Vulnerability to poverty: An empirical comparison of alternative measures

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Abstract. The recent common feeling about a skyrocketing economic risk has drawn increasing attention to its role and consequences on individuals' welfare. In literature one of the concepts that aims to measure it is vulnerability to poverty, that is the probability, today, of being in poverty or to fall into deeper poverty in the future (The World Bank, 2011).
This paper compares empirically the several measures of individual vulnerability proposed in the literature, in order to understand which is the best signal of poverty that can be used for policies purposes. To this aim the Receiver Operating Characteristic (ROC) curve, the Pearson and Spearman correlation coefficients are used as precision criteria.
The results show that two groups of indexes can be identified, high- and low-performers, and, among the former, that proposed by Dutta *et al.* (2011) is the most precise.

Keywords: Poverty, Risk, Vulnerability, Receiver Operating Characteristic curve (ROC)

JEL Codes: D63, I32

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I. Introduction

The recent financial crisis and the increasing recognition that there are considerable flows into and out of poverty (Baulch and Hoddinott, 2000) gained the attention of governments, researchers and foundations in several countries on economic risk and its role as *threat*.

In the economic literature we find two concepts related to economic hazard: *economic insecurity* and *vulnerability to poverty*. These concepts have evolved quite independently, but a common basis exists between them. Both concepts deal with an economic risk that produces anxiety (Osberg, 1998) and represents a threat (Dercon, 2006), but, according to Osberg (2010), they differ in terms of countries analysed, perspective and risk exposure consequences.

The main difference, in my opinion, is that economic insecurity, unlike vulnerability to poverty, concerns more the *ex post* subjective measurement of the lack of safety rather than an objective poverty danger. Everyone could feel economically insecure but only a part of the population, those vulnerable, are likely to become poor in the future.

Therefore, if the interest is to provide information for anti-poverty protection strategies, vulnerability to poverty is the concern. Vulnerability aims to identify the poor in advance representing an *ex ante* information source for policies design. Chaudhuri *et al.* (2002), for example, write that what really matters for forward-looking anti-poverty interventions is vulnerability to poverty. Zhang and Guanghua (2008) argue that measuring vulnerability is important because it allows the identification of those who are not currently poor but may fall into poverty. Vulnerability therefore can be used, once those vulnerable to poverty are identified, to design appropriate policies to prevent them from falling into poverty. Also Jamal (2009), by highlighting the distinction between *ex ante* poverty prevention and *ex post* poverty alleviation interventions, considers vulnerability assessments as a way to improve risk-management policies.

This paper tries to understand which index, among those proposed in literature, can detect with more precision the individuals at risk of poverty in the next year. I believe that this exercise is useful since it identifies the most precise *ex ante* information source for policies purposes.

II. Literature review

Vulnerability to poverty

According to The World Bank definition, vulnerability to poverty is the probability, today, of being in poverty or to fall into deeper poverty in the future. Vulnerability is very different from the standard analysis of poverty because it recalls a forward-looking perspective rather than an *ex post* assessment, allowing the design of protection policies that can prevent households and individuals from experiencing welfare losses.

The concept of vulnerability to poverty stems its roots in a seminal article by Jalan and Ravaillon (1998) on transient and chronic poverty. Here the authors noticed how in rural China variability in consumption accounts for a large part of the observed poverty: half of the mean squared poverty gap and over a third of the mean poverty gap is transient and directly attributable to year-to-year consumption fluctuations.

While theoretically vulnerability to poverty is almost well-defined as the risk of experiencing poverty, three different definitions can be recognized empirically: vulnerability as expected poverty (VEP), vulnerability as low expected utility (VEU) and vulnerability as uninsured exposure to risk (VER). These definitions are all equally used in literature, since they describe the poverty risk according to three different perspectives.

