than doubled due to worsening aggregate conditions. Furthermore, the authors stress the

[2] Chaudhuri *et al*. (2002), in fact, apply their methodology to the first round of a two period panel, and then implement a validation exercise with the second panel, as discussed in Section 4 below.

relevance of aggregate shocks for both the threat of deprivation and poverty itself, motivated by the finding that the fraction of those at risk (defined as the sum of the poor and the vulnerable) represented less than one-fifth of the population before the crisis, but one-third after it. Other applications of the cross-section methodology provide findings along similar lines. These include Albert *et al.* (2007) for the Philippines, who found a substantial gap in the level of vulnerability of households in rural and urban areas. For Latin America, Tesliuc and Lindert (2002) study the case of Guatemala and Gallardo (2009) that of Nicaragua. In general, previous evidence finds that vulnerability is widespread, with vulnerable households usually outnumbering those that become poor. Moreover, some studies find several household characteristics that are associated with vulnerability levels (for instance, gender of the household head, educational levels, employment status and area of residence).

Other approaches to vulnerability measurement in applied work involve the use of panel data and repeated cross-sections.[3] Studies using the former include Suryahadi *et al.* (2000) for Indonesia, Kamanou and Morduch (2002) for Cote d'Ivoire, Chaudhuri (2003) for China, Kasirye (2007) for Uganda, and Gaiha and Imai (2008) for rural India. The limited availability of panel data in Latin America implies a focus on studies based on cross-sections in this review.

Continuous and periodical household surveys are relatively more available in several developing countries, and this has motivated the development of vulnerability measures based on pseudo-panels (or a time series of cross-sections). Christiaensen and Subbarao (2005) develop a general framework to estimate household vulnerability to poverty using these data sources. Their application to rural Kenya indicates that idiosyncratic shocks substantially affect the volatility of consumption. This methodology motivated a number of studies, such as Sarris and Karfakis (2006) for Tanzania, Kurosaki (2007) for Pakistan, and Makoka and Kaplan (2008) for Tajikistan and Malawi. Other studies of vulnerability based on pseudo panel data include Bourguignon *et al.* (2004), Carballo and Bongiorno (2007), Naudé *et al.* (2008) and Zhang and Wan (2008).

The growing body of case studies and methodological developments on vulnerability prompted the critical assessment of the framework. Most notably, some studies have relied on panel data to undertake a validation exercise of cross-sectional vulnerability estimates and contrasting them with observed future individual poverty states and aggregate poverty rates (Chaudhuri *et al*., 2002; Chaudhuri, 2003; Albert *et al*., 2007 and Zhang and Wan, 2008). Exercises of this type find that cross-sectional estimates of expected poverty provide relatively good approximations to realised rates, although with some caveats. They are

[3] Details about the benefits and limitations of panel and repeated cross-sections are discussed in Section 5 below. Hoddinott and Quisumbing (2008) also present an overview on these topics.

discussed in more detail in Section 4 of this report, which presents a validation exercise of this type for short term and long term panel data from Argentina and Chile.

A further strand of the literature has pointed out some of the drawbacks of the vulnerability approach, and has prompted alternative developments. For instance, some studies highlight the limitations of the headcount measure, which does not account for the depth of deprivation below the poverty line, and thus reduce its usefulness as an indicator of vulnerability (Kurosaki, 2007; Hoddinott and Quisumbing, 2008). Christiaensen and Subbarao (2005) and Kamanou and Morduch (2002) suggest using the expected squared poverty gap. Another issue is the time horizon used to assess expected poverty. As pointed out by Hoddinott and Quisumbing (2008), uncertainty should rise as the timeframe expands. With similar concerns, Suryahadi *et al.* (2000) define household vulnerability as the probability of observing at least one spell of poverty in *n* periods, instead of only one. Finally, other studies propose to operationalise vulnerability with different sets of tools. For instance, Kamanou and Morduch (2002) generate a distribution of possible future household outcomes by means of non-parametric bootstrap techniques, based on the observed characteristics and outcome fluctuations of 'comparable' households.

2.4 Methodology and empirical strategy

This section outlines the methodology for obtaining vulnerability estimates from cross-section data in a more formal setting. It first derives the standard model, and then details a series of aspects pertaining to particularities of the application. Finally, some important issues which might arise in the estimations are briefly discussed.

2.4.1 *Vulnerability to poverty: the basic approach*

The definition of vulnerability adopted in this document is the ex ante risk that a household will be poor if it is currently not poor, or that it will remain in poverty if it is currently poor.[4] The above definition implies that vulnerability may best be summarised as a probability. Chaudhuri *et al.* (2002) and Chaudhuri (2003), formally define this probability as:[5]

$$V_{ht} = \Pr(y_{h,t+1} \leq z) \tag{1}$$

where $y_{h,t+1}$ is a measure of household welfare at time *t+1*, and *z* is an exogenous poverty line. To obtain estimates for vulnerability, it is necessary to define the level of minimum acceptable welfare (the poverty line) and the level of future welfare. The first element does

[4] This section draws on Chaudhuri *et al.* (2002) and Chaudhuri (2003).

[5] This is actually the simplest approach to vulnerability measurement. A series of extensions are possible, since the vulnerability indicators are based on the Foster, Greer and Thorbecke (1984) measures of poverty. In the general Chaudhuri (2003) setup, this case corresponds to the headcount index (FGT measures with *α=0*).

not pose any significant issues; the second, however, is far more complex. To estimate future welfare, it is necessary to make assumptions about how it is generated, which involves a discussion of its determinants and dynamics. As a starting point to address these concerns, consider the following general reduced form for a future income generating function:

$$y_{h,t+1} = f(X_h, \beta_t, \alpha_h, e_{h,t}) \tag{2}$$

where X_h represents a set of observable household and community characteristics, β_t is a vector of parameters at time t, α_h is an unobserved time-invariant household effect, and e_{ht} is a mean-zero disturbance term that captures idiosyncratic factors. Since the methodology obtains these estimates from a single point in time, the unobserved household level heterogeneity cannot be properly estimated. Nevertheless, this pitfall is overcome somewhat by the extensive information on household and community characteristics in these data sources. Substituting (1) into (2), household vulnerability may be rewritten as:

$$V_{ht} = \Pr(y_{h,t+1} = f(X_h, \beta_{t+1}, \alpha_h, e_{h,t+1}) \leq z \mid X_h, \beta_{t+1}, \alpha_h, e_{h,t+1}) \tag{3}$$

The above expression suggests that if proper estimates of future welfare are available, vulnerability as expected poverty may be feasibly estimated by (3). Implicitly, (3) defines the fundamental identifying assumption of the approach. First, future levels of welfare are relatively stationary from one period to the next.[6] Second, it implies that welfare is determined by observable factors as well as unexpected shocks, i.e. vulnerability may be due either to low expected welfare or high volatility of well-being. The specification of the welfare generating process (and thus its distribution) implies that both the mean and the variance need to be taken into account.

This reduced form model indicates the steps needed to consistently estimate vulnerability: (i) make distributional assumptions; (ii) specify the welfare generating process and estimate the relevant parameters from the data source; and (iii) obtain the probability of being poor. The next subsection discusses how this document undertakes these steps for its empirical application to Latin America.

2.4.2 *Empirical strategy*

The selection of the welfare proxy is crucial for the estimation vulnerability. In this study, welfare is measured using household per capita income, since surveys in Latin America do

[6] Of course, this is a highly restrictive assumption which also depends on the timeframe from which conclusions are meant to be drawn. For instance, it is probable that welfare does not vary significantly from one year to the next. However, as this extrapolation period expands, this assumption is not likely to hold. See Christiaensen and Subbarao (2005) for a discussion of this topic.

not collect consumption or expenditure data regularly. For the purpose at hand, income can be assumed to be distributed as a lognormal random variable. This approximation greatly simplifies the estimation of vulnerability, since lognormal distributions can be characterised by their mean and variance.[7]

The second step is less straightforward. A standard cross sectional model for income commonly used in applied work takes the following form:

$$\ln y_h = X_h \beta + e_h \tag{4}$$

where X_h represents a set of observable household and community characteristics. In the estimates in this report, and following previous work in the vulnerability literature, the covariates in X_h include a series of structural characteristics of the household: gender of the head, its age (and age squared), household size and its square, number of young children in the household, number of employed members, educational attainment of the head (using educational level indicators), and whether the household resides in urban or rural areas. This specification is selected primarily due to comparability across the surveys in the sample and across time, and constitutes a set of household characteristics related to its structural poverty status and its income generating process. The error term, e_h, comprises all other unobservable effects.

The next step implies the estimation of the variance of expected income. Chaudhuri *et al*. (2002) and Chaudhuri (2003) assume that the disturbance term e_h captures both community specific effects and idiosyncratic shocks on household income, and that its variance is correlated with observable household and environment characteristics. This explicitly assumes that expected income variance is heteroscedastic. A simple parametric way to express this characteristic is to model the variance using the following linear functional form:

$$\sigma^2_{e,h} = X_h \theta \tag{5}$$

Standard regression analysis based on ordinary least squares (OLS) assumes homoscedasticity, and estimates of β and θ will be unbiased but inefficient if this assumption does not hold. To deal with this problem, Chaudhuri (2003) applies a three-step feasible generalised least squares (FGLS) method to obtain consistent estimates of β and

[7] In the case of other distributions, distinct parameters need to be retrieved in addition to the first and second moments (Rice, 2006).

θ[8]. Using the consistent and asymptotically efficient estimators $\hat{\beta}$ and $\hat{\theta}$ obtained by FGLS, the expected log income and variance may be estimated for each household:

$$\hat{E}[\ln \hat{Y}_h \mid X_h] = X_h \hat{\beta}_{FGLS} \tag{6}$$

$$\hat{V}[\ln \hat{Y}_h \mid X_h] = \hat{\sigma}^2_{e,h} = X_h \hat{\theta}_{FGLS} \tag{7}$$

Estimates of (6) and (7) are then used to compute the probability that a household will be poor in the future. Since income is assumed to be lognormal, the estimated conditional probability is given by:

$$\hat{V}_h = \widehat{\Pr}(\ln y_h < z \mid X_h) = \Phi\left(\frac{\ln z - X_h \hat{\beta}}{\sqrt{X_h \hat{\theta}}}\right) \tag{8}$$

where Φ denotes the cumulative density of the standard normal distribution.

2.4.3 *Some estimation issues*

In the results presented in this report, equation (4) is estimated separately by time comparable geographic regions within each country.[9] This disaggregated estimation strategy accounts for potential differences in the structure of local economies, a source of heterogeneity which would be unaccounted for when using pooled data.[10]

Some additional issues related to the estimation of the variance of income arise in the implementation of the procedure outlined above. First, there might be systematic measurement error in the observed welfare outcome. Income has a tendency to be underreported in household surveys, which may lead to significant underestimation of its variance. This consequently biases the vulnerability estimates upward. A suggested solution is to scale up the variance to account for this measurement error. However, given that the measurement error generating process is unknown, this study makes no adjustments to avoid imposing further assumptions. Therefore, if measurement error implies an underestimation of income variance, the estimates presented here may be regarded as a lower bound of the probability of future poverty. In second place, the linear specification of the variance implies that there might be negative estimates of the variance for certain

---

[8] For details of this method see Amemiya (1977).

[9] For details about the regions and their definitions, see the Socio Economic Database for Latin America and the Caribbean - SEDLAC (CEDLAS and World Bank, 2010).

[10] However, it should be noted that robustness tests indicate that the estimation of vulnerability at a more aggregate level (for instance, nationally) yield fairly similar results.

households. If this proportion of households is high, then vulnerability estimates may be affected. However, in practice this problem is found to be minor, and negative observations were dropped from the sample.

Finally, the specification of the income generating process defined by equation (4) is also closely linked to the set of X variables specified in the previous section. The literature on vulnerability has debated how to model welfare (proxied by income, consumption or expenditure) from a variety of sources (cross-sections, pseudo-panels and longitudinal data). In the context of an application to Latin America, the relevant discussion is on the fit of cross-sectional models of vulnerability and their validity for estimating income dynamics. The standard income model accounts for a sizeable proportion of variability, but it is by no means a perfect fit: for instance, the goodness of fit measures for Argentina and Chile are in the 0.45 to 0.55 range. While this is fairly high for a specification based on a reduced set of observable characteristics, there is still a substantial variability not captured by the income generating model. While comparability is paramount in the context of this report, country-specific studies would benefit from econometric specifications that take into account both structural and idiosyncratic factors in a particular country's environment.

2.4.4 Vulnerability indicators and measures

The probabilities obtained from equation (8) in this framework may be presented, interpreted and discussed in several ways. First, it is possible to calculate a series of indicators to depict the key properties of the underlying distribution. The most intuitive measure would be the mean level of vulnerability, which indicates the mean probability to become poor for households in a given country. A second possibility is to classify households into states, vulnerable and not vulnerable. This implies setting a probability threshold, above which households are considered to be vulnerable. The main concern with this indicator is the arbitrariness in choosing the threshold, although there seems to be a consensus in the applied literature in using two thresholds: the current aggregate poverty rate, and a value of 0.50. These two will be referred to in the rest of this document as the relative and absolute vulnerability thresholds, respectively. Finally, the ratio of vulnerable households to poor households can be interpreted as a measure of dispersion. This provides an idea of where the vulnerable comes from. For instance, a high vulnerability to poverty ratio suggests that vulnerable households may be poor or non-poor, indicating a more dispersed distribution of vulnerability. A lower ratio indicates higher concentration of the vulnerable among the poor.

However, these summary measures may not capture what is happening across the entire distribution. For this purpose, the document also follows Chaudhuri's (2003) suggestion of plotting the proportion of vulnerable households across the entire range of possible vulnerability thresholds.

3 Data sources

3.1 Cross-sectional data

The estimates reported in this document were computed from a large database of household surveys, the Socio-Economic Database for Latin America and the Caribbean-SEDLAC (CEDLAS and World Bank, 2010), compiled and homogenised by CEDLAS (Universidad Nacional de La Plata) and the World Bank's LAC poverty group (LCSPP)[11].

For this study, a sample of 18 countries with time comparable survey data and with information on the variables of interest was selected. There is information for most countries at four points in time, beginning in the early 1990s, although in some cases comparability issues and gaps in survey collection limit the amount of periods available to two. The selected country surveys, detailed in Table 3.1, contain information on income and socioeconomic characteristics for households and their heads. Descriptive statistics for each country and year are presented in Tables 3.2 and 3.3. A characterisation of the sample shows that 68 percent of households in Latin America reside in urban areas,[12] average household size is four members and at least half of adult members are active in the labour market. A detailed characterisation of household heads indicates that male-headed households are predominant in the region (approximately 67.2 percent), and are for the most part individuals with low to medium levels of education.

The following section calculates vulnerability measures for each country and year in the sample, providing a regional evolution of vulnerability over time that complements the few studies available, based on individual countries.[13] The results also illustrate trends in mean vulnerability and in the percentage of vulnerable households, and allow the construction of vulnerability profiles. Finally, the discussion also covers the level of overlap between the threat of poverty (as measured by vulnerability) and realised poverty.

[11] See Gasparini (2007) for a full description of the dataset.

[12] This calculation does not include Argentina, Uruguay and Venezuela, where surveys cover only urban areas. In the case of Uruguay, a small rural sample was incorporated starting in 2007. However, 94 percent of households in the survey remain urban.

[13] Due to space constraints, it is not possible to report the estimates of equation (4) for each country, region and period of time. All regression outputs are available upon request.

3.2 Panel data for validation exercises

3.2.1 Argentina: one year panels

Argentina's *Encuesta Permanente de Hogares* (EPH) allows the re-construction of its rotating sampling structure from 1995 to 2003.[14] This structure implies that it is possible to track a percentage of the total sample for a period of time. In particular, 25 percent of the sample could be tracked throughout four consecutive waves (semesters), or 50 percent can be potentially observed in one year intervals (see Cruces and Wodon, 2007, for more details).

A general problem with longitudinal data is attrition. In the case of Argentina's rotating panels, approximately 16 percent of households dropped out over the four waves (Gutierrez, 2004). A detailed analysis of this data source, however, reveals that this attrition can be considered random (Albornoz and Menéndez, 2002), and thus does not bias estimates.[15] In this study, the data are assembled into yearly panels, i.e. the same household is observed once in the baseline and again one year later,[16] using balanced panels (which does not affect the estimates presented here since attrition is not a significant issue).

Besides observing households in two survey rounds over a one year period, the rotating panel nature of the sample implies that it is also possible to construct 'cohorts' of households entering the sample in the same round. The data allows assembling a total of seven cohorts, running from 1995-1996 to 2001-2002. The main advantage of this timeframe is that it captures behaviour during growth (1995-1998), recession (1999-2000), and crisis (2001-2002) episodes in Argentina. This feature of the data provides a test of the method's sensitivity to changing aggregate conditions.

The sample used for the estimates is described in Table 3.4. The total number of households in each cohort is somewhere above 7000. The typical household contains an average of four members, and of those, at least one is a minor. Most households have a male head (73 percent).

---

[14] The survey design changed in 2003 from the rotating panels to a continuous sampling framework.

[15] It should be emphasized that problems of attrition and measurement errors may influence poverty estimates and estimates of other relevant variables in studies based on panel data (Alderman *et al*. 2000; Baulch and Hoddinott 2000). Alderman *et al*. (2000) analyze the extent and implications of attrition for three developing countries and conclude that attrition can bias the estimates of outcome and certain family background variables. Their findings, however, suggest that attrition does not generally affect the consistency of coefficient estimates in linear regressions and models with categorical dependent variables. The methodology in this document relies on linear regressions models.

[16] Households were interviewed in October of each year.

3.2.2 *Chile: five and ten year panels*

Chile's *Encuesta de Caracterización Socioeconómica* (CASEN) is the country's main socio-economic survey, which periodically provides representative microdata on households at the regional and national levels. In 1996, the Statistics Institute (INE) selected 5210 households in four regions to be tracked in subsequent years,[17] to cover the gap in availability of longitudinal data for Chile. In 2009, two follow-up rounds were available: the first corresponding to 2001, and the second to 2006.[18] The main advantage of the CASEN panel is its span of ten years, which provides information on relatively long-term outcomes.

The Chilean data allows the observation of the same households throughout the entire timeframe, contrary to the Argentine case where households are only tracked for one year. Hence, an overall balanced panel contains households observed in all three rounds (1996, 2001 and 2006). To test the performance of vulnerability estimates over the medium and the long term, the analysis is carried out over three samples: two five-year panels (1996-2001 and 2001-2006), denoted as short-length periods, and the long-length period covering the initial and final rounds, 1996 to 2006.

Unlike the case of the short Argentine panels, Bendezú *et al.* (2007b) find that attrition is higher for the CASEN panel. Of the initial number of surveyed individuals, 25 percent dropped out in the first follow-up, and by the final follow-up only half of the original sample remained.[19] The solution to the potential bias which may arise from this attrition is the use of longitudinal expansion factors, provided with the data, and used for all the estimations in this study.[20]

The sample for Chile is described in Table 3.5. The balanced sample includes 3090 households which are observed throughout the entire timeframe and for each period defined above. An average household in the sample has four members, and includes at least one child. Once again, the evidence points to predominance of male-headed households, with an average of eight years of education.

---

[17] The households belong to the third, seventh, eighth and metropolitan regions.

[18] The last follow-up was carried out in 2009. However, these data are not yet available. For technical details of the CASEN panel see Bendezú *et al.* (2007a)

[19] Moreover, the Bendezú *et al.*. (2007b) detailed study of individuals who dropped concludes that this loss of information was non-random. In particular, individuals who left the sample are younger (between 20 and 29 years) or older (more than 75 years), tend to own property and are inactive in the labour market. However, as stated in footnote 21, this is not a particularly important concern within the regression-based vulnerability estimates discussed in this document.

[20] Details about construction of longitudinal expansion factors are provided by Bendezú *et al*. (2007).

4 Vulnerability to poverty in Latin America

4.1 Mean vulnerability in Latin America

This section presents an analysis of cross-country levels and trends of vulnerability for Latin American countries. The discussion uses the $4 USD international poverty line and absolute threshold (0.50) to define vulnerability, since the first approximates the official poverty lines of several countries in the region, and the second constitutes the usual approach in the studies using the vulnerability framework.[21] Table 4.1 presents the main estimates by country and time period.