The very first VEP version translates vulnerability into a probability measure of facing poverty in the future. More precisely, when welfare is defined in terms of consumption or income, then vulnerability of the h^{th} household (or individual), at time t, is V_{ht}, the probability that consumption or income tomorrow, $y_{h,t+1}$, falls below the poverty line, z, that is

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

Ligon and Schechter (2003) proposed a different measure, based on utility, to take properly into account risk sensitivity. They pointed out that a policy-maker, who allocates resources to minimize the expected value of one of the Foster *et al.* (1984) (FGT) indexes, would tend to assign too much risk to poorer households. Therefore they defined vulnerability as the difference between the utility derived from some level of certainty-equivalent, z_{CE}, at and above which the household h would not be considered vulnerable, and the expected utility of consumption, c_h,

$$V_h = U_h(z_{CE}) - EU_h(c_h). \tag{2}$$

This approach, while appealing in terms of risk considerations, has some drawbacks since it is necessary to specify a utility functional form for U_h and a value for the risk aversion parameter. VEU has been used less extensive compared to VEP because it measures vulnerability in terms of utility units, with a less straightforward interpretation of the results.

The third approach, VER, even if based on intertemporal variability of consumption as VEP and VEU, is very different in terms of perspective. Vulnerability as uninsured exposure to risk is backward-looking, while the formers methods are forward-looking. VER is in fact an *ex post* assessment of the extent to which a negative income shock caused a welfare loss in terms of consumption. This third approach is based on the consumption smoothing and risk sharing literature, where the degree of vulnerability is defined by the extent to which the growth rate of household consumption covaries with the household income growth rate (Gerry and Li 2010, Skoufias and Quisumbing 2003). VER aims to understand if households are able to spread the effects of income shocks through formal or informal insurance strategies, with the following interpretation in terms of vulnerability: if consumption and income are correlated, then the households use not so effective risk management instruments, increasing their vulnerability to negative income shocks. Using the following equation

$$\Delta c_{h,t,v} = \beta \Delta ln y_{h,t,v} + \delta X_{h,t,v} + \sum_{t,v} \delta_{t,v} D_{t,v} + \Delta \epsilon_{h,t,v}, \tag{3}$$

where $\Delta c_{h,t,v}$ denotes the growth rate from $t-1$ to t of the total consumption of household h in the community v, $\Delta ln y_{h,t,v}$ is the growth rate of income, X is a vector of household characteristics, $D_{t,v}$ are other controls and $\Delta \epsilon_{h,t,v}$ is a household-specific error term, the parameter of interest for VER is β.

For this analysis, since I am interested in the ability of vulnerability measures to identify in advance the future poor, I will focus on the first approach mentioned, VEP, that has a forward-looking perspective and is easier to interpret as its value is expressed in monetary terms.

Vulnerability to poverty has been often studied in developing countries (see among others Gaiha and Imai 2008, Gaiha *et al.* 2011, Imai *et al.* 2009, Jha *et al.* 2009) because poverty risk is in relative terms quantitatively more important, but volatile incomes are commonly encountered also in developed countries and are, under certain conditions, symptoms of being prone to poverty. Bandyopadhyay and Cowell (2007) for instance estimate vulnerability to poverty for the United Kingdom using the VER approach and quantile regressions. They found that, apart from those households around the poverty line, there are some, well away from the poverty zone, that are susceptible to be income shocks vulnerable.

In this paper different data sources on some EU countries, UK, Germany and Italy are used. The choice is driven mainly by the quality of data available necessary to estimate properly vulnerability and to highlight the differences among measures. To emphasize the features of each index a sufficiently long longitudinal component is needed and information on the household disposable income has to be collected accurately. I will estimate therefore vulnerability exploiting the British Household Panel Survey (BHPS), the German Socio-Economic Panel Study (SOEP) and the Survey on Household Income and Wealth (SHIW) for Italy, datasets that meet all the requirements.

Measuring Vulnerability as Expected Poverty

One of the first papers formalizing the idea of a measure that can anticipate the poverty status is Pritchett *et al.* (2000), where the authors point out how many households, while not currently in poverty, are vulnerable to events such as jobloss, or unexpected expenditures due to illnesses or economic downturns. As vulnerability to poverty is intended to be an expected poverty, the authors propose an expansion of the traditional poverty measures to quantify an *ex ante* vulnerability to poverty and to measure the risk for a household of falling into poverty in the future,

$$V_t^h\left(p,n,z\right) = I\left[R_t^h\left(n,z\right) > p\right] \tag{4}$$

$$R_t^h\left(n,z\right) = 1 - \left[\left(1 - Pr(y_{h,t+1} < z)\right) * ... * \left(1 - Pr(y_{h,t+n} < z)\right)\right]. \tag{5}$$

The general definition that they state is then clarified in terms of risk and time, *falling into poverty at least once in the next few years*. Therefore the vulnerability of the household h for n periods is the probability of observing, in the time span considered, at least one episode of poverty, i.e. the complementary probability of observing no episodes of poverty, see Equations 4 and 5.