The mean probability of future deprivation – or mean vulnerability to poverty – at country level is plotted in Figure 4.1 for the countries in the region. According to this figure, the Southern Cone countries (Argentina, Chile and Uruguay) show the lowest overall vulnerability during the entire period, and have similar trends to the entire region. Indeed, Argentina, Chile and Uruguay are the countries with the lowest overall level of mean vulnerability in Latin America. The Andean region (Bolivia, Colombia, Ecuador, Peru and Venezuela) seems to be the most homogenous, with most countries close to the regional mean. Countries in Central America show evidence of salient intraregional differences, with Nicaragua and Honduras having the highest mean vulnerability and Costa Rica the lowest.

Figure 4.2 shows that all countries except for Argentina, the Dominican Republic, Uruguay and Venezuela reduced their mean vulnerability, which is interesting given that the last two are among that least vulnerable. This finding is related to the documented downward trend in aggregate poverty over the same period (Gasparini *et al.*, 2010). The most significant reduction in the region, however, was experienced by Brazil, whose mean vulnerability level fell substantially – almost 30 percent – making it one of the least vulnerable countries by the end of the period. Some countries experienced increases in these indicators over the period. Argentina and Paraguay's mean vulnerability grew substantially, fuelled primarily by the deep macroeconomic crisis of 2001 and 2002 (Gasparini and Cruces, 2010). Since then, vulnerability has fallen for both countries, but remains at higher levels than at the beginning of the period considered in this document.

4.2 Counting the vulnerable

Figure 4.3 depicts the evolution of vulnerable households, calculated by classifying households as vulnerable if their mean vulnerability is greater than the absolute threshold of

---

[21] Results for alternative poverty lines and with relative thresholds are presented in a companion extended report (Cruces *et al.*, 2010), which is available from the authors upon request. This report also presents an analysis of vulnerability estimates' sensitivity to threshold selection.

0.50.[22] This figure confirms the country rankings found before. Argentina, Chile and Uruguay are the countries with the lowest level of incidence of vulnerability on average, while Guatemala, Honduras and Nicaragua present the largest proportion of vulnerable households.

Figure 4.4 summarises the change in the proportion of vulnerable households for each country between the first and last time period. The incidence of vulnerability was higher in Argentina, Colombia, the Dominican Republic, Uruguay and Venezuela. On the contrary, Brazil, Ecuador, El Salvador and Honduras are the countries that show the largest reductions of vulnerable households under the absolute threshold.

4.3 Poverty and vulnerability patterns

The conceptual and methodological discussion in Section 2 highlighted the close link between poverty rates and vulnerability computed as the threat of future deprivation. Therefore, it might be expected that vulnerability and poverty levels would evolve similarly over time, i.e. the trend in the percentage of poor households should be highly correlated by the proportion of vulnerable households. It would be worthwhile to compare the obtained prediction (vulnerability) to the observed household poverty state in the future, but this is not possible with cross sectional data – this will be the subject of the following section. The comparison below is carried out within the same time period.

Figure 4.5 captures the evolution of poverty (measured by FGT measures) and vulnerability (the percentage of vulnerable households). The analysis of states shows that trends in vulnerable households follow the evolution of poverty quite closely – the trends of vulnerability and poverty are similar across all countries.

This is evident when evaluating trends in individual countries. For instance, Argentina's 2001 to 2002 macroeconomic crisis increased poverty substantially, after a continuing upward trend in chronic poverty over the period of 1995 to 2002 (Cruces and Wodon, 2003). This pattern is also found in the data for Latin America, and is echoed by the vulnerability measures for Argentina in Figure 4.5. Brazil, on the contrary, has exhibited the opposite case in terms of poverty trends, with marked improvement in several welfare measures over the last 15 years, especially in terms of inequality and poverty (Paes de Barros *et al.*, 2006; Gasparini *et al.*, 2010). Again, the vulnerability measures seem to mimic this pattern, showing a reduced risk of Brazilian households falling into poverty.

The differences between poverty and vulnerability estimates, however, indicate that the two measures might be capturing different phenomena. The extent to which this is true is

[22] This procedure is analogous to selecting a poverty line to classify households into poor or non-poor states, and thus the value becomes somewhat arbitrary. For a discussion, see Zhang and Wan (2008).

addressed in the following section, which establishes whether the household characteristics associated to the two phenomena are the same.

4.4 A profile of vulnerable households

The vulnerability estimates presented in this section provide a cross sectional view of the proportion of households at risk of becoming poor in the future. However, this analysis does not indicate which types of households are most vulnerable to fall into poverty.

The results presented here differ from poverty profiles, since these only indicate what characteristics the poor *currently* have. Even though there might be a level of overlap between the characteristics of households at risk and those observed to be poor, this tool provides at best a highly imperfect policy guide (see the discussion in Section 2).[23]

Table 4.5 presents a detailed series of characteristics of vulnerable households for different periods in time. These include attributes of the household head such as gender, educational attainment and type of employment, as well as statistics pertaining to the entire household, such as area of residence (urban and rural) and income quintile.

In general, vulnerable households have a relatively balanced proportion in terms of the household head's gender. Indeed, gender disparities are relevant only in Costa Rica and Venezuela. On the other hand, vulnerable households seem to be concentrated in rural areas. Urban and rural differences are highest in Peru, where approximately 69 percent more of households are vulnerable than in urban areas.

As would be expected, the relationship between education and vulnerability is negative, with low education households being the most vulnerable. The educational gaps are highest in most Central American countries, Bolivia, Ecuador and Peru, with almost the entirety of low educated households being classified as vulnerable to future poverty.

Considering labour outcomes, it seems that households which obtain the majority of their earnings from self-employment activities face higher risks of future poverty. In contrast, salaried workers show more stability, as evidenced by the unchanged proportion of vulnerable households in this category. Self-employed heads of households face significantly higher risk than salaried employees in Bolivia, Honduras, Panama, Paraguay and Peru, while these differences are relatively minor in Southern Cone countries (Argentina, Chile and Uruguay).

[23] A companion extended report (Cruces *et al.,* 2010) presents a comparison of vulnerability and poverty profiles.

Finally, as expected, there is a strong relationship between vulnerability and the household's ranking on the income distribution, and this pattern is evident for all countries – higher levels of current household income imply a lower probability of being classified as vulnerable.

5 Vulnerability measures and future poverty: a comparative assessment based on panel data

This section presents a series of validation exercises of the vulnerability estimates developed and presented in the previous section. The interpretation of these results as stemming from variability in future welfare levels depends crucially on the methodology's identification assumptions about income dynamics, which cannot be tested with cross-sectional data. However, it is still possible to establish the extent to which cross sectional data can capture ex-ante vulnerability in specific settings where longitudinal data is available. While these exercises can only assess the internal validity of the estimates for the specific countries and data under study, positive validation results would indicate a degree of robustness of vulnerability estimates.

The exercises consist of comparing predicted levels of vulnerability with future realised welfare outcomes, much in the spirit of time series' one step ahead forecasts. Specifically, as in Chaudhuri *et al*. (2002), Chaudhuri (2003) and Zhang and Wan (2008), measures of vulnerability in one period are compared to the actual poverty outcome in the following period. The findings presented in this section encompass a series of contributions with respect to the performance of vulnerability measures as predictors of future poverty. First, the analysis assesses how well vulnerability predicts poverty at the national (or aggregate) level. Second, the discussion below also focuses on how effectively the estimates predict whether a specific household will be poor in the future, quantifying misclassifications – poor households classified as not vulnerable in the previous period, and non-poor households originally classified as vulnerable. While previous validation exercises concentrated on aggregate vulnerability and poverty levels, the discussion below argues that the usefulness of the estimates for social policy and focalisation depends on how well they can identify household-specific rather than aggregate poverty outcomes. Third, Chaudhuri *et al*. (2002) and Chaudhuri (2003) based their exercises on short run (one year) panels. The exercise below presents results for a similar short term panel from Argentina, but also from a longer (five and ten year) longitudinal dataset from Chile. Moreover, in the case of Argentina the panel comprises the 2001 and 2002 crisis period, making it possible to observe the sensitivity of vulnerability estimates to growth, recession and crisis episodes.

The series of exercises presented here, thus, allow an extensive robustness check of the cross-sectional approach to vulnerability. The discussion will determine whether the framework of expected poverty fares better as an aggregate predictor of poverty (at the country level), or whether it is more effective in identifying household-specific risks at the micro-level – and thus useful, for instance, for targeting beneficiaries of social programs. It will also shed light on the efficacy of household level predictions across the income distribution, by observing errors for each income decile. Finally, the exercises also compare several deprivation indicators and their performance as predictors of future poverty with respect to the vulnerability measures computed in this document.

5.1 Assessing the robustness of vulnerability estimates

The validation exercise presented here exploits the longitudinal nature of the data for Argentina and Chile, where the same households can be observed at times *t* and *t+1*. The exercise consists of estimating vulnerability by cross-sectional methods at time *t*, and then comparing these to future realised outcomes in *t+1*. The evaluation proceeds in two stages, distinguishing between the aggregate and the micro levels. The first is an overall assessment of how well mean vulnerability predicts future aggregate poverty levels. The second is a micro-level assessment that counts the proportion of misclassified households – i.e. poor households classified as not vulnerable in the previous period, and non-poor households originally classified as vulnerable.

The first stage computes mean vulnerability for the entire sample at time *t*, and compares to the overall poverty rate in *t+1*. Therefore, it provides an insight on whether vulnerability captures current and future aggregate poverty levels, and it is possible to compute the magnitude of any potential discrepancies.

The second stage is more elaborate. On the one hand, the analysis focuses on misclassifications with respect to the entire population. In this part of the exercise, the proportion of households which are not classified correctly is calculated using the total population as the reference point. This allows counting the overall error at the household level, which consists of the sum of those households which were classified as vulnerable but did not become poor, and the non-vulnerable households which actually became poor. The results are presented in matrix form, in the following manner:

Definition of misclassified households

	t+1		
t	Poor	Non-poor	**TOTAL**
Expected poor	**a** Correctly classified	**c** Misclassified	***EP***
Expected non-poor	**b** Misclassified	**d** Correctly classified	***ENP***
TOTAL	***P***	***NP***	***N***

Overall misclassifications can be computed as $M = \frac{b+c}{N}$. It should be stressed that even if the income generating process is correctly specified and cross-sectional data provides enough information for an assessment of each household's probability of becoming poor in the following period, one should not expect all vulnerable households to be poor and all non-vulnerable to be non-poor in *t+1*, since this is a probabilistic and not an exact prediction. However, this extreme case provides a plausible metric for the methodology's classification errors.

On the other hand, misclassifications can also be computed with respect to a more restricted reference population, for instance, the poor. In the above matrix, this ratio would imply calculating the level of misclassification using the column totals instead of the entire population. This is an important distinction. For instance, if the proportion of poor households is relatively small, misclassifications might appear high with respect to this group, but low with respect to the total population. The intuition for the relevance of these classification errors is given by the potential policy applications of vulnerability estimates. For a policymaker devising a transfer-based safety net, vulnerable households (those with high probabilities of becoming poor in the future) constitute the target population. In this scenario, misclassifying vulnerable households as non-vulnerable carries a high exclusion cost: these households would not receive the transfer, although they would require it. This type of misclassification can be labelled as Type I (exclusion) errors (in an analogy with the statistics literature), and corresponds to the proportion of currently poor households which were classified as not vulnerable in the previous period. In the previous notation, this case would correspond to $Type\,I: \frac{b}{P}$. The second type of misclassification implies labelling non-vulnerable households as vulnerable – they were more likely on average to become poor, but did not. These inclusion errors can be labelled as Type II, and correspond to the fraction of currently non-poor households which were classified as vulnerable in the preceding period, or $Type\,II: \frac{c}{NP}$. In this case, these households would not require the transfer. From the policy maker's perspective (weighting equity over efficiency), Type I (exclusion) errors seem more serious than Type II (inclusion) errors (although budgetary concerns might change this perspective).

5.2 Robustness of vulnerability estimates: short-run evidence from Argentina

5.2.1 *Expected poverty and actual poverty at the aggregate level*

The results for the aggregate validation are presented in Table 5.1 using the standard vulnerability specification ($4 USD poverty line and absolute threshold)[24]. Figure 5.1 summarises this information by plotting the actual poverty rate in the second year of each cohort (*t+1*), and the aggregate expected poverty rate computed from the information available in *t*.

[24] Results for alternative poverty lines and thresholds are presented in a companion extended report (Cruces *et al.,* 2010), which is available from the authors upon request.

In general, with the exception of the last cohort, which covers the extraordinary macroeconomic crisis of 2001 and 2002, expected poverty levels are fairly close to actual poverty rates. The divergence between the two increases from the 1999-2000 cohort onwards, which coincides with the start of the recession that culminated in the crisis. When entering the recession, vulnerability actually underestimates realised poverty rates. This problem is exacerbated with the 2001 and 2002 crisis, where the vulnerability assessment based on 2001 data grossly underestimates the 2002 poverty rate by more than ten percentage points.[25] This substantial underestimation highlights the difficulties of accounting for exogenous future shocks in a cross-sectional setting.[26]

Hence, the validation exercise indicates that aggregate vulnerability estimates in the short-run predict aggregate poverty relatively well during stable growth periods, when the stationarity assumption is more likely to hold.[27] However, in the case of negative shocks, there is a clear risk of underestimating of the level of future poverty for the country. This finding also implies that a positive shock might overestimate poverty. In an extreme case, the difference may be quite substantial; however, these shocks must be particularly strong (such as the 2001-2002 crisis in Argentina) to cause significant deviation from actual poverty. Therefore, these estimates may be considered as a lower bound for future poverty in the absence of external shocks.

5.2.2 *Classification at the household level*

While illustrative, the discussion presented above suggests that aggregate vulnerability levels may not be necessarily relevant from a policy perspective. Safety nets and other similar initiatives require the assessment of vulnerability at the household level. The results for the micro-level validations are presented in Table 5.2 for each cohort of the Argentine panels. The results for *M* (the misclassification indicator defined in the previous subsection) indicate that 86 percent of all households are classified correctly (averaging results for all cohorts). This total corresponds to 79 percent of non-poor households and seven percent of poor households. The remaining 14 percent of households are classified incorrectly, with

[25] As noted by Chaudhuri *et al.* (2002), vulnerability estimates will probably differ from future poverty rates in the presence of large shocks, but with no group specific shocks the average expected poverty should coincide with the current (rather than the future) poverty rate. This effect is apparent in Figure 5.1: while not necessarily an accurate predictor of future poverty, the expected poverty is fairly similar to the same year's observed value.

[26] The stationarity assumption in the income equation plays a fundamental role in this behaviour, since this decision does not contemplate potential shocks to the economy that might have a direct impact on welfare outcomes. However, modelling these shocks into the economy is not straightforward. Moreover, Latin America's economies do not depend strongly on observable shocks (e.g., rainfall and other factors related to climate), and without data on these factors, their inclusion does not seem to be feasible. See Ferreira *et al*. (2004), Christiaensen and Subbarao (2005) and Hoddinott and Quisumbing (2008) for a discussion of how to incorporate shocks into income equations.

[27] Calculations of income correlation across periods for Argentina evidence high income persistence, between 76-84 percent. Notably, the lowest level of correlation is found during the crisis period.

three percent corresponding to non-poor households in *t+1* deemed vulnerable in *t*, and 11 to poor households in *t+1* classified as not vulnerable with data from period *t*.

Considering the same indicators for each cohort, there is clear evidence of a higher precision of the estimates during growth and stability periods, when almost 90 percent of all cases are correctly classified. Entering the recession (the 1999-2000 cohort), *M* drops to 85 percent, and is worst in 2001-2002, where precision falls by more than ten percentage points to 79 percent. Once again, it is evident that unaccounted shocks are a source of noise to the vulnerability estimates, resulting in increased error levels. However, it should be stressed that more than three quarters of total households are correctly classified – although these figures refer to proportions of the whole population. Classification errors with respect to those in poverty might show a different picture.

The estimation of Type I and Type II errors for Argentina are presented in Table 5.3. These estimates may be interpreted as the percentage of incorrectly classified households with respect to the entire poor population (Type I) and with respect to the non-poor population (Type II). The results in these tables indicate that, on average over the period under study, more than 61 percent of the poor are wrongfully classified i.e. a majority of poor households are classified as not vulnerable. The fraction of Type II (inclusion) errors (the fraction of non-poor households classified as vulnerable) is substantially lower, ranging from three to four percent for all cohorts.

During growth periods, Type I error is greater (64 percent in 1995), and actually improves slightly during recession (63 percent in 1999) and during the crisis (58 percent in 2001). However, this improvement is small in magnitude, and even in the best episode, more than half of the poor are not classified as vulnerable. The opposite is true for Type II (inclusion) errors: in worse aggregate economic conditions, the amount of non-poor classified as vulnerable increases. Nevertheless, the results indicate that the magnitude of the imprecision is small (see Figure 5.2).

In general, the findings for short term panels from Argentina suggest that although estimates of vulnerability classify a substantial majority of all households correctly, misclassification errors are substantial when focusing on the poor only. In fact, three out of five poor households would be categorised as not vulnerable.[28] These findings cast some doubts about the usefulness of cross sectional vulnerability estimates for targeting, as discussed below. Additionally, the evidence also shows that the effect of aggregate shocks on Type I and II errors is relatively minor: both types of misclassifications seem to remain fairly stable across different economic conditions. In this case study, Type I misclassifications remain at a

[28] While this is considered a misclassification according to the benchmark defined in the previous setting, some of these households might in fact be experiencing a transient spell of poverty, but have structural characteristics that make them non-vulnerable. This possibility is discussed below.

high level and Type II misclassifications are always low, regardless of the state of the overall economy.

5.3 Robustness of vulnerability estimates: long-run evidence from Chile

The validation exercise above used short term (one year) panel data to evaluate the performance of vulnerability estimates. In this section, the same evaluation is carried out on a different country and based on data with a substantially longer timeframe. Although this setting suggests a lower degree of income persistence than with yearly data,[29] it is still possible that the variables capturing the household's income generating process are better suited to predict long-term prospects rather than short term fluctuations. Whether vulnerability estimates fare better over longer periods of time is ultimately an empirical question which the following estimates seek to clarify.

5.3.1 Expected poverty and actual poverty at the aggregate level

The methodology to assess the performance of vulnerability is the same used for Argentina, but with different timeframes. In particular, the cohorts are spaced out into two five-year (short-length) periods and a longer ten-year window (long-length). The first two cases correspond to 1996 to 2001 and 2001 to 2006, while the longest period comprises households tracked from 1996 to 2006. In what follows, results are presented for all three cases. It should be stressed that during this period the Chilean economy did not experience the large aggregate fluctuations observed in the Argentine case, but rather a sustained period of growth (between four and six percent per year) and poverty reduction. While it is thus not possible to observe the effect of adverse shocks on vulnerability estimates, it is still possible to explore whether these estimates can account for a markedly upward trend in aggregate economic conditions.

The estimates for the aggregate vulnerability levels are detailed in Table 5.4 and are summarised in Figure 5.3. In general, the results indicate that at the aggregate level vulnerability overestimates actual poverty in Chile. The results for Argentina indicate that vulnerability underestimates poverty, especially during recession periods. During sustained periods of poverty reduction, as in the case of Chile over the period, the method is more 'pessimistic', since the methodology cannot account for diminishing poverty trends. Moreover, this feature seems to be exacerbated by length of the timeframe considered. For instance, for both short-length periods the difference in expected and realised poverty is between three to nine percentage points. When considering the longer period, the incongruity rises to 12 percentage points. This evidence indicates that cross-sectional

[29] Correlations for the five-year periods are lower than those estimated for Argentina by almost 20 percentage points (ranging between 0.52-0.62).

vulnerability estimates are less precise for long-run estimates, at least in the presence of marked trends in poverty.

5.3.2 *Classification at the household level*

The results for the micro-level validation exercise of the Chilean case are presented in Table 5.5. The level of misclassification as a proportion of the whole population, *M*, indicates that 84 percent of total households are classified correctly when averaging all time periods. Separating by poverty status, these correspond to 78 percent of non-poor households and six percent of poor households. The remaining 16 percent of households are classified incorrectly, with nine percent corresponding to non-poor households deemed vulnerable, and seven percent to poor households classified as not vulnerable.