According to Pritchett *et al.* (2000), vulnerability is a risk measured in terms of probability, $R_t^h\left(n,z\right)$, that depends on the time horizon, n, and the poverty line, z; $I\left[\cdot\right]$ is an indicator function that translates vulnerability into a state variable, by defining a probability threshold, p. The authors observe that everybody face a certain degree of poverty risk, also the richest individuals, therefore, to have a more reliable aggregate measure of poverty risk, called *Headcount Vulnerable to Poverty Rate*, they introduce the function, $I\left[\cdot\right]$, that takes value 1 if the probability computed is higher than the chosen threshold level, 0.5, and zero otherwise. As already noticed in literature this approach fails to consider explicitly the depth of poverty (Hoddinott and Quisumbing, 2003), but this issue is relatively straightforward to redress by writing the following

$$V_t^h = \sum_s^S p_s P\left(y_{h,t+1}, z\right) = \sum_s^S p_s I\left[y_{h,t+1}, z\right].\left[\left(z - y_{h,t+1}\right)/z\right]^{\alpha}. \tag{6}$$

Expression 6 echoes the FGT index of poverty, where α is the relative weight attached to extreme poverty, S are the *possible states of the world*, p_s is the probability that the s^{th} state occurs and $I\left[\cdot\right]$ is a function that allows to consider only those states in which the expected income, $y_{h,t+1}$, falls below the chosen poverty line z. The drawback of the adoption of this index, based on income or consumption standard deviation, is to fail to consider the persistence of the phenomenon.[1]

Despite the discussed drawbacks, vulnerability expressed in terms of probability has been extensively used because easy to interpret, even if very demanding in terms of data when it is translated empirically. When estimating Pritchett *et al.* (2000)'s vulnerability in fact some assumptions have necessarily to be made: to compute probabilities information about the distribution of the welfare measure, either consumption or income, is needed not only at the aggregate level but also at the household (or individual) level. This is the reason why in the empirical applications, to preserve computational simplicity, the distribution of the welfare measure is always assumed to be normal (see among others Azam and Imai 2009, Chaudhuri *et al.* 2002, Gaiha *et al.* 2011, Jha *et al.* 2009, Zhang and Guanghua 2008). Nevertheless, in some cases other problems related to the quality of data could arise: measurement errors for instance are something to account for in this type of analysis; when this problem contaminates data, in fact, it is important to consider the part of the measured shocks which is not true risk, that leads to a potential over-estimation of the poverty danger.

[1] Kamanou and Morduch (2002) propose a simple example on this problem. Let us suppose to observe two household consumption patterns over 8 periods, the former is (1, 2, 3, 4, 5, 6, 7, 8), while the latter is (7, 5, 2, 6, 3, 1, 4, 8). If we base our analysis on standard deviations, both series are identical, but the trend of consumption is very different, in the latter case we notice a steady upward path. As highlighted by Kamanou and Morduch (2002, p. 9), "*labeling them both as identically vulnerable misses the key part of their stories*".

As the majority of the restrictions are imposed by the empirical analysis, part of the literature on vulnerability as expected poverty has focused on overcoming the limitations of the data by improving the estimates of income or consumption variability. Chaudhuri *et al.* (2002) and Chaudhuri (2003), for instance, using the same measure of Pritchett *et al.* (2000), compute vulnerability when only cross-sectional data are available, with a consistent estimate of the variance, while Kamanou and Morduch (2002) propose a non-parametric approach, based on a bootstrap technique, to compute an aggregate index of vulnerability.

As it is difficult to find a broadly recognized procedure for vulnerability, Hoddinott and Quisumbing (2003) summarized all the attempts used in the literature, highlighting the drawbacks of each approach. About the expected poverty version, they criticize mainly the fact that downside and upside risks are weighted the same way.

After the first empirical focus, the literature has developed towards a more formal attempt to test if some desirable properties were satisfied by the measures proposed, this is what is called *axiomatic approach.* In their definition, Calvo and Dercon (2005) consider as vulnerability the *magnitude of the threat of poverty* and the *sense of insecurity*, they clarify how their view of vulnerability is not simply low expected welfare, as often turns out from previous studies, but is related to dangers or threats, as opposed to uncertainties in general. The two authors formally require that their measure of vulnerability satisfies the following properties:

- Symmetry: This axiom ensures that the measure used for vulnerability does not consider differently two possible states of the world, if they do not differ in terms of probabilities and outcomes. An illness or a bad harvest are equivalent if they occur with equal probability and have the same effect on the outcome.
- Focus: Changes in outcomes of good states of the world do not affect individuals' vulnerability to poverty. This axiom clarifies that the threat of future poverty will not be mitigated by simultaneous (*ex ante*) possibilities of being well-off.
- Probability-dependent effect on outcomes: If the outcome in one state of the world improves, the consequent effect on vulnerability does not depend on the outcomes or probabilities of other states of the world but on the likelihood of that particular state of the world.
- Probability transfer: Vulnerability is linear in probabilities and, as long as outcomes are below the poverty line, its increases are monotonically related to decreases in outcomes.
- Risk sensitivity: Risk leads to higher vulnerability.
- Scale invariance: This axiom requires that the index does not depend on the unit of measurement because what matters is only the relative distance from the poverty line.

Even if the often used vulnerability version of the Foster-Greer-Thorbecke poverty index (6) satisfies the desiderata listed by the two authors, it fails to meet the *Probability transfer* and *Risk sensitivity* axioms under the most frequently used values of α, i.e. with $\alpha = 0$ or $\alpha = 1$. Moreover, even if we consider $\alpha > 1$, satisfying all properties, the risk sensitivity axiom implies that better outcomes will exacerbate the extent to which the individual fears an increase in risk exposure, against empirical evidences. Therefore to have alternative risk aversion attitudes, more consistent with data, Calvo and Dercon (2005) propose two other classes of measures that satisfy additional properties, not imposed as forcefully:

$$V_\alpha = 1 - E\left[\left(\frac{min\,(y_{h,t+1}, z)}{z}\right)^\alpha\right] \quad 0 < \alpha < 1, \tag{7}$$

$$V_\beta = E\left[\frac{e^{\beta(1-x_{h,t+n})} - 1}{e^\beta - 1}\right] \quad \beta > 0, \quad x_h = \frac{min\,(y_{h,t+1}, z)}{z}. \tag{8}$$

The former class, 7, satisfies the constant relative risk sensitivity, i.e. the *efficiency loss* due to risk is determined as a constant proportion of expected outcome, $E[\cdot]$

denotes expectations in the formula. The latter, 8, meets the constant absolute risk sensitivity, i.e. the *efficiency loss* is a constant value of $y^{ce} - \hat{y}_{t+1}$, where y^{ce} is the certainty-equivalent outcome. While different risk attitudes are the main innovation proposed by Calvo and Dercon (2005) in measuring vulnerability, Dutta *et al.* (2011) have recently highlighted the importance of current living standard in this context, by proposing the following measures

$$V(L) = \sum_{s=1}^{S} p_s \left(R(z, y_t) - y_{t+1}^{s} \right)^{\gamma}, \quad \gamma > 1, \tag{9}$$

$$R(z, y_t) = z^{1-\alpha} y_t^{\alpha}, \quad 0 \geq \alpha \geq 1, \tag{10}$$

$$R(z, y_t) = z^{1+\alpha} \setminus y_t^{\alpha}, \quad 0 \geq \alpha \geq 1. \tag{11}$$

Dutta *et al.* (2011) argue that the threat of poverty depends not only on the poverty line, but also on the current living standard that can exacerbate or mitigate against the welfare loss; they propose therefore an index of vulnerability based on an individual reference line $R(z, y_t)$ rather than a general poverty line z, as all the previous studies have done, that depends also the current income or consumption level, y_t. Moreover, their measure is flexible enough to catch two opposite effects of the current living standard on the individual vulnerability, positive or negative. The index 10 considers a reference line $R(z, y_t)$ that reflects the idea of worse consequences in term of vulnerability for those with higher current living standard, while 11, on the contrary, says that low current income exacerbates the potential drops in welfare.

In this analysis, the index proposed by Kamanou and Morduch (2002) is not considered, even if it is an *ex ante* poverty risk measure. The reason for this is that they define vulnerability directly at the society level, as difference between the expected value of a poverty measure, the poverty head count ratio, and its current value rather than estimating a degree of poverty risk for each household or individual. Their approach therefore does not aim at identifying the vulnerable, but has the purpose to estimate poverty indexes using a non-parametric technique based on a large number of boostrap samples.