The magnitude of these results is unchanged when the analysis focuses on short-length or long-length periods. Perhaps the most salient finding is that the results from the longest period (1996-2006) are both the worst and the best depending on which type of misclassification is observed. On the one hand, only five percent of poor households were incorrectly estimated to be not vulnerable, which is the lowest of the three periods. On the other hand, 10.6 percent of non-poor households were expected to be poor, which is the highest value compared to the shorter periods. Hence, it seems that time length also has an effect on how well the estimates behave.

The calculations for Type I and Type II errors for Chile are presented in Table 5.6 and show that, on average, more than half of the poor are incorrectly classified. It is noteworthy that although this type of error is relatively high (especially from a targeting perspective), its magnitude is lower than that for Argentina. Also, the fraction of Type II (inclusion) errors ranges between nine to 12 percent for all time periods, which is more than three times larger than for Argentina. Comparing both types of errors, the results show that in the long-run, the method performs just as ineffectively when focusing on poor households, but that it also falters with respect to the non-poor. The method seems to fare with low precision in both cases, but slightly more so when extrapolating over a longer time period.

The results are relatively unchanged when analysing each particular time period. For the first (1996-2001) cohort, Type I error is lower (51 percent), and it worsens for the following cohort (63 percent). For the ten year period, the level of error is lower (52 percent). However, as in the case of Argentina, even the best case scenario excludes more than half of the poor. Figure 5.4 summarises these findings, and plots the evolution of both error types for each period.

In general, the findings for Chile show that the cross sectional vulnerability estimates classify most households correctly when taking the entire population as a reference point, much like the case for Argentina. However, when focus is placed on the poor, the level of misclassification is still high, with the method classifying roughly half of poor households incorrectly. The validation exercise shows that cross sectional vulnerability estimates do not perform noticeably better or worse over a longer time period.

5.4 Vulnerability measures: effectiveness across the income distribution

The results of these validation exercises indicate that vulnerability estimates have a relatively high degree of misclassification. However, it should be noted that these classification errors are average estimates which may hide heterogeneities across the income distribution. Since vulnerability measures are mainly motivated as tools to capture welfare variability among those close to the poverty line, this section analyses the issue of misclassification for different income groups. From a policy point of view, vulnerability measures should prove useful as a targeting mechanism to provide social protection to households at risk. This section and the next can be interpreted as attempts to evaluate the methodology from this perspective.

An example might prove useful to illustrate this argument. Exclusion (Type I) errors represent the percentage of households classified as non-vulnerable, but that eventually become poor in a future point in time. These errors might be lower for households in the lowest percentiles (for instance, the extreme or chronically poor) than for households which are prone to transitory poverty spells, and whose incomes tend to fluctuate around the poverty line. Average error estimates would mask this heterogeneity. Therefore, this section tests for potential heterogeneity in the method's efficacy across the distribution by analysing errors by income groups.

The decomposition exercise presented below estimates Type I (exclusion) and Type II (inclusion) errors by income deciles. The income deciles are specified at time *t*, when vulnerability is estimated, and the errors are defined in *t+1*.[30] As in the previous section, these validation exercises rely on panel data, and mimic a policymaker's problem in assigning limited resources in *t+1* based on information collected in *t*, and using the realised status in *t+1* to measure the indicator's effectiveness. As with the previous results, estimates are carried out for vulnerability measures using the $4 USD poverty line and setting the vulnerability threshold at an absolute cut-off point (0.50).

The general structure of the results presented in the tables below is as follows. The first column presents the participation of each decile in the relevant population, i.e. for Type I (Type II) errors, the proportion of poor (non-poor) households as a function of the decile they

[30] Using income groupings in *t+1* would be counterintuitive. For instance, exclusion (Type I) errors are defined over households who become poor in *t+1*. Hence, income deciles in this period would concentrate only on the lower end of the distribution and omit movements across the entire spectrum. The logic is the same for inclusion errors, although in this case the reference population is the non-poor.

occupied in the income distribution in the previous period. These proportions offer an *ad hoc* indicator of mobility, since they indicate where in the distribution in *t* the poor in *t+1* come from. The second column of the tables summarises the group-specific errors. The average error presented in the prior sections may be obtained as a weighted mean of these errors (using the proportions in the first column as weights).

Tables 5.7 and 5.8 present the results of the decomposition for Argentina. In the previous section, the average estimates revealed that the method would incorrectly classify on average about 60 percent of poor households as non-poor in *t+1* (exclusion error). The results in Table 5.7 indicate that most of the future poor are located in the lower end of the original income distribution, particularly in the first three deciles. Within these groups, the vulnerability measure is most effective for households in the 1st decile, with values of the exclusion error (Type I) around 36 to 38 percent, and with a very low value of 13.8 percent corresponding to the 2001-2002 crisis. Exclusion errors are substantially higher for the next two deciles. Finally, the very high exclusion errors (above 90 percent) for households above the median of the income distribution represents, in fact, a relative success of the methodology. As indicated by the 'fraction poor in t+1' column in the table, there are very few better-off households that end up poor in the following period. The methodology classifies most of these households as non-vulnerable because of their income generating capacity in *t*, and cannot be expected to capture these few outliers. These general findings hold irrespective of the aggregate economic conditions, as shown in Figure 5.5 which compares a relatively stable period (1995-1996) with a deep aggregate crisis (2001-2002).

The results on Type II (inclusion) errors in the previous section indicate a lower level of incorrect classifications of around four percent of non-poor households. The results in Table 5.8 indicate that these errors are highest in the poorest deciles, although these represent a small proportion of the future non-poor. On average, less than three percent of the non-poor in *t+1* were in the first decile in *t*. This confirms that the vulnerability estimates are relatively precise at identifying the non-poor across the entire distribution (Figure 5.5).

Tables 5.9 and 5.10 present the same results for Chile for both short (1996-2001) and long (1996-2006) periods. The average estimates of exclusion errors for the Chilean panel reveal that about half of poor households would be incorrectly classified as non-poor in the following observation period. As with the short (one year) panels for Argentina, a large fraction of the poor in *t+1* (2001) or *t+2* (2006) were located in the first three deciles of the per capita income distribution in the initial period *t* (1996). The vulnerability estimates have substantially lower exclusion errors for the lowest decile. Interestingly, the efficacy of the methodology seems to be higher when taking the longest longitudinal span (ten-year period 1996-2006). Inclusion (Type II) errors, on the other hand, were substantially lower than for the Argentina data, even when analysing them by income decile. Table 5.10 indicates that inclusion errors are highest among the poor, who represent a small fraction of the future non-poor. The estimates are quite precise for the middle and upper end of the income distribution (see Figure 5.6).

5.5 A comparative assessment of deprivation indicators

5.5.1 *Comparing the performance of indicators*

The evaluation carried out above indicates that cross-sectional vulnerability estimates seem to capture the probability of future poverty for households, especially for those at the bottom of the income distribution, although with some exclusion errors. This result, however, lacks a benchmark for comparison. This section carries out a comparative assessment of several deprivation indicators' capacity to identify the future poor, and thus provides the possibility of contrasting the performance of the vulnerability measure relative to other indicators.

The deprivation measures discussed below include alternative specifications of vulnerability (using absolute and relative thresholds), regression-based income predictions, indicators of basic needs deficits (or 'structural' poverty) and multidimensional poverty measures. This list includes several types of indicators that are currently in use to target safety net and cash transfer programs in a number of countries in Latin America (e.g. Mexico, Honduras and Nicaragua).[31] Hence, the results from this assessment complete the robustness analysis of vulnerability measures by providing a comparison of the targeting performance of all selected indicators. It should be stressed that some of the indicators (for instance, multidimensional poverty measures) were not designed with the purpose of predicting future risk or outcomes, which is an explicit objective of vulnerability measures, but their application in policy settings justifies their inclusion. Moreover, materialisations of future poverty states are not necessarily good indicators of ex-ante risk distributions, but the availability of several longitudinal datasets provides a useful (if not necessarily complete) assessment of the methodologies.

The motivation of the exercise is, again, a setting in which a policy maker has information on household income and other characteristics in time *t*, and has to allocate a safety net budget in time *t+1* from the information in *t*. The empirical strategy in this section consists of three main steps. First, the analysis computes each deprivation measure for each household in period *t*, and classifies the population in terms of broadly defined vulnerability groups – they are classified as vulnerable if deprived according to the indicator, and not vulnerable otherwise. The second step compares this classification in *t* with *observed* income poverty in *t+1*, which allows obtaining Type I (exclusion) and Type II (inclusion) errors for each indicator (as in Section 5.2.2). Finally, these errors are presented for the two poorest deciles of the income distribution to measure efficiency in predicting poverty for households with low income.

[31] Appendix 1 at the end of the document details the specification of these indicators.

5.5.2 *Which indicator best identifies the future poor?*

Tables 5.11 to 5.14 present estimates of exclusion and inclusion errors for the first and second deciles of the income distribution (defined in period *t*). The first column corresponds to vulnerability estimates using the absolute threshold, which will be taken as the point of comparison. The following columns summarise results for the alternative indicators: vulnerability using the relative cut-off, income predictions, unsatisfied basic needs (UBN), and different specifications of the Alkire-Foster measure (A&F). Figures 5.7 to 5.10 depict the corresponding results for both countries and selected periods.

For Argentina's one year panels, the results for Type I (exclusion) errors indicate a relatively wide range in the performance of different indicators among households in the first decile (first panel of Figure 5.7). The estimated errors range from low levels of five to 15 percent (vulnerability with relative threshold, UBN) to 30 to 40 percent (vulnerability with absolute threshold, income prediction and A&F measures). The results are qualitatively similar for the second decile of the income distribution (second panel of Figure 5.7), but the level of exclusion errors increases for all measures, indicating more efficiency in identifying the chronic poor. As Figure 5.7 shows, this change is particularly important for the income prediction indicator and vulnerability with the absolute threshold.

In general, the measure with the highest level of accuracy in identifying the future poor is vulnerability using the relative threshold (with ten percent error on average), followed closely by UBN. The worst performers for the two poorest deciles are vulnerability with the absolute threshold, income predictions and the A&F measure. Moreover, these conclusions carry over regardless of the aggregate conditions.

Type II (inclusion) errors show the opposite behaviour. As stressed throughout this document, there is a trade-off between the two types of error, and minimising exclusion errors causes high inclusion errors. The budget of social programs and the cost of gathering information are some of the factors that must enter a cost-benefit analysis of the conflicting objectives of minimising inclusion and exclusion errors (see Ravallion and Chao, 1989 and Coady *et al*., 2004 for a more detailed discussion of targeting trade-offs). The cases of the UBN and the vulnerability measure based on a relative threshold, which performed well in terms of low exclusion errors, illustrate this trade-off, with relatively high Type II (inclusion) errors for deciles one and two of the income distribution (Figure 5.8).

The results for the longer Chilean panels (five and ten years) are qualitatively similar to those for Argentina (Figure 5.9). For the first decile of per capita income, the vulnerability measure based on a relative threshold is fairly accurate in identifying the future poor, showing levels of exclusion error less than eight percent in both selected time periods. However, unlike for Argentina, vulnerability with the absolute threshold (the standard or most commonly used measure of vulnerability) appears to be quite effective, with low error levels close to the results from UBN measures. For the second decile of the income distribution, the magnitude of the exclusion errors increases for all indicators, and the relative measure of vulnerability once again appears to be the most effective. The results remain relatively unchanged when analysis focuses on short-length or long-length periods. The most salient finding is that for the longest period (1996 to 2006) the performance of vulnerability based on a relative threshold and the UBN are quite close to those for the short-length period.

For Type II (inclusion) errors, the same trade-offs between inclusion and exclusion are evident (Figure 5.10). Vulnerability based on a relative threshold and UBN show on average the highest levels of inclusion errors, regardless of the place on the income distribution or the time span.

In summary, for both countries the results indicate a relatively better performance of vulnerability and UBN measures to identify households that become poor in the future, especially among those in the bottom decile of the income distribution. The most accurate (or error-minimising) predictors of poverty seem to be vulnerability using the relative threshold and UBN, but at the cost of high inclusion errors. The magnitude of error increases when the identification focuses on the second decile of household income, except for the two best-performers. Although the level of exclusion errors of the A&F multidimensional poverty indicator is relatively large, it shows little variation between the two income deciles considered here (particularly for the Argentinean case). Finally, with respect to the Type II (inclusion) errors, not surprisingly, for all measures considered in the exercise the levels of inclusion errors are more important when the exclusion errors are low.[32]

[32] This finding is consistent with the analysis of vulnerability threshold sensitivity in Cruces *et al.* (2010), which is available from the authors upon request.

6 Conclusions

The main findings of this study indicate that for the LAC region as a whole vulnerability levels decreased from the early 1990s to the mid 2000s, although they increased during most of the 1990s. At the country level, the results suggest that Argentina, Chile and Uruguay are the countries with the lowest level of vulnerability; while Guatemala, Honduras and Nicaragua are the most vulnerable on average. Countries which did not reduce their level of vulnerability across time include Argentina, the Dominican Republic, Uruguay and Venezuela. The most significant reduction was observed for Brazil. The comparison of the evolution of poverty and vulnerability indicated the presence of similar patterns across all countries. Measures of vulnerability thus seem to closely follow poverty levels. This fact can be seen in countries where welfare changed sharply (Argentina during the 2001-2002 financial crisis), or in a smooth way (the Brazilian case).

Household vulnerability profiles indicated that this phenomenon in Latin America is correlated to residence in rural areas, with self-employed household heads with low educational levels. In most other characteristics, the vulnerable are highly similar to the poor. However, differences between countries, both in levels and in these characteristics, are substantial, indicating the need of country-specific initiatives to reduce vulnerability. It should be noted that vulnerable households, as defined by this methodology, are both poor and non-poor. This evidence suggests that cross-sectional poverty assessments may not be capturing the full extent of future welfare variability.

These results, however, have to be analysed in the light of the validation exercises presented in the document. The analysis provided a series of robustness checks of cross-section vulnerability estimates as predictors of future poverty, and quantified the potential misclassifications of households for both short term (Argentina) and long term (Chile) data. The findings for Argentina suggest that estimates of vulnerability classify most households correctly when taking the entire population as a reference point, but show a relatively high level of misclassification when considering the poverty status of individual households over time. However, the errors are substantially lower among households in the bottom ten and 20 percent of the income distribution. The results for Chile, based on longer tem panels, are similar to those for Argentina. The specific contexts of both case studies (wide aggregate fluctuations for Argentina, sustained growth and falling poverty for Chile) illustrate the potential but also highlight the limitations of cross-sectional estimates of vulnerability as predictors of future poverty.

The validation exercise also compared the efficacy of vulnerability measures with respect to other deprivation indicators. The comparative assessment indicated that the lowest exclusion errors with respect to future materialised poverty states are attained with vulnerability measures based on a relative threshold and with UBN indicators, although at the cost of high inclusion errors. Vulnerability measures based on an absolute threshold, on the other hand, showed a more balanced performance, with a relatively low level of combined error.

These results suggest that cross sectional vulnerability estimates might provide useful information for analysts and policy makers, but that the results from the methodology need to be complemented with further background information. For instance, vulnerability profiles should help to distinguish which of the poor households classified as not vulnerable are truly only experiencing a temporary poverty spell, and which ones are true classification errors. Moreover, the estimates can benefit greatly from information on overall economic conditions, or on aggregate or group-specific shocks, and at the same time can inform policymakers of distributional trends without full national household surveys (Mathiassen, 2009). While the exercises presented here analysed the performance with respect to monetary income, assessing the effectiveness of different deprivation indicators in targeting a wider set of dimensions is an interesting direction for future research.

References

Albert, J., L. Elloso and A. Ramos, (2007). 'Towards Measuring Household Vulnerability to Income Poverty in the Philippines'. Discussion Paper Series, 2007-16. Manila: Philippine Institute for Development Studies.

Albornoz, F. and M. Menendez (2002). 'Analyzing income mobility and inequality: The case of Argentina during the 1990s'. Unpublished manuscript, DELTA.

Alderman, H., J. Behrman, H. Kohler, J. Maluccio and S. Watkins (2000). 'Attrition in Longitudinal Household Survey Data: Some Tests for Three Developing-Country Samples'. Policy Research Working Paper No. 2447. Washington, D.C: World Bank.

Alkire, S. and J. Foster (2009). 'Counting and Multidimensional Poverty Measurement'. Revised and Updated, OPHI Working Paper No. 32. Oxford: Oxford Poverty and Human Development Initiative (OPHI).

Amemiya, T. (1977). 'The Maximum Likelihood estimator and the non-linear three stage least squares estimator in the general nonlinear simultaneous equation model'. *Econometrica*, 45, 955-968.

Barrientos, A. (2007). 'Does vulnerability create poverty traps?'. CPRC Working Paper 76. Manchester, UK: Chronic Poverty Research Centre.

Barrientos, A. and A. Shepherd (2003). 'Chronic poverty and social protection'. Mimeo, paper presented at the CPRC Conference on Chronic Poverty, University of Manchester, April 2003.

Battiston, D., G. Cruces, L. Lopez Calva, M. Lugo and M. Santos (2009). 'Income and Beyond: Multidimensional Poverty in six Latin American countries'. OPHI Working Paper No. 17 and CEDLAS Working Paper 90. Oxford: Oxford Poverty and Human Development Initiative (OPHI).

Baulch, B. and J. Hoddinott (2000). 'Economic Mobility and Poverty Dynamics in Developing Countries'. *Journal of Development Studies*, 36(6), 1-24.

Bendezú, L., A. Denis, C. Sánchez, P. Ugalde, and J.R. Zubizarreta (2007a). 'La Encuesta Panel CASEN: metodología y calidad de datos'. (Eds) J.R. Zubizarreta, Documento Metodológico Nº 1, Observatorio Social, Universidad Alberto Hurtado.

Bendezú, L., A. Denis and J.R. Zubizarreta (2007b). 'Análisis de la atrición de la muestra de la Encuesta Panel CASEN'. Documento de Trabajo Nº 1, Observatorio Social, Universidad Alberto Hurtado.

Bourguignon, F., C. Goh and D.I. Kim (2004). 'Estimating individual vulnerability to poverty with pseudo-panel data'. World Bank Policy Research Working Paper 3375. Washington, D.C: World Bank.

Carballo, J. and M. Bongiorno (2007). 'Vulnerabilidad Individual: Evolución, Diferencias Regionales e Impacto de la Crisis. Argentina 1995-2005. Un Análisis por Cohortes'. CEDLAS Working Paper No. 51. Buenos Aires: Universidad Nacional de la Plata

CEDLAS and World Bank, (2010). *SEDLAC Socio-Economic Database for Latin America and the Caribbean.* Available at http://sedlac.econo.unlp.edu.ar/

Chaudhuri, S., J. Jalan and A. Suryahadi (2002). 'Assessing household vulnerability to poverty from cross-sectional data: A methodology and estimates from Indonesia'. *Economics Department Discussion Papers* No. 117. New York: Columbia University.

Chaudhuri, S. (2003). 'Assessing vulnerability to poverty: Concepts, empirical methods and illustrative examples'. Mimeo. New York: Columbia University.

Christiaensen, L.J. and K. Subbarao (2005). 'Towards an Understanding of Household Vulnerability in Kenya'. *Journal of African Economies*, 14(4), 520-558.

Coady, D., M. Grosh and J. Hoddinott (2004). 'Targeting of Transfers in Developing Countries: Review of Lessons and Experience'. Washington D.C: IFPRI and World Bank.

Cruces, G. (2005). 'Income Fluctuations, Poverty and Well-Being Over Time: Theory and Application to Argentina'. *STICERD-DARP Working Paper* 76. London: London School of Economics.

Cruces, G., and Q. T. Wodon, (2003) 'Transient and chronic poverty in turbulent times: Argentina 1995-2002.' *Economics Bulletin*, Vol. 9(3), 1-12.

Cruces, G., and Q. T. Wodon, (2007). 'Risk-Adjusted Poverty in Argentina: Measurement and Determinants'. *Journal of Development Studies*, 43(7), 1189–1214.

Cruces, G., L. Gasparini, M. Bérgolo and A. Ham, (2010). 'A Report on Vulnerability to Poverty in Latin America: Empirical Evidence from Cross-Sectional Data and Robustness Analysis with Panel Data'. Unpublished Report, Chronic Poverty Research Centre and CEDLAS.

Dercon, S., (2001). 'Assessing vulnerability'. Mimeo. Oxford: CSAE, Department of Economics, Oxford University.

Dercon, S. (2005). 'Vulnerability: A microperspective'. Mimeo. Oxford: CSAE, Department of Economics, Oxford University.

Elbers, C. and J.W. Gunning, (2003). 'Estimating vulnerability'. Paper presented at the conference Staying Poor: Chronic poverty and development policy, University of Manchester, 2003.

Feres, J.C. and X. Mancero, (2001). 'El Metodo de las Necesidades Basicas Insatisfechas (NBI) y sus aplicaciones en America Latina'. Estudios Estadisticos y Prospectivos No. 7. Santiago, Chile: ECLAC.

Ferreira, F., P.G. Leite, L.A. Pereira da Silva and P. Pichetti, (2004). 'Can the Distribution impact of Macroeconomic Shocks be predicted? A comparison of the performance of macro-micro models with historical data for Brazil'. World Bank Policy Research Working Paper 3303. Washington, D.C: World Bank.

Fields, G. and E.A. Ok, (1999). 'Measuring movement of incomes'. *Economica*, 66(264), 455-471.

Foster, J.E., J. Greer and E. Thorbecke (1984). 'A Class of Decomposable Poverty Measures'. *Econometrica*, 52(3).

Gaiha, R. and K. Imai (2008). 'Measuring Vulnerability and Poverty. Estimates for Rural India'. UNU-WIDER Research Paper No. 2008/40. Helinski: UNU-WIDER.

Gallardo Altamirano, M., (2009). 'Estimación de corte transversal de la vulnerabilidad y la pobreza potencial de los hogares en Nicaragua'. CEDLAS Working Paper No. 86. Buenos Aires: Universidad Nacional de la Plata.

Gasparini, L., (2007). A Guide to the SEDLAC: Socioeconomic Database for Latin America and the Caribbean. CEDLAS and World Bank. See: http://sedlac.econo.unlp.edu.ar/eng/

Gasparini, L. and G. Cruces (2010). 'A Distribution in Motion: The Case of Argentina'. In *Declining Inequality in Latin America: A Decade of Progress?.* (Eds) Luis Felipe López Calva and Nora Lustig. Washington, D.C: Brookings Institution Press.

Gasparini, L., G. Cruces and L. Tornarolli (2010). 'Recent Trends in Income Inequality in Latin America'. *Economía* 10 (2).

Günther, I. and K. Harttgen, (2006). 'Households' vulnerability to Covariate and Idiosyncratic Shocks'. *Mimeo.* Göttingen: Department of Economics, University of Göttingen.

Gutierrez, F., (2004). 'Dinamica Salarial y Ocupacional: Analisis de panel para Argentina 1998-2002'. CEDLAS Working Paper No. 11. Buenos Aires: Universidad Nacional de la Plata.

Haveman, R and A. Bershadker (1998). 'Self Reliance as Poverty Criterion: Trends in Earnings-Capacity Poverty, 1975-1992'. *American Economic Review*, 88(2), 342-347.

Hoddinnott, J. and A.R. Quisumbing, (2008). 'Methods for Econometric Risk and Vulnerability'. Mimeo. Washington, D.C: International Food Policy Research Institute.

Jalan, E. and M. Ravallion, (1998). 'Transient Poverty in Postreform Rural China,' *Journal of Comparative Economics*, 26, 338–357.

Jalan, J. and M. Ravallion, (2000). 'Is Transient Poverty Different? Evidence for Rural China'. *Journal of Development Studies*, 36, 82-99.

Just, R.E. and R.D. Pope, (2003). 'Agricultural Risk Analysis: Adequacy of Models, Data and Issues'. *American Journal of Agricultural Economics*, 85(5), 1249-1256.

Kamanou, G. and J. Morduch, (2002). 'Measuring Vulnerability to Poverty'. UNU-WIDER Discussion Paper No. 2002/58.

Kasirye, I. (2007). 'Vulnerability and Poverty Dynamics in Uganda, 1992-1999'. MPRA Paper 8557, University Library of Munich, Germany.

Kurosaki, T., (2007). 'Targeting the Vulnerable and Choice of Vulnerability measures: Review and Application to Pakistan'. Mimeo. Tokyo: Hitotsubashi University, Japan.

Ligon, E., and L. Schecter, (2003). 'Measuring vulnerability'. *The Economic Journal*, 114, 95-102.

Makoka, D. and M. Kaplan, (2005). 'Poverty and Vulnerability: An Interdisciplinary Approach'. Unpublished manuscript.

Mathiassen, A. (2009). 'A model based approach for predicting annual poverty rates without expenditure data'. *Journal of Economic Inequality* 7, 117–135.

Naudé, W., M. McGivillray and S. Rossouw, (2008). 'Measuring the vulnerability of subnational regions'. UNU-Wider Research Paper No. 2008/54. Helinksi: UNU-WIDER.

Paes de Barros, R., M. de Carvalho, S. Franco and R. Mendonça (2006). 'Conseqüências e causas imediatas da queda recente na desigualdade de renda brasileira'. Texto para Discussão, Nº. 1201. Rio de Janeiro: IPEA.

Prowse, M. (2003). ‘Towards a clearer understanding of ‘vulnerability’ in relation to chronic poverty’. CPRC Working Paper 24. Manchester, UK: Chronic Poverty Research Centre.

Ravallion, M. and K. Chao (1989). ‘Targeted Policies for Poverty Alleviation under Imperfect Information: Algorithms and Applications.’ *Journal of Policy Modeling* II(2), 213–24.

Rice, J.A., (2006). *Mathematical Statistics and Data Analysis*. Belmont, CA: Duxbury Press.

Santos, M., M. Lugo, L. López Calva, G. Cruces and D. Battistón. (2010). ‘Refining the Basic Needs Approach: A multidimensional analysis of poverty in Latin America’. *Research on Economic Inequality*, 18.

Sarris, A. and P. Karfakis, (2006). ‘Household vulnerability in Rural Tanzania’. Paper presented at the 2006 CSAE Conference: Reducing Poverty and Inequality: How can Africa be included?, Oxford, England, UK, 19-21 March 2006.

Suryahadi, A. and S. Sumarto (2003) ‘Poverty and Vulnerability in Indonesia before and after the Economic Crisis,’ *Asian Economic Journal*, 17(1), 45-64.

Suryahadi, A., S. Sumarto and L. Pritchett, (2000). Quantifying vulnerability to poverty: A proposed measure applied to Indonesia. Jakarta: Social Monitoring and Early Response Unit, UNDP.

Tesliuc, E., and K. Lindert, (2002). Vulnerability: A quantitative and qualitative assessment, Guatemala Poverty Assessment Program. Washington D.C: World Bank.

Zhang, Y. and G. Wan, (2008). ‘Can we predict Vulnerability to Poverty?’. UNU-Wider Research Paper No. 2008/82. Helinksi: UNU-WIDER.

Appendix 1: Alternative deprivation indicators

Inability to generate income

Haveman and Bershadker (1998). among other authors, have focused their analysis of poverty on households' ability to generate resources, rather than on their effective availability. They define a household's capacity to generate income as the sum of the potential earnings of its members, based on observable characteristics. These authors attempt to structurally model the income generation capacity, and use the results from the regressions to compute fitted values for income, and compare this potential income with an exogenous poverty line. This methodology is clearly related to the model in equation (6) in section 2.4.2, which serves a similar purpose. The analysis presented here uses the basic 'vulnerability' model to obtain household income predictions. These values classify households as vulnerable if the fitted values of income are below the poverty line in *t+1*, and as not vulnerable otherwise. The difference between this methodology and the one used in other sections of this document is that vulnerability measures include a further transformation of the predicted income, since it implies computing the conditional probability of being poor. The comparison of the Haveman and Bershadker (1998) approach and the vulnerability measures provides a benchmark to test whether this additional step adds information or mitigates measurement error over the simple income prediction.

Unsatisfied Basic Needs (UBN)

The Unsatisfied Basic Needs (UBN) approach is a non-income method widely used Latin America (most notably by ECLAC, see Feres and Mancero, 2001 and Santos *et al*., 2010) to capture structural poverty at the household level. The approach classifies a household as poor according to the UBN criterion if it exhibits a deficit in at least one the following dimensions (see Santos *et al*., 2010 for specific details of the dimensions employed here):

- Overcrowding: more than 4 dwellers per room
- The household's dwelling is located in a 'poor or precarious' location (e.g. shanty towns)
- The dwelling is made of low-quality materials
- The dwelling does not have access to the water network
- The dwelling does not have a hygienic restroom
- There are children aged 7 to 11 not attending school
- The household head does not have a primary school degree
- High dependency ratio: a combination of two conditions, the household head does not have a high-school degree and there are more than 4 household members for each income earner.

Deprivation as UBN is a 'union' indicator, hence households are classified as vulnerable if they have deficiencies in at least one of the above dimensions and not vulnerable otherwise.

Multidimensional deprivation

This section also estimates one measure of the family of multidimensional poverty indicators developed by Alkire and Foster (2009). The criterion identifies the poor in two stages, first by defining a threshold for each considered dimension and second, exogenously defining the number of dimensions in which the household should be deprived to be considered poor. The second stage allows evaluating both union (poor in at least one dimension) and intersection (poor in all dimensions) criteria, but is flexible enough to allow intermediate cases. Once identified, the poor are aggregated by a counting approach based on the Foster, Greer and Thorbecke – FGT – (1984) measures of poverty.

Specifically, the analysis below employs the *dimension-adjusted headcount ratio measure* (hereafter, A&F(0,*k*)) which may be seen as a result of two components; a multidimensional headcount ratio (*H*) and the average deprivation share across the poor (*A*). Formally, it is defined as:

$$A\&F(0,k) = H \cdot A = \frac{1}{nd}\sum_{i=1}^{n} c_i \pi_k (x_i; z)$$

with $H = \frac{1}{n}\sum_{i=1}^{n} \pi_k (x_i; z) = \frac{q_k}{n}$ and $A = \frac{1}{q_k d}\sum_{i=1}^{n} c_i \pi_k (x_i; z)$

where d represents the number of considered dimensions, n the number of households in the sample population, x_i is the outcome of household i in dimension k and z the deprivation line for that dimension. c_i depicts the sum of weighted deprivations for each household[33]. The term $\pi_k (x_i; z)$ represents a multidimensional identification function relating to a cut-off level k, such that it takes value 1 if $c_i \geq k$, indicating that the household is multidimensionally poor (taking value 0 in otherwise). The aggregation of $\pi_k (x_i; z)$ across the sample population results in the number of poor q_k, identified by both sets of cut-offs. Taking averages, this provides the multidimensional headcount ratio H. On the other hand, A is obtained by summing the (weighted) deprivations of all poor households and dividing by the maximum number of possible deprivations. In words, A represents the fraction of possible dimensions d in which the average multidimensionally poor household is deprived.

Therefore, A&F(0,*k*) can be expressed as a product between the percentage of multidimensional poor (*H*) and the average deprivation share across the poor (*A*). It may thus be interpreted as a headcount measure adjusted by the fraction of (weighted) dimensions in which poor households are deprived. The advantage of the weighting adjustment is that it

[33] Each dimension has a weight attached, and the weights are such they add up to the total number of dimensions *d*.

allows the measure to satisfy a desirable property, monotonicity across dimensions[34]. The A&F(0,*k*) measure estimated here uses the following dimensions and thresholds:

Definition of dimensions and thresholds for A&F(0,*k*) measure

Dimension	Indicator	Weight	Trheshold
Education	Education of household head in years	1	6 years
Income	Per capita income	1	U$S 4 poverty line
Overcrowding	Person per room	1	3 persons persom per room
Access to water	Dwelling has access to water	1	Yes/No
Housing quality	Dwelling is made of low-quality materials	1	Yes/No

All dimensions are equally weighted which assumes a ‘neutral’ criterion about each component’s relative importance. The inclusion of both ‘structural’ and money metrics of poverty follows the criteria set by Battiston *et al.*’s (2009) application to Latin America. Finally, deprived households are defined in three ways: k = 1,2,5. The first corresponds to a union approach, the second to an intermediate case and the last to the intersection approach.

[34] According to Alkire and Foster (2009) this property requires that an expansion in the range of deprivations experienced by a poor person is reflected in the overall level of poverty.

Appendix 2: Tables

Table 3.1: Household surveys used in this study

Country	Early 1990s	Late 1990s	Early 2000s	Late 2000s
Latin America				
Argentina	1992	1996	2002	2006
Bolivia	n.a.	1997	2002	2007
Brazil	1992	1996	2002	2007
Chile	1992	1996	2000	2006
Colombia	n.a.	1996	2001	2006
Costa Rica	1992	1997	2002	2007
Dominican Republic	n.a.	n.a.	2002	2007
Ecuador	1995	1998	n.a.	2006
El Salvador	1991	1996	2002	2007
Guatemala	n.a.	n.a.	2000	2006
Honduras	1992	1997	2002	2006
Mexico	1992	1996	2002	2006
Nicaragua	1993	1998	2001	2005
Panama	1991	1997	2001	2006
Paraguay	1995	1999	2002	2007
Peru	n.a.	1997	2002	2007
Uruguay	1992	1997	2002	2007
Venezuela	1992	1998	2002	2006

n.a. – Not available

Source: Own calculations from SEDLAC database

Table 3.2: Descriptive statistics: household

Country	Households	Urban	Household Size	Dependency Ratio	Proportion of Persons employed
Argentina					
1992	17,981	100.0	3.4	0.5700	57.0
1996	17,955	100.0	3.4	0.6088	60.9
2002	11,747	100.0	3.4	0.5937	59.4
2006	15,745	100.0	3.3	0.5997	60.0
Bolivia					
1997	8,462	67.7	4.3	0.3997	40.0
2002	5,746	64.0	4.4	0.3804	38.0
2007	4,148	65.8	4.0	0.4598	46.0
Brazil					
1992	84,362	81.3	3.7	0.4197	42.0
1996	91,706	81.7	3.6	0.4453	44.5
2002	115,432	85.8	3.3	0.4969	49.7
2007	126,144	85.0	3.2	0.5548	55.5
Chile					
1992	35,948	84.2	3.9	0.5237	52.4
1996	33,636	85.1	3.9	0.5193	51.9
2000	65,036	87.1	3.8	0.5515	55.2
2006	73,720	87.3	3.7	0.6853	68.5
Colombia					
1996	31,264	62.1	4.3	0.4726	47.3
2001	32,104	73.9	4.1	0.5228	52.3
2006	31,539	75.3	3.7	0.5483	54.8
Costa Rica					
1992	8,479	45.7	4.3	0.4024	40.2
1997	9,923	43.9	4.1	0.4263	42.6
2002	11,094	58.7	3.9	0.4476	44.8
2007	12,361	59.4	3.7	0.5206	52.1
Dominican R.					
2002	5,720	65.2	3.9	0.5375	53.8
2007	7,649	64.6	3.7	0.5598	56.0
Ecuador					
1995	5,801	65.4	4.7	0.3974	39.7
1998	5,774	61.1	4.5	0.4297	43.0
2006	13,581	77.4	4.0	0.4799	48.0
El Salvador					
1991	18,954	53.0	4.8	0.4337	43.4
1996	8,670	58.7	4.6	0.4896	49.0
2002	16,479	63.2	4.3	0.5478	54.8
2007	16,764	66.2	4.0	0.5369	53.7
Guatemala					
2000	7,275	43.2	5.2	0.3362	33.6
2006	13,686	53.6	4.9	0.3761	37.6
Honduras					
1992	4,757	44.4	5.4	0.3641	36.4
1997	6,362	46.4	5.3	0.3696	37.0
2002	21,188	52.0	4.9	0.3930	39.3
2006	21,076	61.1	4.6	0.4485	44.8
Mexico					
1992	10,187	76.1	4.8	0.3647	36.5
1996	13,687	77.0	4.6	0.4052	40.5
2002	16,797	77.7	4.2	0.4699	47.0
2006	20,875	78.5	4.0	0.4974	49.7
Nicaragua					
1993	4,454	58.6	5.6	0.3798	38.0
1998	4,016	56.7	5.4	0.3908	39.1
2001	3,705	62.1	5.3	0.4122	41.2
2005	6,861	58.3	5.2	0.5051	50.5
Panama					
1991	8,867	58.2	4.3	0.5231	52.3
1997	9,897	63.2	4.0	0.5239	52.4
2001	13,372	65.1	4.2	0.5459	54.6
2006	12,865	65.5	3.8	0.5823	58.2
Paraguay					
1995	4,667	54.1	4.6	0.4222	42.2
1999	5,101	60.9	4.5	0.4209	42.1
2002	3,789	60.7	4.5	0.4403	44.0
2007	4,812	61.1	4.3	0.4853	48.5
Peru					
1997	6,487	66.7	4.7	0.4338	43.4
2002	18,598	65.2	4.4	0.4761	47.6
2007	22,204	65.6	4.2	0.5243	52.4
Uruguay					
1992	9,282	100.0	3.2	0.6457	64.6
1997	20,003	100.0	3.2	0.6839	68.4
2002	18,421	100.0	3.1	0.6840	68.4
2007	49,135	93.5	2.9	0.6607	66.1
Venezuela					
1992	62,744	18.7	5.0	0.4540	45.4
1998	16,750	16.7	4.7	0.4758	47.6
2002	53,124	14.0	4.4	0.4935	49.4
2006	38,492	100.0	4.3	0.5305	53.0

Source: Own calculations from SEDLAC database

Table 3.3: Descriptive statistics: household heads

Country	Males	Age	Primary Incomplete	Primary Complete	Secondary Incomplete	Secondary Complete	Tertiary Incomplete	Tertiary Complete
Argentina								
1992	76.6	50.2	15.7	34.5	15.6	15.0	6.8	9.3
1996	74.5	50.3	15.1	33.3	16.3	16.3	7.7	11.1
2002	72.6	49.8	13.3	31.1	17.6	16.2	9.6	12.1
2006	68.4	49.3	11.8	28.6	15.9	19.1	10.4	14.1
Bolivia								
1997	81.2	45.0	54.6	5.0	11.5	11.6	5.5	11.9
2002	80.3	44.1	55.5	5.7	12.2	10.6	7.1	8.9
2007	74.8	45.3	46.7	6.1	10.6	15.0	8.6	12.8
Brazil								
1992	78.4	44.3	73.0	7.5	3.1	9.1	2.6	4.5
1996	76.8	45.3	68.6	8.6	3.4	10.5	2.8	5.8
2002	72.6	45.6	61.9	8.7	4.2	14.5	3.8	6.5
2007	67.7	46.6	54.0	9.8	4.7	17.1	4.6	9.5
Chile								
1992	79.4	47.8	37.7	9.7	15.7	16.8	2.7	4.9
1996	78.0	48.1	28.3	14.1	20.0	20.7	4.1	11.4
2000	76.5	49.0	25.4	13.5	18.8	22.9	4.8	13.6
2006	70.2	51.2	24.9	14.7	17.9	23.4	4.9	13.8
Colombia								
1996	75.7	46.3	37.3	21.4	19.2	12.5	2.2	6.9
2001	71.7	47.1	34.9	19.8	17.6	15.6	3.0	8.9
2006	68.3	47.7	31.3	17.5	17.9	16.7	4.5	11.9
Costa Rica								
1992	80.6	45.0	35.1	29.3	13.6	10.2	9.0	2.0
1997	79.3	45.9	30.1	32.7	14.0	9.8	11.0	2.0
2002	75.3	45.9	26.8	30.9	15.4	10.0	13.8	2.5
2007	70.4	47.4	23.9	30.2	16.4	11.2	14.8	3.4
Dominican R.								
2002	69.7	47.4	56.1	10.5	11.2	8.9	4.3	8.9
2007	69.9	47.7	51.5	12.1	11.5	11.2	4.2	9.5
Ecuador								
1995	81.7	45.2	34.2	26.5	17.5	8.0	5.5	8.2
1998	81.5	45.8	31.8	28.1	16.3	8.9	6.0	8.8
2006	78.5	45.8	22.8	25.5	18.7	12.9	8.2	11.8
El Salvador								
1991	73.7	45.8	78.8	6.2	8.0	0.1	3.8	2.1
1996	71.3	47.6	74.7	7.8	2.0	8.8	3.0	3.3
2002	66.2	48.6	66.1	9.6	2.5	10.9	2.3	6.1
2007	64.7	48.6	65.5	10.9	2.5	11.8	4.6	4.7
Guatemala								
2000	81.8	44.3	65.5	13.1	7.4	5.1	2.8	3.8
2006	77.3	45.2	60.3	14.4	8.4	8.8	3.6	4.0
Honduras								
1992	78.9	45.4	60.7	19.7	4.9	10.3	1.1	3.4
1997	77.3	45.2	59.7	19.2	7.3	9.1	1.6	2.8
2002	73.4	44.6	55.5	21.9	7.5	9.4	2.3	3.2
2006	65.4	45.7	46.2	25.0	11.6	9.0	1.3	4.4
Mexico								
1992	86.4	43.7	44.4	19.6	17.6	7.0	4.0	7.5
1996	84.4	44.3	39.1	19.5	20.1	8.7	4.2	8.3
2002	80.3	46.8	35.0	19.0	22.7	9.5	4.8	9.0
2006	75.8	46.6	29.0	19.0	26.3	10.1	3.4	12.1
Nicaragua								
1993	71.6	44.1	63.6	12.1	13.4	5.5	1.9	3.1
1998	72.1	45.3	60.8	12.9	14.1	6.0	1.9	3.8
2001	71.6	46.4	60.9	13.0	14.2	5.3	2.4	4.3
2005	68.5	48.7	58.7	13.9	13.5	6.3	2.0	5.6
Panama								
1991	75.9	48.2	28.3	24.8	17.2	15.9	7.1	6.7
1997	74.3	47.2	22.8	22.8	19.3	19.1	7.4	8.6
2001	76.5	47.3	22.7	25.3	19.2	17.7	7.9	7.3
2006	73.0	48.5	19.2	23.0	20.4	19.3	9.6	8.5
Paraguay								
1995	79.7	45.6	48.2	22.1	13.9	8.5	3.3	4.1
1999	74.5	46.1	40.9	22.8	19.5	8.5	4.1	4.2
2002	74.1	46.3	41.9	25.0	15.4	9.5	3.6	4.5
2007	72.9	47.5	46.2	15.7	17.8	9.0	5.7	5.6
Peru								
1997	81.4	46.9	29.9	18.0	13.1	20.5	4.5	13.4
2002	79.4	48.0	30.4	16.6	14.0	20.2	4.9	13.2
2007	77.5	49.5	27.3	15.9	13.4	21.2	6.1	16.1
Uruguay								
1992	74.8	54.1	25.6	27.9	19.4	6.1	10.6	5.1
1997	71.0	55.0	27.1	26.5	22.6	5.3	7.1	6.5
2002	67.2	54.5	19.1	26.9	24.3	8.3	7.5	8.6
2007	65.5	53.1	18.1	25.5	33.1	7.8	6.4	9.1
Venezuela								
1992	79.0	45.9	30.0	27.4	20.2	11.2	4.1	7.2
1998	73.3	46.2	27.2	25.1	33.8	1.0	3.1	9.5
2002	70.8	45.7	22.7	24.1	37.7	1.4	3.7	10.0
2006	67.2	47.1	20.2	24.0	38.8	1.4	3.9	11.4