All these indexes are rich in terms of information summarized and they focus on different and equally relevant aspects of poverty risk. The index proposed by Pritchett *et al.* (2000) or Chaudhuri (2003) for instance summarizes upward and downward variability of income, stressing the role of fluctuations in general to forecast poverty; the FGT version instead focuses especially on the downward variability and accounts for different types of weights that can be attached to extreme poverty, highlighting implicitly that not only the number of cases in which poverty is experienced matters but also the magnitude of the shock could be relevant in predicting the poverty status. Calvo and Dercon (2005) consider instead the risk attitude important, they stress therefore the role of risk sensitivity as key element in their measure; finally Dutta *et al.* (2011)'s measures are different from the others because they suggest that the current financial situation affects, in two opposite ways, the importance of the potential drops in income. It is not possible to distinguish *a priori* which is the best signal of poverty, since they favor different sides of the same phenomenon. Therefore I try to evaluate their effectiveness empirically and classify them according to precision criteria.

III. Data

Vulnerability to poverty will be estimated using data from the British Household Panel Survey (BHPS), the German Socio-Economic Panel Study (SOEP) and the Survey on Household Income and Wealth (SHIW) for Italy.

The BHPS follows a representative sample of British individuals over the period 1991-2005; it was designed as an annual survey of each adult member for a nationally representative sample of about 5000 households, making a total of approximately 10000 individual interviews. The same individuals are re-interviewed in successive waves and, in case of split-off from the original household, all adults of the new household are also interviewed, preserving the representativeness of the British population.

Additional sub-samples were added in 1997 and 1999, respectively Scotland-Wales and Northern Ireland. The aims of the extensions were to increase the relative small Scottish and Welsh samples size and to cover Norther Ireland properly, for a UK analysis rather than England only. It must be kept in mind that in this analysis sample weights are not used, even if that is the conventional way to mitigate against potential attrition biases and new sub-samples effects. This is because the longitudinal weights supplied in the BHPS refer to a rather specific sample. The results therefore can be sensitive to the characteristics of the data used, especially to information on the net annual equivalized households income,[2] provided for those households in which all eligible adults gave a full interview.

The final sample is composed by 5735 households,[3] whose characteristics are summarized in Table 1. Missing information on education or region was retrieved from the previous waves. For Pritchett *et al.* (2000)'s and Chaudhuri (2003)'s approach, information on the age of the household head, the percentage of household members respectively with O-level of education or lower, A-level or equivalent and with a degree or higher education, is exploited as well as the percentage of children and earners.

In order to understand if the rank of vulnerability measures, estimated using the BHPS, is stable and reliable, another database is used, the SOEP, that is very similar to the British one. The German survey was started in 1984 as a longitudinal survey of private households and individuals in the Federal Republic of Germany, then it was extended to the territory of the German Democratic Republic in June 1990. The analysis is restricted to the period 1991-2005 in order to have a representation of the whole German residential population. In the SOEP there are several sub-samples for households whose head does not belong to the main foreigner groups, for households with a Turkish, Greek, Yugoslavian, Spanish or Italian household head, and for immigrants which started in 1994-1995. In 1998 and 2000 also new samples as refreshments were added from the population of private households in Germany. As in the BHPS case, information on the household disposable income,[4] the education level and the employment status of each member is used; the final sample size is 9597.

I use also the SHIW, that gathers information for a representative sample of the Italian population on the households disposable income[5] and its sources, as well as the characteristics of the individuals and their occupational status. Even if it is possible to find the same data in the SHIW, the questionnaire is slightly different from the BHPS and the SOEP because conducted every two years instead of yearly.[6] The time period considered for the analysis is 1989-2004.[7] For the SHIW, the final sample size is 2519 households, imposing the same restrictions for the sample selection in the two previous cases; in Table 1 I describe also the Italian sample. As for the BHPS and the SOEP, sample weights are not used.