Source: Own calculations from SEDLAC database

Table 3.4: Argentina panel data: descriptive statistics

Years	Households	Regions	Household Size	Children	Male Head	Years of education of Household Head
1995-1996	9,174	5	3.9	1.3	77.1	8.7
1996-1997	8,712	5	3.8	1.2	74.9	8.9
1997-1998	7,392	6	3.8	1.2	74.9	8.9
1998-1999	8,012	6	3.8	1.2	73.0	9.0
1999-2000	7,170	6	3.8	1.2	73.0	9.1
2000-2001	7,053	6	3.7	1.2	72.0	9.3
2001-2002	6,829	6	3.8	1.1	71.0	9.1

Source: Own calculations on Argentina panel data

Table 3.5: Chile panel data: descriptive statistics

Years	Households	Regions	Household Size	Children	Male Head	Years of education of Household Head
1996-2001	3,090	4	4.2	1.3	74.9	8.0
2001-2006	3,090	4	4.0	1.0	71.6	8.4
1996-2006	3,090	4	4.1	1.2	71.5	8.4

Source: Own calculations from Chile panel data

Table 4.1: Indicators of vulnerability, $4 USD line

Country	FGT(0)	FGT(1)	FGT(2)	Mean Vulnerability	Vulnerable households	Vulnerability to Poverty Ratio
Argentina						
1992	10.7	2.7	1.2	10.5	4.4	0.41
1996	13.7	4.7	2.3	14.7	8.4	0.61
2002	30.7	13.6	8.0	33.0	27.9	0.91
2006	13.6	5.1	2.8	14.2	7.9	0.58
Bolivia						
1997	45.4	23.2	15.5	46.5	45.6	1.01
2002	51.6	27.5	19.1	51.5	52.8	1.02
2007	43.6	20.8	12.8	43.4	43.3	0.99
Brazil						
1992	46.6	22.2	13.6	47.5	45.9	0.98
1996	34.1	15.0	8.6	34.7	28.3	0.83
2002	33.3	13.6	8.0	33.5	27.7	0.83
2007	16.4	6.2	3.3	17.4	11.3	0.69
Chile						
1992	28.7	9.9	4.8	28.5	18.7	0.65
1996	22.2	7.6	3.7	23.1	15.1	0.68
2000	12.0	3.8	1.9	13.6	6.3	0.52
2006	12.7	3.8	1.8	14.4	6.0	0.47
Colombia						
1996	41.0	17.7	10.4	41.5	39.6	0.97
2001	51.0	24.0	14.9	51.1	54.3	1.07
2006	44.7	22.0	14.1	46.3	46.1	1.03
Costa Rica						
1992	34.6	13.8	7.8	36.6	31.6	0.91
1997	26.0	9.6	5.1	27.2	19.3	0.74
2002	24.4	9.3	5.0	25.7	17.7	0.73
2007	17.4	5.6	2.6	18.1	9.0	0.52
Dominican R.						
2002	29.7	11.8	6.5	30.8	24.2	0.81
2007	32.5	12.3	6.3	33.2	26.6	0.82
Ecuador						
1995	43.7	22.4	15.1	45.1	44.9	1.03
1998	49.5	24.6	16.1	50.4	53.8	1.09
2006	25.5	11.2	6.7	27.8	19.4	0.76
El Salvador						
1991	48.5	22.7	14.0	48.7	51.8	1.07
1996	42.0	18.3	10.7	42.9	41.7	0.99
2002	38.7	18.5	11.9	41.3	39.4	1.02
2007	30.8	11.9	6.6	33.1	27.0	0.88
Guatemala						
2000	49.8	22.3	13.3	50.2	53.6	1.08
2006	45.3	20.8	12.5	45.9	48.1	1.06
Honduras						
1992	66.3	35.9	23.8	65.6	73.1	1.10
1997	62.1	31.6	20.3	61.2	69.2	1.11
2002	55.4	29.8	20.0	55.9	61.9	1.12
2006	46.4	22.3	14.0	47.5	49.0	1.06
Mexico						
1992	34.2	14.3	8.3	35.6	29.3	0.86
1996	47.4	21.8	13.2	47.6	48.0	1.01
2002	30.6	12.1	6.8	31.9	25.8	0.84
2006	23.5	8.8	4.8	25.4	16.1	0.69
Nicaragua						
1993	67.9	39.1	27.2	67.5	75.7	1.12
1998	61.6	30.9	19.6	60.9	68.9	1.12
2001	58.6	28.0	16.9	57.7	62.0	1.06
2005	55.9	26.4	15.8	56.0	58.1	1.04
Panama						
1991	29.5	15.1	10.1	32.3	28.7	0.97
1997	22.0	10.5	6.7	24.7	18.3	0.83
2001	25.2	11.7	7.4	24.4	16.8	0.67
2006	20.0	8.7	5.1	18.4	10.2	0.51
Paraguay						
1995	33.4	15.5	9.5	34.1	30.8	0.92
1999	33.4	15.6	9.8	34.3	30.9	0.93
2002	44.7	22.7	14.7	46.4	46.6	1.04
2007	29.9	12.1	6.9	31.3	21.2	0.71
Peru						
1997	43.8	20.4	12.6	43.8	42.0	0.96
2002	44.9	20.7	12.3	45.2	43.3	0.96
2007	35.8	15.4	8.8	36.7	34.6	0.97
Uruguay						
1992	5.5	1.7	0.8	6.0	2.2	0.41
1997	6.3	1.9	0.9	6.5	2.6	0.41
2002	9.3	2.7	1.2	9.0	4.3	0.46
2007	10.8	3.2	1.4	10.4	5.3	0.49
Venezuela						
1992	26.3	9.3	4.7	27.8	21.2	0.81
1998	40.3	17.3	10.0	42.6	39.3	0.97
2002	51.2	23.1	13.7	51.7	53.6	1.05
2006	30.1	11.2	5.9	31.8	23.7	0.79

Source: Own calculations from SEDLAC database

Table 4.2: Vulnerability profile, $4 USD line

Country		Gender of the Household Head		Area		Educational Attainment			Employment		Per Capita Income Quintiles				
	Total	Male	Female	Urban	Rural	Low	Medium	High	Salaried Worker	Self-Employed	1	2	3	4	5
Argentina															
1992	4.4	4.9	2.6	4.4	n.a.	7.2	1.7	0.0	5.6	4.8	23.9	4.2	0.9	0.1	0.1
1996	8.4	8.6	7.7	8.4	n.a.	12.3	2.6	0.2	9.1	9.2	46.4	12.0	3.0	0.5	0.2
2002	27.9	29.9	22.5	27.9	n.a.	41.4	22.9	1.0	30.7	27.1	78.8	56.3	32.6	9.7	1.2
2006	7.9	7.5	8.8	7.9	n.a.	15.8	3.3	0.0	8.1	6.7	38.5	13.7	2.0	0.5	0.1
Bolivia															
1997	45.6	46.4	42.5	28.2	82.2	63.9	28.4	3.8	30.7	62.3	89.8	65.8	45.8	29.4	14.4
2002	52.8	56.0	39.9	30.5	92.3	72.5	32.3	2.6	37.9	68.2	96.0	78.9	60.4	37.2	14.0
2007	43.3	43.6	42.4	24.3	79.3	67.1	26.4	1.7	32.2	59.5	88.4	65.6	45.6	27.0	12.5
Brazil															
1992	45.9	46.1	45.2	38.3	78.9	55.5	7.5	0.1	47.1	55.0	89.7	74.9	53.9	29.9	10.2
1996	28.3	28.6	27.5	21.2	60.3	36.1	2.1	0.0	28.4	36.1	80.6	51.8	24.6	10.6	2.9
2002	27.7	28.2	26.3	23.2	54.4	37.0	6.0	0.0	29.7	33.6	81.2	53.0	23.2	8.7	2.0
2007	11.3	11.4	11.3	8.7	26.4	16.8	2.2	0.0	11.6	13.9	53.2	17.5	4.0	1.0	0.4
Chile															
1992	18.7	18.9	17.6	15.7	34.4	26.3	13.6	0.7	19.7	18.1	57.7	27.6	13.0	5.5	2.5
1996	15.1	15.4	14.3	11.6	35.0	26.5	7.0	0.0	15.4	14.8	53.8	21.8	8.0	2.4	0.8
2000	6.3	6.1	6.8	5.1	14.1	12.4	2.3	0.0	5.4	5.4	29.2	7.3	1.8	0.7	0.1
2006	6.0	5.1	8.1	5.2	11.5	11.3	2.9	0.0	4.4	4.5	26.5	6.2	1.8	0.7	0.1
Colombia															
1996	39.6	39.4	40.3	22.3	68.1	56.8	19.1	0.1	36.7	41.1	80.5	67.2	46.0	24.1	6.8
2001	54.3	54.2	54.6	43.9	83.8	77.0	36.1	1.9	47.9	57.1	88.2	80.9	68.4	49.8	16.0
2006	46.1	44.8	49.1	35.9	77.5	70.4	32.6	2.0	39.1	47.7	83.9	78.6	60.5	33.3	9.3
Costa Rica															
1992	31.6	29.8	38.9	19.6	41.7	41.6	10.6	0.5	25.5	32.5	77.8	53.1	29.2	12.5	4.0
1997	19.3	18.1	24.0	8.4	27.9	26.3	4.8	0.0	15.8	20.1	56.1	34.5	12.4	6.1	1.0
2002	17.7	16.6	21.3	9.1	30.1	26.0	3.7	0.1	13.8	17.2	55.4	30.1	11.7	3.6	0.9
2007	9.0	8.0	11.5	5.0	14.8	13.9	2.0	0.0	7.7	7.6	35.5	11.1	2.8	0.9	0.3
Dominican R.															
2002	24.2	23.5	25.6	15.0	41.2	32.3	11.7	1.4	14.9	29.0	69.2	35.3	20.2	9.4	2.3
2007	26.6	23.0	35.0	22.3	34.3	35.5	15.2	2.9	19.0	26.1	73.2	42.7	21.4	11.1	3.4
Ecuador															
1995	44.9	46.3	38.7	20.7	90.6	61.3	14.7	2.6	40.1	52.5	86.6	73.3	51.4	30.9	11.0
1998	53.8	53.7	54.3	30.2	90.7	73.2	26.0	1.9	46.1	64.0	88.9	82.1	62.0	41.6	15.4
2006	19.4	19.7	18.4	10.5	50.0	31.6	7.8	0.2	22.9	14.4	57.4	36.4	17.0	6.0	0.9
El Salvador															
1991	51.8	51.9	51.5	25.2	81.8	63.4	11.5	0.7	43.3	54.2	89.5	81.6	63.3	39.4	14.6
1996	41.7	44.1	35.9	17.7	75.8	53.5	9.1	0.7	36.2	46.8	84.6	70.4	47.7	25.2	7.1
2002	39.4	42.4	33.3	16.8	78.1	53.4	11.4	0.6	31.3	43.6	81.3	67.3	44.4	22.9	7.8
2007	27.0	30.2	21.1	10.6	59.0	44.3	5.9	0.0	23.7	29.6	69.2	44.6	26.5	12.6	3.1
Guatemala															
2000	53.6	55.5	45.1	25.6	74.9	63.1	9.0	0.0	51.6	59.1	82.2	78.8	64.8	44.3	17.5
2006	48.1	50.8	38.9	23.8	76.2	60.2	3.8	0.0	42.7	58.8	90.0	77.8	58.4	32.2	10.3
Honduras															
1992	73.1	71.5	79.2	53.0	89.0	84.7	23.6	1.9	58.8	83.7	98.5	95.3	91.8	70.6	32.6
1997	69.2	67.1	76.4	49.7	86.1	80.2	23.4	0.0	54.2	78.1	97.1	94.2	82.1	62.0	32.6
2002	61.9	62.7	59.5	36.5	89.3	74.9	10.2	0.3	48.9	71.6	95.6	89.2	73.4	51.3	21.8
2006	49.0	47.6	51.5	30.2	78.4	63.7	8.4	0.0	44.6	46.3	88.3	75.8	56.0	31.9	12.8
Mexico															
1992	29.3	30.8	20.2	15.1	73.8	42.0	4.5	0.2	24.9	41.6	76.7	49.0	28.7	14.1	4.0
1996	48.0	48.3	46.5	36.3	87.4	68.2	20.3	0.6	42.3	59.6	88.4	78.3	60.1	34.7	11.1
2002	25.8	26.2	24.2	14.1	66.6	40.9	7.2	0.1	23.0	34.4	70.7	46.1	21.7	8.7	2.4
2006	16.1	16.3	15.5	9.9	39.0	27.5	5.5	0.0	14.2	18.2	49.1	27.2	13.2	4.6	1.1
Nicaragua															
1993	75.7	76.5	73.6	61.5	95.8	84.3	44.2	3.8	67.9	77.4	97.8	95.4	91.8	75.0	38.6
1998	68.9	68.6	69.7	54.8	87.3	78.7	31.6	2.3	63.4	70.2	95.6	91.7	79.5	62.0	33.3
2001	62.0	62.5	60.8	48.9	83.4	71.3	30.8	0.5	57.6	63.5	93.9	88.9	75.4	54.0	22.6
2005	58.1	60.7	52.5	38.1	85.9	68.9	25.6	0.9	51.2	65.2	95.7	86.3	69.7	46.6	18.1
Panama															
1991	28.7	29.1	27.4	10.4	54.0	44.9	7.9	0.0	19.3	47.1	75.6	54.4	28.2	11.9	3.4
1997	18.3	17.8	19.8	6.6	38.5	31.7	5.4	0.1	12.4	26.1	56.3	35.9	15.9	4.0	0.9
2001	16.8	17.2	15.5	6.9	37.1	27.7	6.5	0.2	12.8	24.7	55.3	35.2	14.5	4.0	0.7
2006	10.2	10.3	9.7	4.0	23.2	19.0	3.4	0.1	8.2	15.2	40.4	21.6	5.6	1.1	0.1
Paraguay															
1995	30.8	32.2	24.9	8.7	56.8	39.7	2.9	0.0	19.3	42.8	76.6	53.3	30.9	14.4	4.7
1999	30.9	31.7	28.7	12.3	59.9	41.8	5.4	0.2	21.3	42.5	87.4	62.2	34.1	15.5	4.0
2002	46.6	47.0	45.2	28.0	75.2	60.1	14.6	0.3	34.8	55.9	86.9	74.3	55.0	31.5	12.2
2007	21.2	19.5	25.8	10.7	37.7	30.5	5.4	0.0	15.4	26.8	55.2	35.4	19.3	8.7	2.9
Peru															
1997	42.0	43.1	37.4	18.7	88.6	60.8	19.4	1.7	27.4	59.9	92.6	74.0	44.7	19.2	4.0
2002	43.3	45.2	35.8	19.2	88.3	65.2	25.8	1.2	27.7	61.2	92.1	73.9	46.3	20.4	5.2
2007	34.6	35.8	30.3	10.1	81.4	56.2	20.2	0.6	20.0	52.8	87.0	61.5	29.7	11.7	2.9
Uruguay															
1992	2.2	2.5	1.4	2.2	0.0	3.4	0.8	0.1	3.0	2.9	14.6	1.6	0.1	0.1	0.0
1997	2.6	2.8	1.9	2.6	0.0	3.9	0.9	0.0	3.6	3.4	16.8	1.8	0.3	0.0	0.0
2002	4.3	4.7	3.6	4.3	0.0	7.0	1.5	0.0	5.2	5.8	26.4	4.8	0.8	0.0	0.0
2007	5.3	5.1	5.6	5.4	3.6	8.7	1.7	0.0	5.8	6.3	32.7	5.7	0.9	0.2	0.0
Venezuela															
1992	21.2	19.1	29.0	5.4	24.8	29.5	6.9	0.3	17.2	21.0	66.6	35.5	17.1	6.2	1.5
1998	39.3	36.1	48.1	10.2	45.2	51.7	26.9	1.9	34.9	35.8	80.2	67.2	44.2	21.9	6.7
2002	53.6	51.4	59.1	25.4	58.2	68.2	45.6	3.2	48.5	51.3	88.4	83.1	67.2	42.2	15.3
2006	23.7	21.0	29.4	23.7	0.0	33.5	16.7	0.9	19.8	22.0	64.9	44.8	21.9	7.8	2.2

Source: Own calculations from SEDLAC database

Table 5.1: Argentina: vulnerability as expected poverty and actual poverty, $4 USD line

Year	Expected Poverty	Actual Poverty
1995-1996	14.0	12.8
1996-1997	13.9	14.3
1997-1998	15.8	14.2
1998-1999	15.7	14.9
1999-2000	15.7	17.7
2000-2001	18.4	20.7
2001-2002	22.3	31.8

Source: Own calculations on Argentina panel data

Table 5.2: Argentina: misclassifications, $4 USD line

	1996	
1995	Poor	Non-poor
Expected poor	4.6	3.3
Expected non-poor	8.3	83.9

	1997	
1996	Poor	Non-poor
Expected poor	4.9	2.7
Expected non-poor	9.4	83.0

	1998	
1997	Poor	Non-poor
Expected poor	5.7	3.3
Expected non-poor	8.6	82.5

	1999	
1998	Poor	Non-poor
Expected poor	5.9	3.3
Expected non-poor	9.0	81.8

	2000	
1999	Poor	Non-poor
Expected poor	6.5	3.6
Expected non-poor	11.2	78.7

	2001	
2000	Poor	Non-poor
Expected poor	8.1	3.4
Expected non-poor	12.7	75.9

	2002	
2001	Poor	Non-poor
Expected poor	13.4	2.8
Expected non-poor	18.4	65.4

Source: Own calculations on Argentina panel data

Note – All calculations use as the denominator the entire population

Table 5.3: Argentina: error types, $4 USD line

Year	Error Types	
	Type I	Type II
	Poor households estimated as not vulnerable (Type I)	Non-poor households estimated as vulnerable (Type II)
1995-1996	64.3	3.8
1996-1997	66.0	3.2
1997-1998	60.3	3.9
1998-1999	60.5	3.9
1999-2000	63.2	4.4
2000-2001	61.2	4.2
2001-2002	57.8	4.1

Source: Own calculations on Argentina Panel

Notes: -Type I households are the fraction of poor households in t+1 which are classified as not vulnerable in t

-Type II households are the fraction of non-poor households in t+1 which are classified as vulnerable in t

Table 5.4: Chile: vulnerability as expected poverty and actual poverty, $4 USD line

Year	Expected Poverty	Actual Poverty
1996-2001	21.7	18.0
2001-2006	19.1	9.3
1996-2006	21.7	9.0

Source: Own calculations on Chile panel data

Table 5.5: Chile: misclassifications, 4 USD line

	2001	
1996	Poor	Non-poor
Expected poor	8.9	7.5
Expected non-poor	9.2	74.5

	2006	
2001	Poor	Non-poor
Expected poor	3.4	8.6
Expected non-poor	5.9	82.1

	2006	
1996	Poor	Non-poor
Expected poor	4.3	10.6
Expected non-poor	4.7	80.5

Source: Own calculations on Chile panel data

Note – All calculations use as the denominator the entire population

Table 5.6: Chile: error types, $4 USD line

Year	Error Types	
	Type I	Type II
	Poor households estimated as not vulnerable (Type I)	Non-poor households estimated as vulnerable (Type II)
1996-2001	50.8	9.1
2001-2006	63.6	9.5
1996-2006	52.5	11.6

Source: Own calculations on Chile Panel

Notes: -Type I households are the fraction of poor households in t+1 which are classified as not vulnerable in t

-Type II households are the fraction of non-poor households in t+1 which are classified as vulnerable in t

Table 5.7: Argentina: Type I (exclusion) errors by income decile, $4 USD line

1995-1996		Type I Errors	
Decile in *t*	Fraction poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.309	37.3	13.3
2	0.322	63.3	24.8
3	0.168	81.9	41.8
4	0.069	79.8	31.6
5	0.058	99.4	52.8
6	0.036	99.7	62.8
7	0.003	100.0	79.0
8	0.016	100.0	95.9
9	0.020	100.0	62.1
10	0.000	100.0	100.0
Overall error		**64.3**	**29.6**
1996-1997		**Type I Errors**	
Decile in *t*	Fraction poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.308	36.9	13.2
2	0.336	66.1	20.8
3	0.145	88.1	20.2
4	0.069	96.9	46.4
5	0.064	89.8	64.0
6	0.026	100.0	91.4
7	0.013	96.6	45.9
8	0.022	76.0	52.4
9	0.012	100.0	100.0
10	0.005	100.0	100.0
Overall error		**66.0**	**27.1**

(continued) Table 5.7. Argentina: Type I (exclusion) errors by decile, $4 USD line

1997-1998		Type I Errors	
Decile in *t*	Fraction poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.414	43.1	10.2
2	0.300	61.6	20.6
3	0.115	75.2	38.2
4	0.101	82.3	34.9
5	0.026	99.6	72.0
6	0.023	98.6	78.2
7	0.006	100.0	95.8
8	0.007	100.0	61.5
9	0.007	100.0	92.4
10	0.001	100.0	100.0
Overall error		**60.3**	**23.7**

1998-1999		Type I Errors	
Decile in *t*	Fraction poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.377	36.4	7.2
2	0.277	55.9	15.5
3	0.133	88.2	31.5
4	0.081	89.0	54.2
5	0.052	86.5	40.9
6	0.028	94.1	72.3
7	0.034	100.0	89.9
8	0.009	100.0	100.0
9	0.006	100.0	97.0
10	0.004	100.0	100.0
Overall error		**60.5**	**24.6**

1999-2000		Type I Errors	
Decile in *t*	Fraction poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.346	38.4	9.7
2	0.273	61.9	15.8
3	0.156	77.7	25.1
4	0.094	87.9	38.9
5	0.070	95.0	63.5
6	0.024	97.0	61.8
7	0.019	100.0	93.6
8	0.014	100.0	97.7
9	0.002	100.0	100.0
10	0.001	64.8	64.8
Overall error		**63.2**	**24.7**

2000-2001	Type I Errors		
Decile in *t*	Fraction poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.309	38.3	8.0
2	0.302	53.5	17.0
3	0.160	77.7	37.3
4	0.102	86.0	44.0
5	0.063	89.7	46.9
6	0.034	97.7	58.1
7	0.015	100.0	81.8
8	0.012	100.0	77.6
9	0.002	100.0	100.0
10	0.001	100.0	100.0
Overall error		**61.2**	**25.4**

2001-2002	Type I Errors		
Decile in *t*	Fraction poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.185	13.8	3.7
2	0.239	45.3	10.6
3	0.242	59.9	25.3
4	0.135	84.5	51.8
5	0.084	89.0	47.4
6	0.051	93.7	70.8
7	0.041	98.8	91.6
8	0.014	98.7	92.1
9	0.008	91.8	90.8
10	0.001	100.0	100.0
Overall error		**57.8**	**29.9**

Source: Own calculations on Argentina Panel

Notes: Deciles are defined at time t

Table 5.8: Argentina: Type II (inclusion) errors by income decile, $4 USD line

1995-1996		Type II Errors	
Decile in *t*	Fraction non-poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.024	37.7	77.9
2	0.062	18.4	68.9
3	0.089	10.7	45.3
4	0.109	3.7	29.1
5	0.105	1.6	23.1
6	0.125	1.0	21.4
7	0.111	0.3	10.9
8	0.125	0.0	5.5
9	0.118	0.1	2.7
10	0.130	0.0	0.9
Overall error		**3.8**	**20.9**
1996-1997		**Type II Errors**	
Decile in *t*	Fraction non-poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.024	46.2	68.5
2	0.063	12.5	68.5
3	0.101	5.2	45.7
4	0.105	3.3	34.5
5	0.110	2.4	30.1
6	0.112	0.8	19.0
7	0.121	0.2	11.2
8	0.118	0.1	6.9
9	0.120	0.0	2.7
10	0.123	0.0	0.3
Overall error		**3.2**	**22.2**
1997-1998		**Type II Errors**	
Decile in *t*	Fraction non-poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.032	32.5	79.2
2	0.070	17.9	66.1
3	0.098	7.1	52.9
4	0.103	4.1	38.7
5	0.119	2.7	33.9
6	0.109	0.8	17.6
7	0.119	0.2	10.4
8	0.120	0.0	7.6
9	0.113	0.0	1.8
10	0.115	0.0	0.2
Overall error		**3.9**	**24.7**
1998-1999		**Type II Errors**	
Decile in *t*	Fraction non-poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.030	40.3	78.8
2	0.068	17.1	68.4
3	0.084	9.5	55.7
4	0.112	3.8	35.9
5	0.109	1.7	28.3
6	0.117	0.7	20.2
7	0.118	0.1	9.5
8	0.125	0.1	7.7
9	0.122	0.1	1.1
10	0.116	0.0	0.9
Overall error		**3.9**	**23.4**

(continued) Table 5.8

Argentina: Type II (inclusion) errors by income decile, $4 USD line

1999-2000		**Type II Errors**	
Decile in *t*	Fraction non-poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.018	34.1	74.2
2	0.063	22.0	60.1
3	0.096	12.7	50.7
4	0.101	6.1	39.0
5	0.116	1.1	28.2
6	0.121	1.3	17.1
7	0.120	1.0	12.0
8	0.124	1.1	7.0
9	0.122	0.0	2.8
10	0.120	0.0	1.2
Overall error		**4.4**	**22.0**
2000-2001		**Type II Errors**	
Decile in *t*	Fraction non-poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.009	42.1	77.7
2	0.041	27.5	72.8
3	0.085	15.2	62.9
4	0.096	7.2	42.3
5	0.112	3.8	33.2
6	0.119	1.8	24.9
7	0.133	0.5	10.9
8	0.134	0.1	6.3
9	0.135	0.0	3.1
10	0.136	0.0	1.3
Overall error		**4.2**	**22.7**
2001-2002		**Type II Errors**	
Decile in *t*	Fraction non-poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.014	40.7	74.5
2	0.020	33.6	64.0
3	0.048	15.5	56.5
4	0.090	10.1	37.5
5	0.111	3.8	33.0
6	0.117	3.6	22.1
7	0.120	0.4	14.9
8	0.164	1.3	7.0
9	0.152	0.3	3.1
10	0.166	0.0	0.5
Overall error		**4.1**	**18.1**

Source: Own calculations on Argentina Panel

Notes: Deciles are defined at time t

Table 5.9: Chile: Type I (exclusion) errors by income decile, $4 USD line

1996-2001		Type I Errors	
Decile in *t*	Fraction poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.429	25.9	7.3
2	0.235	57.5	13.4
3	0.132	66.9	20.2
4	0.096	86.8	69.9
5	0.038	66.0	42.1
6	0.030	93.8	82.2
7	0.024	91.0	85.5
8	0.008	89.9	63.8
9	0.002	100.0	100.0
10	0.006	100.0	65.6
Overall error		**50.8**	**22.9**
2001-2006		**Type I Errors**	
Decile in *t*	Fraction poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.416	35.7	12.2
2	0.204	73.7	17.3
3	0.177	81.6	50.3
4	0.066	93.7	61.5
5	0.060	98.8	79.9
6	0.032	86.1	59.6
7	0.018	92.5	89.9
8	0.005	100.0	100.0
9	0.001	100.0	100.0
10	0.022	100.0	100.0
Overall error		**63.6**	**32.6**
1996-2006		**Type I Errors**	
Decile in *t*	Fraction poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.492	23.9	5.8
2	0.149	68.2	28.2
3	0.069	73.2	48.3
4	0.106	76.5	35.2
5	0.070	98.9	82.8
6	0.013	100.0	82.8
7	0.004	100.0	97.2
8	0.016	100.0	100.0
9	0.004	100.0	100.0
10	0.077	100.0	100.0
Overall error		**53.4**	**31.1**

Source: Own calculations on Chile Panel

Notes: Deciles are defined at time t

Table 5.10: Chile: Type II (inclusion) errors by income decile, $4 USD line

1996-2001		Type II Errors	
Decile in *t*	Fraction non-poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.066	61.4	86.2
2	0.097	22.0	71.5
3	0.099	16.3	55.6
4	0.118	4.2	25.2
5	0.105	2.7	20.3
6	0.093	1.6	8.6
7	0.111	2.1	8.9
8	0.097	0.0	4.8
9	0.108	1.3	2.7
10	0.106	0.0	1.4
Overall error		**9.1**	**25.9**
2001-2006		**Type II Errors**	
Decile in *t*	Fraction non-poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.072	50.0	83.6
2	0.125	28.2	63.2
3	0.096	15.4	58.5
4	0.107	5.9	40.5
5	0.113	1.6	32.5
6	0.088	0.8	19.9
7	0.121	0.1	4.1
8	0.090	0.0	1.9
9	0.086	0.0	0.5
10	0.101	0.0	0.2
Overall error		**9.5**	**30.1**
1996-2006		**Type II Errors**	
Decile in *t*	Fraction non-poor in t+1	Absolute threshold (0.50)	Relative threshold (Poverty rate)
1	0.109	60.0	86.5
2	0.143	19.3	74.4
3	0.124	10.6	40.9
4	0.115	3.8	18.4
5	0.084	3.4	18.3
6	0.097	0.3	6.4
7	0.085	1.6	7.8
8	0.082	1.1	3.8
9	0.083	0.0	0.0
10	0.076	0.0	1.5
Overall error		**11.6**	**30.6**

Source: Own calculations on Chile panel

Notes: Deciles are defined at time t

Table 5.11: Argentina: Type I (exclusion) errors by 1st and 2st decile of household income distribution and selected deprivation indicators

Years	Deciles in *t*	Type I Errors: Absolute threshold (0.50)	Relative threshold (Poverty rate)	$\hat{E}(\ln\hat{Y}_h/X_h)\leq\ln Z$ (1)	UBN (2)	A&F(0,1) (3)	A&F(0,3) (3)
1995-1996	1	37.3	13.3	36.8	14.0	33.4	36.4
	2	63.3	24.8	63.3	21.6	35.4	41.4
1996-1997	1	36.9	13.2	34.1	12.0	31.0	33.3
	2	66.1	20.8	68.4	28.0	40.1	48.7
1997-1998	1	43.1	10.2	44.1	12.5	30.7	32.8
	2	61.6	20.6	61.3	22.5	38.2	47.0
1998-1999	1	43.1	10.2	36.5	10.7	30.3	32.3
	2	61.6	20.6	57.8	25.2	38.2	44.8
1999-2000	1	43.1	10.2	38.2	13.8	29.3	30.9
	2	61.6	20.6	60.4	30.0	37.1	43.0
2000-2001	1	38.3	8.0	37.9	14.7	30.9	33.3
	2	53.5	17.0	53.3	29.9	34.9	36.3
2001-2002	1	38.3	8.0	14.6	11.3	30.3	32.1
	2	53.5	17.0	43.9	22.5	32.7	34.7

Source: Own calculations on Argentina panel data

Notes:

(1) A household is considered poor if estimation of expected log household income is below the log poverty line. The specification of household income model is like used to compute vulnerability.

(2) The basic needs considered are: house rooms, house location, house materials, water, restroom, children education, education of household head and number of earners. A household is considered as poor if they meet at least one of the above conditions.

(3) Multidimensional A&F(0,k) refers to the dimension-adjusted headcount ratio proposed by Alkire and Foster (2009). The parameter k is the cut-off across dimensions. The dimensions considered are: income, education, overcrowding, access to water and housing quality.

Table 5.12: Argentina: Type II (inclusion) errors by 1st and 2st decile of household income distribution and selected deprivation indicators

Years	Deciles in *t*	Type II Errors: Absolute threshold (0.50)	Relative threshold (Poverty rate)	$\hat{E}(\ln\hat{Y}_h/X_h)\leq\ln Z$ (1)	UBN (2)	A&F(0,1) (3)	A&F(0,3) (3)
1995-1996	1	37.7	77.9	37.7	66.6	66.7	66.7
	2	18.4	68.9	18.6	62.9	55.1	54.8
1996-1997	1	46.2	68.5	46.8	71.9	67.5	67.4
	2	12.5	68.5	12.2	57.5	53.5	52.8
1997-1998	1	32.5	79.2	32.0	73.8	66.2	66.2
	2	17.9	66.1	18.6	55.8	55.2	55.0
1998-1999	1	40.3	78.8	40.5	68.0	64.4	64.3
	2	17.1	68.4	17.1	65.9	56.5	56.1
1999-2000	1	34.1	74.2	40.9	83.1	65.8	65.8
	2	22.0	60.1	23.0	55.0	59.8	59.7
2000-2001	1	42.1	77.7	42.1	66.2	65.8	65.8
	2	27.5	72.8	28.0	60.8	65.2	65.1
2001-2002	1	40.7	74.5	40.7	79.0	63.4	63.4
	2	33.6	64.0	34.7	62.0	63.0	63.0

Source: Own calculations on Argentina panel data

Notes: (1) A household is considered poor if estimation of expected log household income is below the log poverty line. The specification of household income model is like used to compute vulnerability.

(2) The basic needs considered are: house rooms, house location, house materials, water, restroom, children education, education of household head and number of earners. A household is considered as poor if they meet at least one of the above conditions.

(3) Multidimensional A&F(0,k) refers to the dimension-adjusted headcount ratio proposed by Alkire and Foster (2009). The parameter k is the cut-off across dimensions. The dimensions considered are: income, education, overcrowding, access to water and housing quality.

Table 5.13: Chile: Type I (exclusion) errors by 1st and 2st decile of household income distribution and selected deprivation indicators

Years	Deciles in *t*	Type I Errors: Absolute threshold (0.50)	Relative threshold (Poverty rate)	$\hat{E}(\ln\hat{Y}_h/X_h)\leq\ln Z$ (1)	UBN (2)	A&F(0,1) (3)	A&F(0,3) (3)
1996-2001	1	25.9	7.3	21.2	24.1	44.8	57.0
	2	57.5	13.4	56.3	25.9	52.0	68.8
2001-2006	1	35.7	12.2	35.6	20.7	46.8	59.2
	2	73.7	17.3	73.2	26.1	51.5	70.2
1996-2006	1	23.9	5.8	24.3	9.9	49.3	68.9
	2	68.2	28.2	59.1	37.5	53.1	70.7

Source: Own calculations on Chile panel data

Notes:

(1) A household is considered poor if estimation of expected log household income is below the log poverty line. The specification of household income model is like used to compute vulnerability.

(2) The basic needs considered are: house rooms, house location, house materials, water, restroom, children education, education of household head and number of earners. A household is considered as poor if they meet at least one of the above conditions.

(3) Multidimensional A&F(0,k) refers to the dimension-adjusted headcount ratio proposed by Alkire and Foster (2009). The parameter k is the cut-off across dimensions. The dimensions considered are: income, education, overcrowding, access to water and housing quality.

Table 5.14: Chile: Type II (inclusion) errors by 1st and 2st decile of household income distribution and selected deprivation indicators

Years	Deciles in *t*	Type II Errors: Absolute threshold (0.50)	Relative threshold (Poverty rate)	$\hat{E}(\ln\hat{Y}_h/X_h)\leq\ln Z$ (1)	UBN (2)	A&F(0,1) (3)	A&F(0,3) (3)
1996-2001	1	61.4	86.2	61.1	83.5	52.8	52.1
	2	22.0	71.5	27.9	60.2	53.1	51.1
2001-2006	1	50.0	83.6	41.8	79.9	58.2	57.6
	2	28.2	63.2	25.0	49.0	49.9	48.3
1996-2006	1	60.0	86.5	60.6	77.9	53.7	52.6
	2	19.3	74.4	24.3	58.6	43.7	41.3

Source: Own calculations on Chile panel data

Notes:

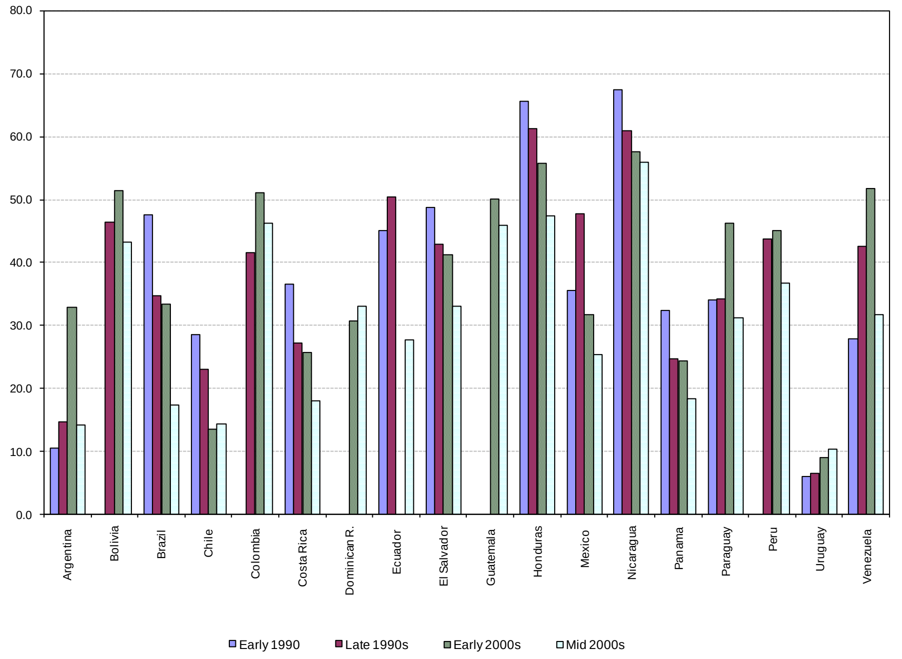
(1) A household is considered poor if estimation of expected log household income is below the log poverty line. The specification of household income model is like used to compute vulnerability.

(2) The basic needs considered are: house rooms, house location, house materials, water, restroom, children education, education of household head and number of earners. A household is considered as poor if they meet at least one of the above conditions.

(3) Multidimensional A&F(0,k) refers to the dimension-adjusted headcount ratio proposed by Alkire and Foster (2009). The parameter k is the cut-off across dimensions. The dimensions considered are: income, education, overcrowding, access to water and housing quality.

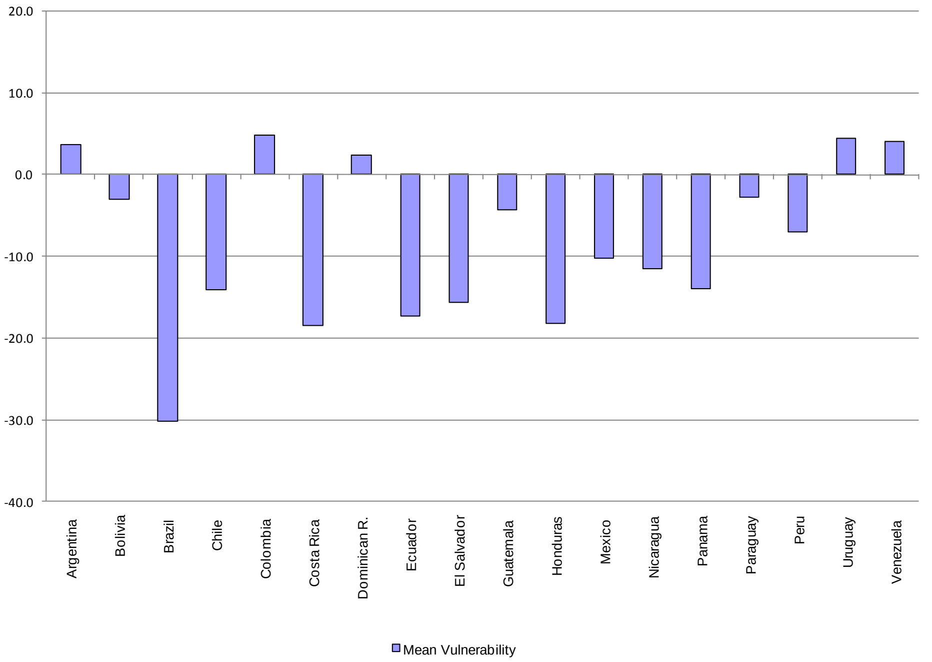
Appendix 3: Figures

Figure 4.1: Mean vulnerability by country: early 1990s-mid 2000s, $4 USD line



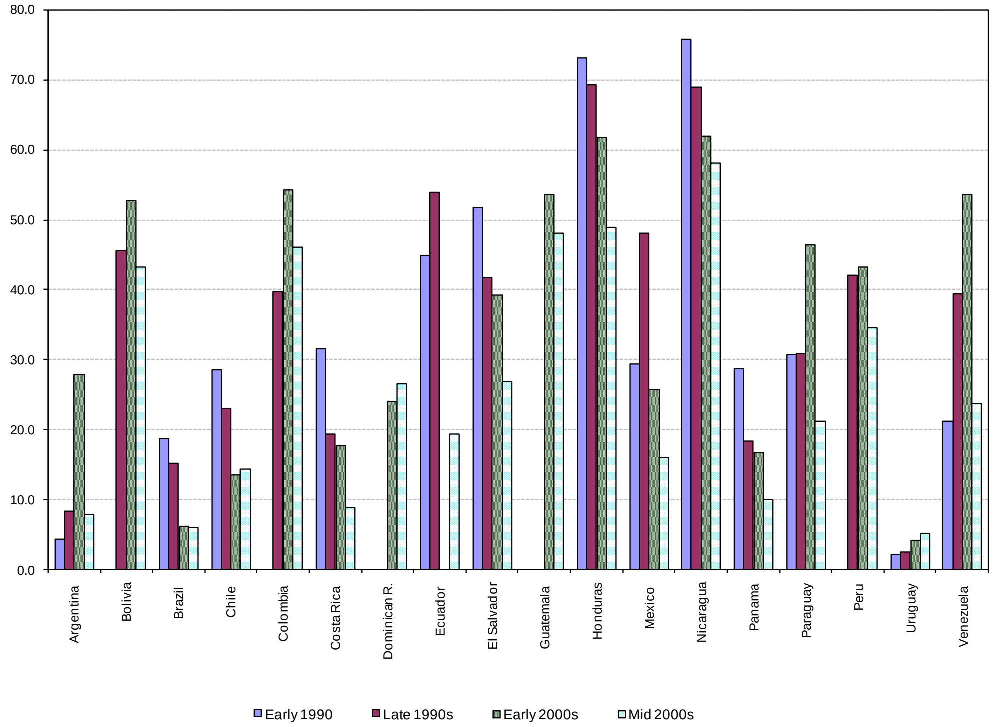
Source: Own calculations from SEDLAC database

Figure 4.2: Change in mean vulnerability by country: early 1990s-mid 2000s, $4 USD line



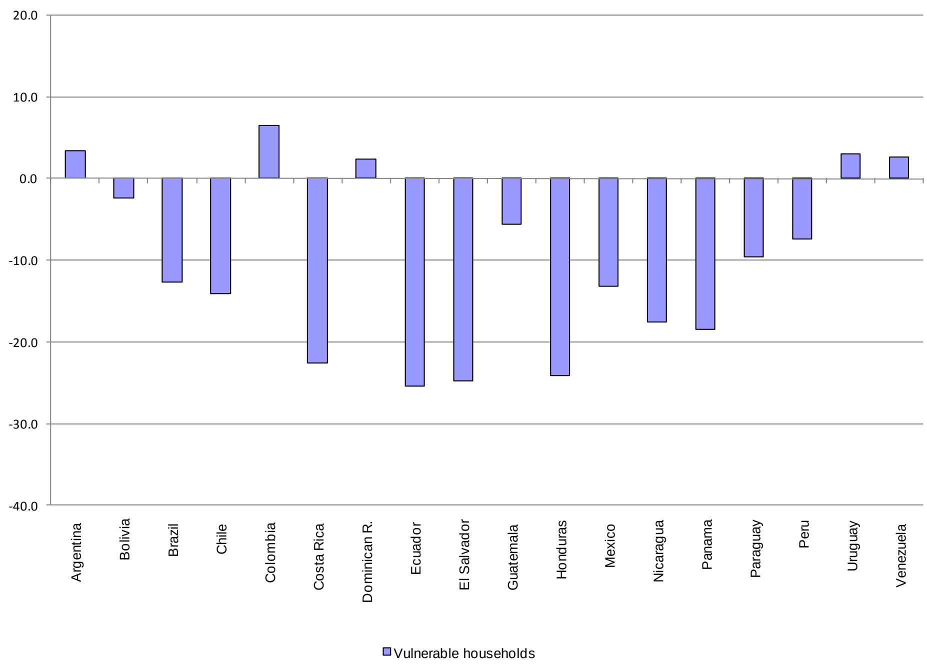
Source: Own calculations from SEDLAC database

Figure 4.3: Proportion of vulnerable households (absolute threshold) by sub-region, $4 USD line (in percentages)



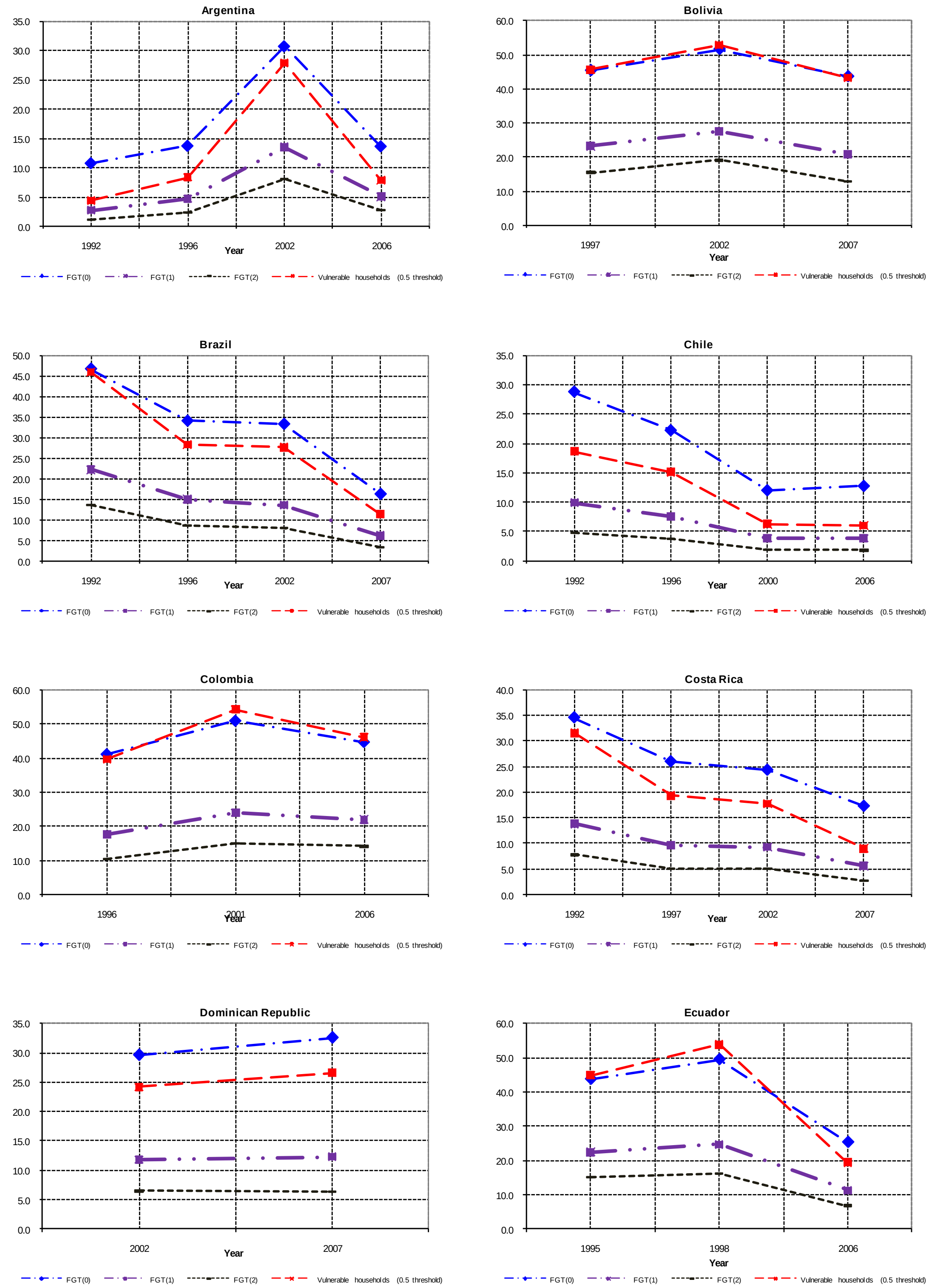
Source: Own calculations from SEDLAC database

Figure 4.4: Change in vulnerability incidence (absolute threshold) by country: early 1990s-mid 2000s, $4 USD line (in percentages)

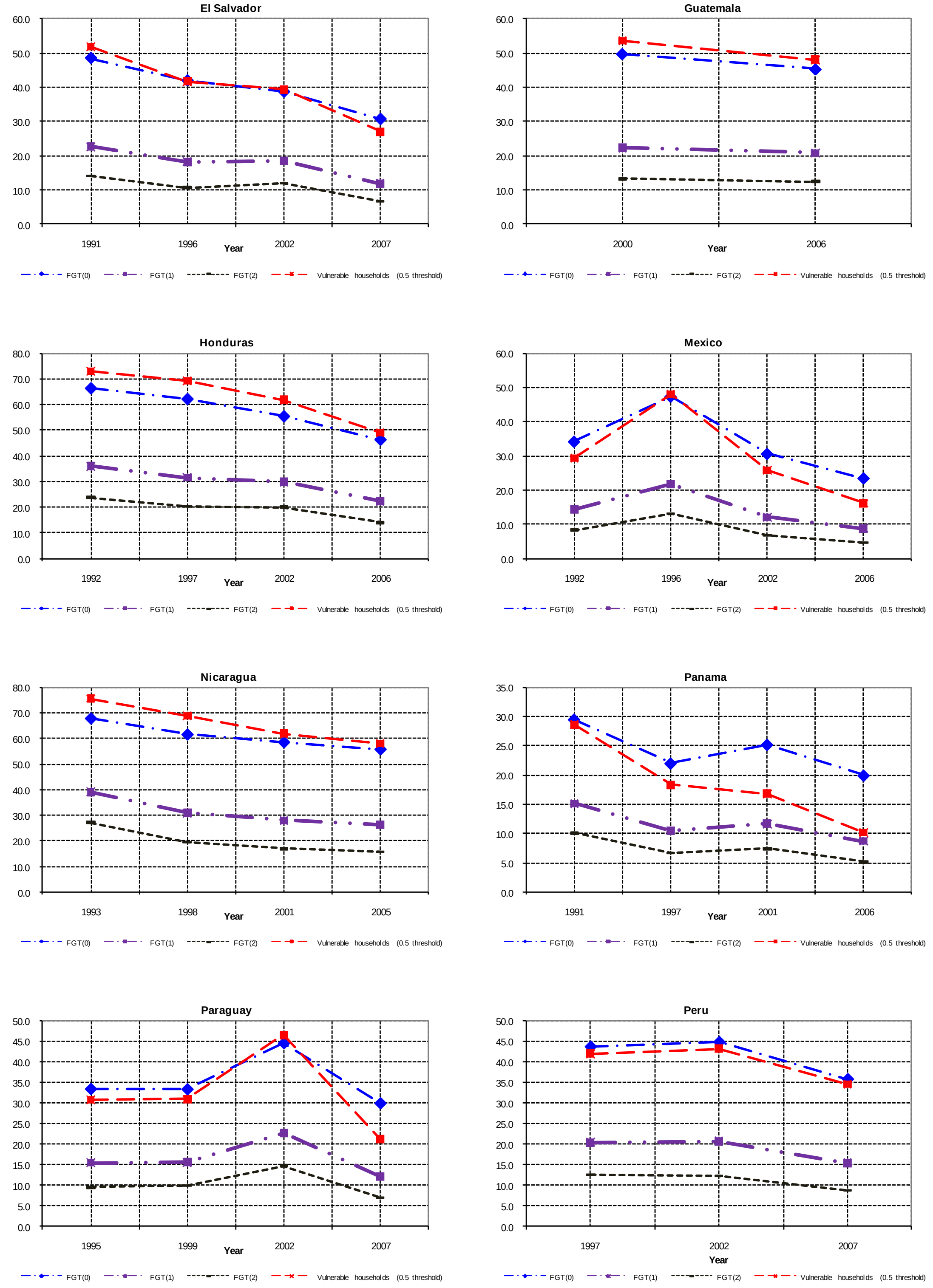


Source: Own calculations from SEDLAC database

Figure 4.5: Evolution of vulnerability and poverty measures, $4 USD line



Source: Own calculations from SEDLAC surveys (continued) Figure 4.5 Evolution of vulnerability and poverty measures, $4 USD line



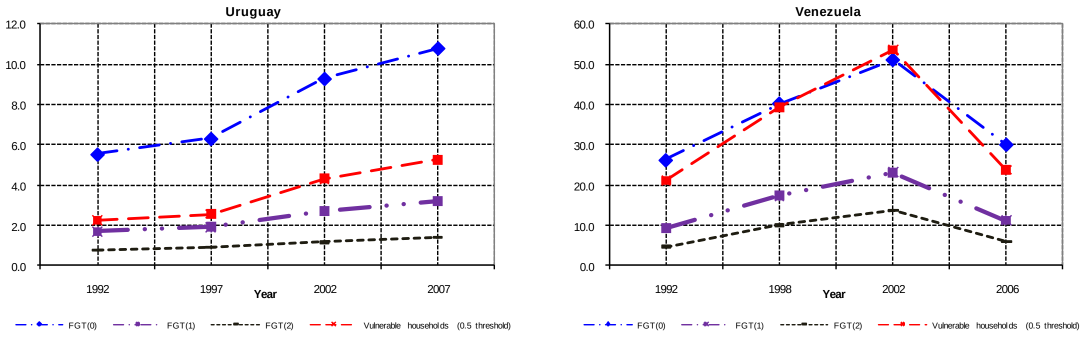
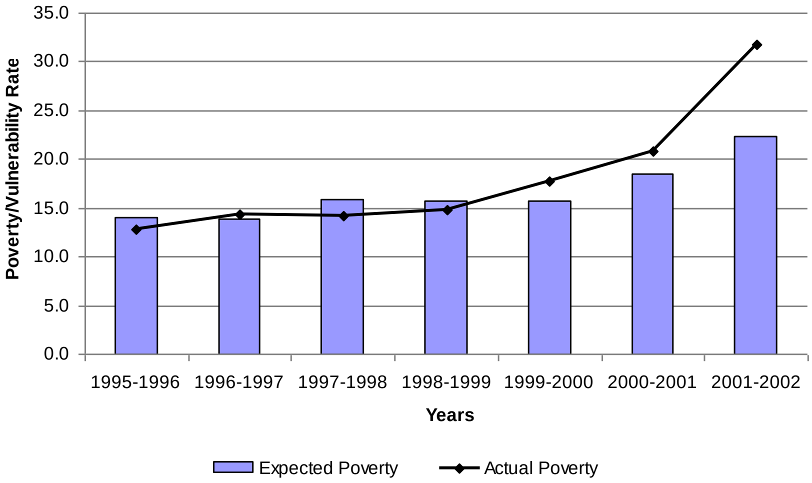
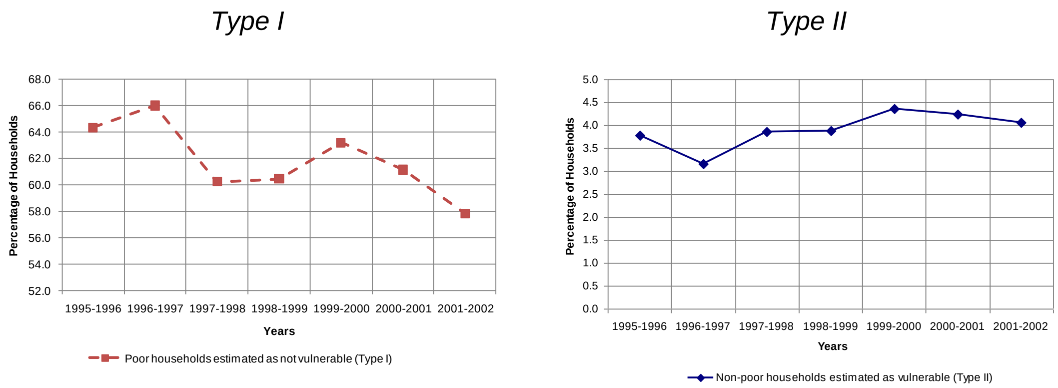


Figure 5.1: Argentina: expected and actual poverty, $4 USD line



Source: Own calculations on Argentina panel data

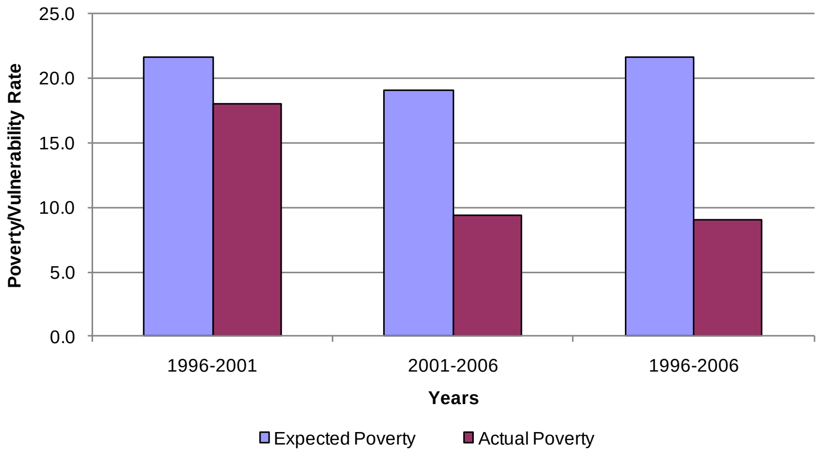
Figure 5.2: Argentina: evolution of misclassified households, $4 USD line



Source: Own calculations on Argentina panel data

Notes: -Type I households are the fraction of poor households in t+1 which are classified as not vulnerable in t
-Type II households are the fraction of non-poor households in t+1 which are classified as vulnerable in t

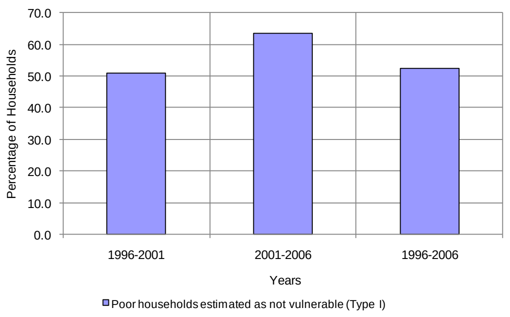
Figure 5.3: Chile: expected and actual poverty, $4 USD line



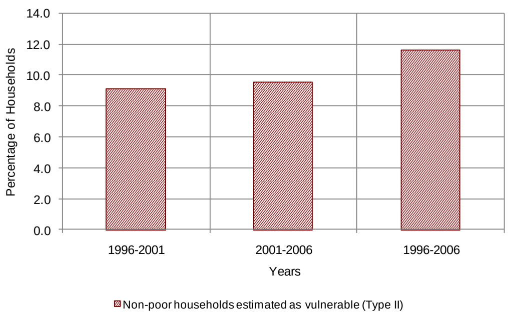
Source: Own calculations on Chile panel data

Figure 5.4: Chile: evolution of misclassified households, $4 USD line

Type I



Type II



Source: Own calculations on Chile panel data

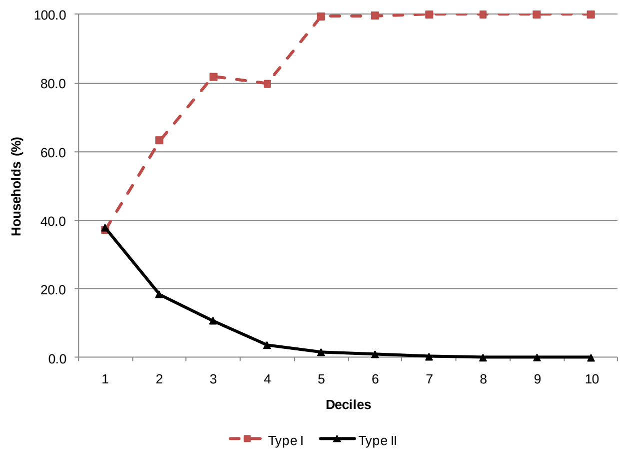
Notes:

-Type I households are the fraction of poor households in t+1 which are classified as not vulnerable in t

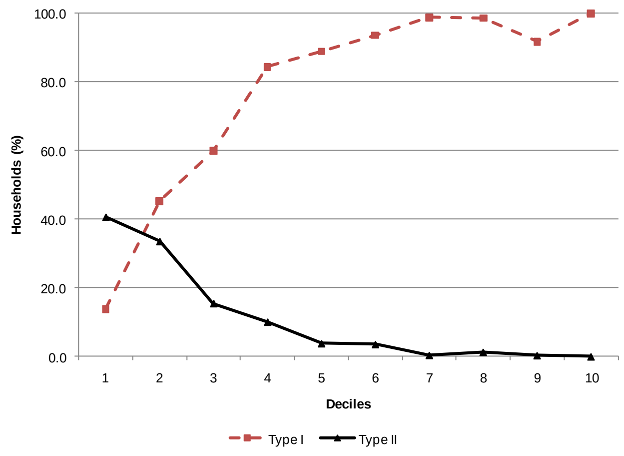
-Type II households are the fraction of non-poor households in t+1 which are classified as vulnerable in t

Figure 5.5: Argentina: errors by income decile

1995-1996



2001-2002



Source: Own calculations on Argentina panel data

Notes:

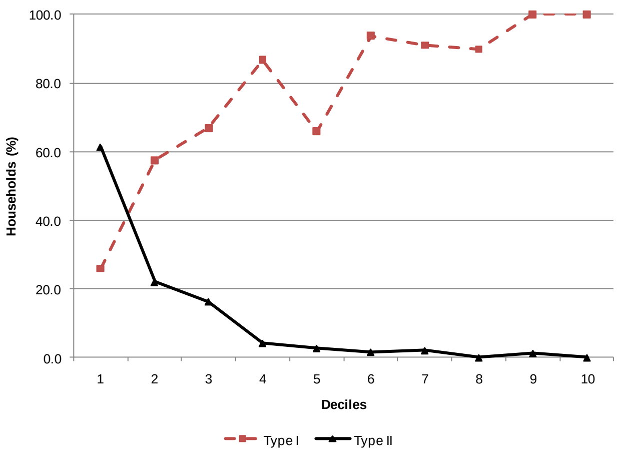
(1) Deciles are defined at time t.

(2) Type I error is the fraction of poor households in t+1 which were classified as not vulnerable in t

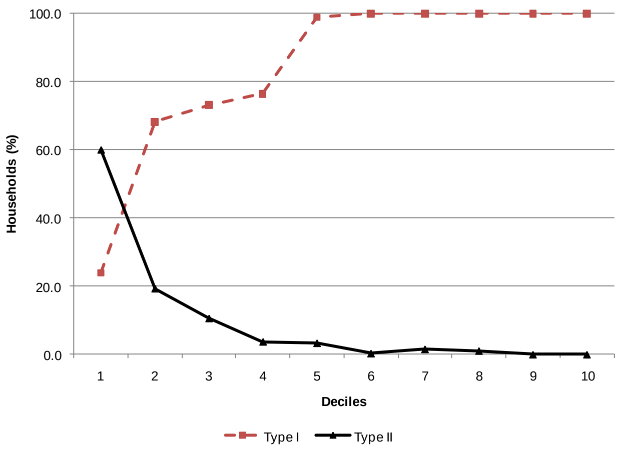
(3) Type II error is the fraction of non-poor households in t+1 which were classified as vulnerable in t

Figure 5.6: Chile: errors by income decile

1996-2001



1996-2006



Source: Own calculations on Chile panel data

Notes:

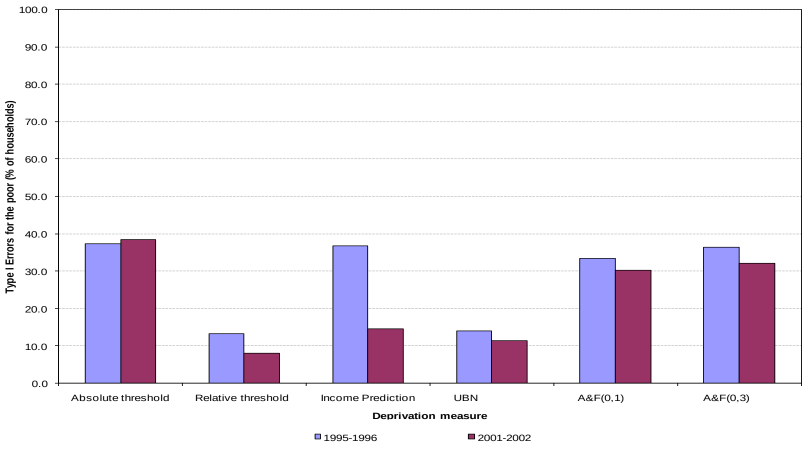
(1) Deciles are defined at time t.

(2) Type I error is the fraction of poor households in t+1 which were classified as not vulnerable in t

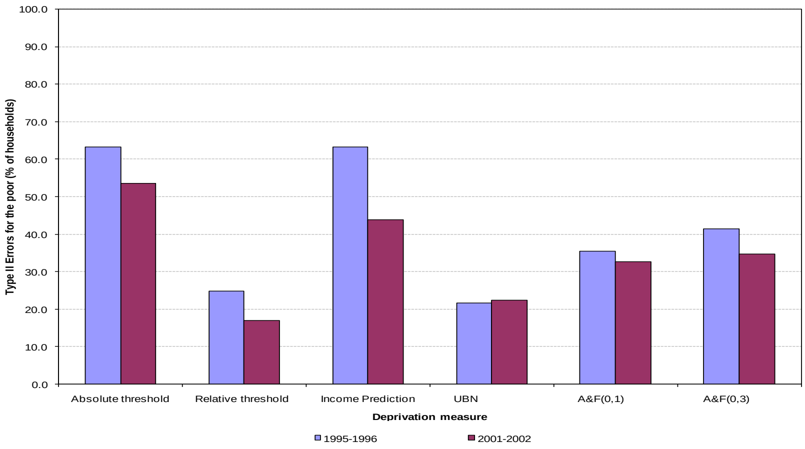
(3) Type II error is the fraction of non-poor households in t+1 which were classified as vulnerable in t

Figure 5.7: Argentina: Type I (exclusion) errors for selected deprivation measures

1st decile of income distribution (time t)



2nd decile of income distribution (time t)



Source: Own calculations on Argentina panel data

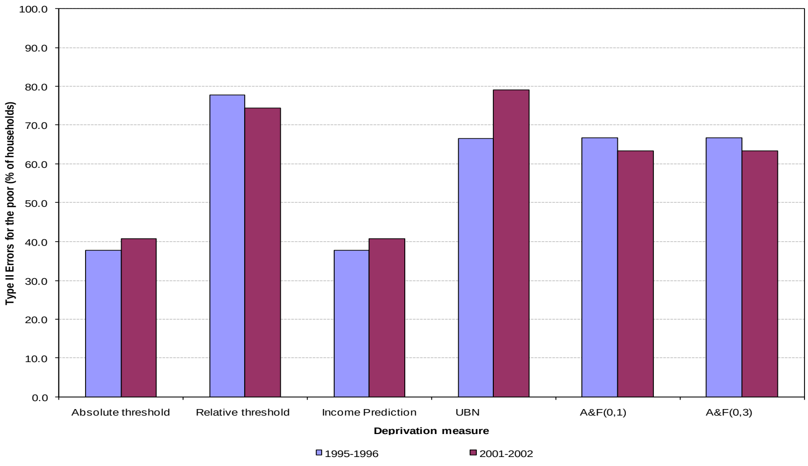
Notes:

(1) Income prediction: a household is considered poor if estimation of expected log household income is below the log poverty line. The specification of household income model is like used to compute vulnerability.

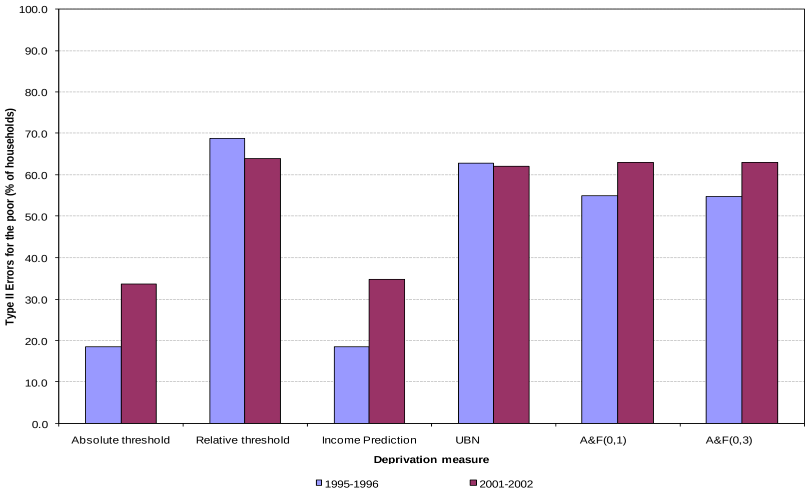
(2) The basic needs considered to compute UBN are: house rooms, house location, house materials, water, restroom, children education, education of household head and number of earners. A household is considered as poor if they meet at least one of the above conditions. (3) Multidimensional A&F(0,k) refers to the dimension-adjusted headcount ratio proposed by Alkire and Foster (2009). The parameter k is the cut-off across dimensions. The dimensions considered are: income, education, overcrowding, access to water and housing quality.

Figure 5.8: Argentina: Type II (inclusion) errors for selected deprivation measures

1st decile of household income distribution (time t)



2st decile of household income distribution (time t)



Source: Own calculations on Argentina panel data

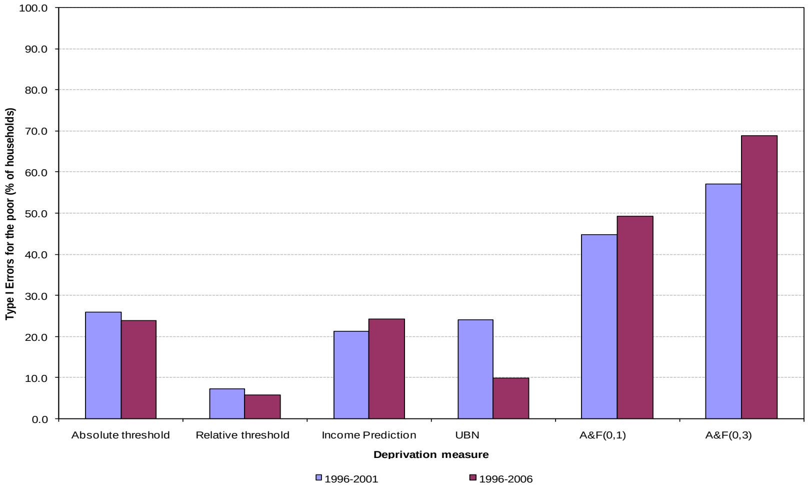
Notes:

(1) Income prediction: a household is considered poor if estimation of expected log household income is below the log poverty line. The specification of household income model is like used to compute vulnerability.

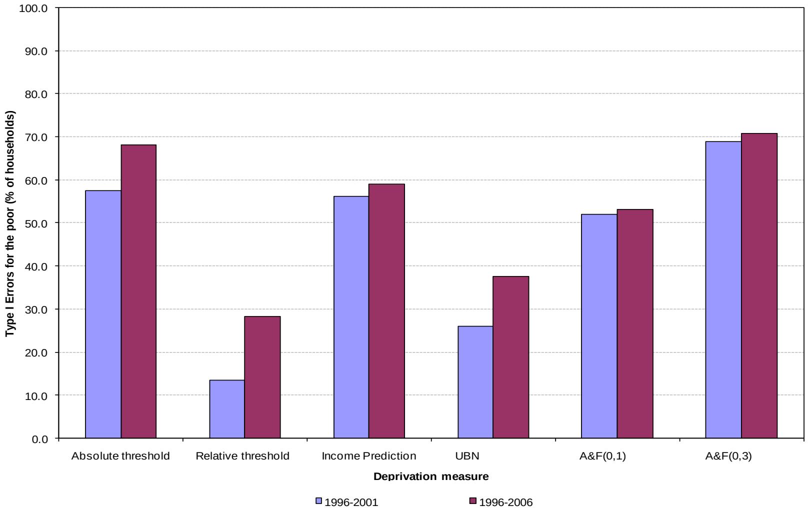
(2) The basic needs considered to compute UBN are: house rooms, house location, house materials, water, restroom, children education, education of household head and number of earners. A household is considered as poor if they meet at least one of the above conditions. (3) Multidimensional A&F(0,k) refers to the dimension-adjusted headcount ratio proposed by Alkire and Foster (2009). The parameter k is the cut-off across dimensions. The dimensions considered are: income, education, overcrowding, access to water and housing quality.

Figure 5.9: Chile: Type I (exclusion) errors for selected deprivation measures

1st decile of household income distribution (time t)



2nd decile of household income distribution (time t)



Source: Own calculations on Chile panel data

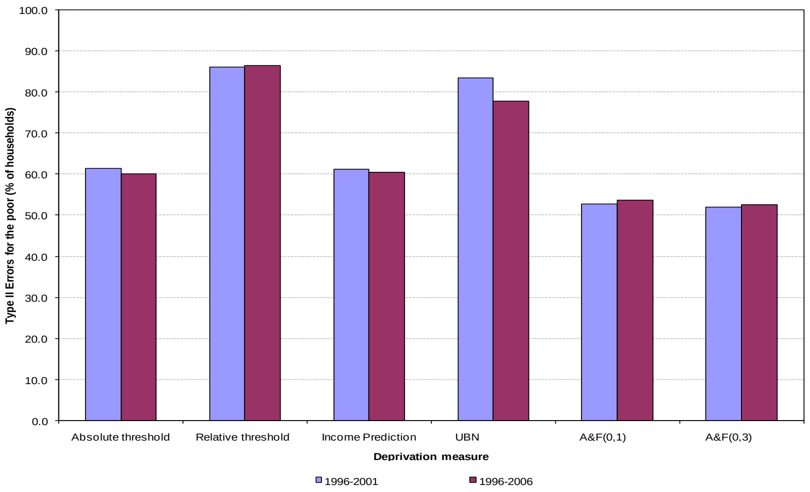
Notes:

(1) Income prediction: a household is considered poor if estimation of expected log household income is below the log poverty line. The specification of household income model is like used to compute vulnerability.

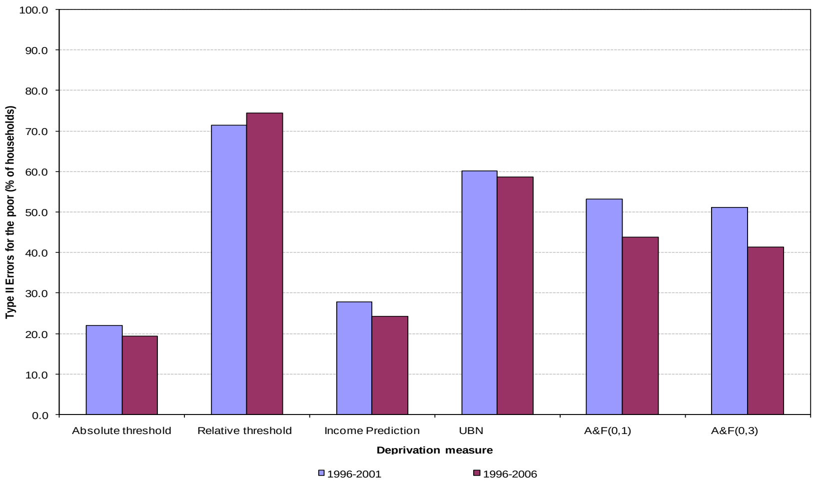
(2) The basic needs considered to compute UBN are: house rooms, house location, house materials, water, restroom, children education, education of household head and number of earners. A household is considered as poor if they meet at least one of the above conditions. (3) Multidimensional A&F(0,k) refers to the dimension-adjusted headcount ratio proposed by Alkire and Foster (2009). The parameter k is the cut-off across dimensions. The dimensions considered are: income, education, overcrowding, access to water and housing quality.

Figure 5.10: Chile: Type II (inclusion) errors for selected deprivation measures

1st decile of household income distribution (time t)



2st decile of household income distribution (time t)



Source: Own calculations on Chile panel data

Notes:

(1) Income prediction: a household is considered poor if estimation of expected log household income is below the log poverty line. The specification of household income model is like used to compute vulnerability.

(2) The basic needs considered to compute UBN are: house rooms, house location, house materials, water, restroom, children education, education of household head and number of earners. A household is considered as poor if they meet at least one of the above conditions. (3) Multidimensional A&F(0,k) refers to the dimension-adjusted headcount ratio proposed by Alkire and Foster (2009). The parameter k is the cut-off across dimensions. The dimensions considered are: income, education, overcrowding, access to water and housing quality.

Chronic Poverty Research Centre

www.chronicpoverty.org

The **Chronic Poverty Research Centre** (CPRC) is an international partnership of universities, research institutes and NGOs, with the central aim of creating knowledge that contributes to both the speed and quality of poverty reduction, and a focus on assisting those who are trapped in poverty, particularly in sub-Saharan Africa and South Asia.

Partners:

Bangladesh Institute of Development Studies (BIDS), Bangladesh

Development Initiatives, UK

Development Research and Training, Uganda

Economic Policy Research Center, Uganda

HelpAge International, UK

Indian Institute of Public Administration, India

IED Afrique, Senegal

Institute of Development Studies, UK

Overseas Development Institute, UK

Programme for Land and Agrarian Studies, South Africa

University of Legon, Ghana

University of Manchester, UK

University of Sussex, UK

Contact:
cprc@manchester.ac.uk