For each database I will compute the different vulnerability measures that aim to anticipate who will be poor in the last period of time observed, that will be respectively 2004 for the SHIW and 2005 for the BHPS and SOEP. More precisely the estimated indexes are those proposed by Pritchett *et al.* (2000), Chaudhuri (2003), Hoddinott and Quisumbing (2003), Calvo and Dercon (2005) and Dutta *et al.* (2011).[8]

[2] The equivalence scales used are the square root of the household size, as well as the Oxford scale and the OECD-modified scale, and all values have been expressed in real terms (deflated to January 1998 prices)

[3] I selected those households that were present in the panel for at least three periods, with observations in the years 2004 and 2005, since I compare the different vulnerability measures computed for the year 2004 with the poverty status in 2005.

[4] Also in this case three different equivalence scales are used, to take into account different degree of *equivalence elasticity*, i.e. different economies of scale within the household. Real income is deflated to 2005 prices.

[5] Real equivalized net income is deflated to 1991 prices.

[6] The data are collected every two years from 1987, with an exception for the year 1998 when information was gathered three years after 1995.

[7] Even if the Bank of Italy provides data from 1977, the longitudinal component starts only from 1987, but I restrict the time period analyzed to 1989-2004 because, as already pointed out in literature (Biagi *et al.*, 2009), two few households remain in the panel from 1987 to 1989.

[8] We will use the following notation: PC = Prittchett, Suryahadi and Sumarto (2000) and Chaudhuri (2003); C = Chaudhuri (2003); FGT = Foster, Greer and Thorbecke; CD=Calvo and Dercon (2005); DFM = Dutta, Foster and Mishra (2010).

Table 1. Sample Characteristics

	UK - BHPS (1991-2005)		**Germany - SOEP (1991-2005)**		**Italy - SHIW (1989-2004)**	
Household Head's age:	Obs	%	Obs	%	Obs	%
$\leq$ 34	827	14.42	1290	13.44	66	2.62
35-44	1184	20.65	2073	21.60	373	14.81
$\geq$ 45	3724	64.93	6234	64.96	2080	82.57
Education:	Mean	S. D.	Mean	S. D.	Mean	S. D.
% O-level or lower in HH	0.35	0.41	0.20	0.33	0.70	0.36
% A-level or equivalent in HH	0.21	0.31	0.52	0.42	0.22	0.30
% Degree or higher in HH	0.12	0.27	0.28	0.39	0.08	0.21
% Earners in HH	0.44	0.40	0.77	0.34	0.32	0.32
% Children in HH	0.13	0.22	0.05	0.14	0.09	0.17

IV. Empirical strategy

Focusing on Chaudhuri (2003) and Pritchett *et al.* (2000)'s approach, if a panel dataset is available, an income generating function can be defined as follows

$$y_{h,t} = y(X_h, \beta_t \alpha_h, e_{h,t}) \tag{12}$$

$$v_{h,t} = E[p_{\alpha,h,t+1}(y_{h,t+1}) \mid F(y_{h,t+1} \mid X_h, \beta_t \alpha_h, e_{h,t})], \tag{13}$$

where X_h represents the observable household characteristics, β_h is a vector of parameters describing the state of the economy at time t, α_h is an unobserved time-invariant household-level effect and $e_{h,t}$ represents any idiosyncratic factors (shocks) that determines the variability of household income. This function will allow us to predict not only the income level at $t+1$, given the information up to time t, but also its variability in the period considered, using the residuals of the model specified.

According to this first method of assessing vulnerability, it is possible to estimate the *conditional probability that the household income falls below the poverty line in the next period of time* (13). Differently from Chaudhuri (2003), income is used as measure of welfare, rather than consumption, simplifying the econometric issues related to *predetermined*, rather than *strictly exogenous* variables[9] and the parameters are estimated using a fixed-effect model, where education, demographics, geographical location and time dummies are the explanatories.

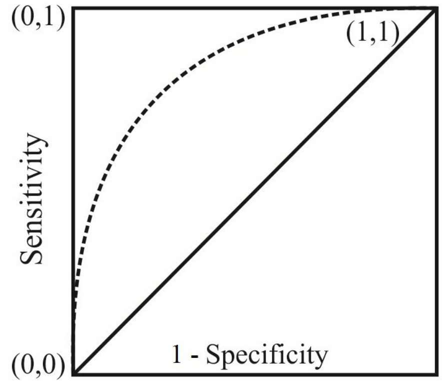
The econometric strategy is slightly different if the data considered are cross-sectional: it is not possible to observe a series of shocks for each household, but the heteroskedasticity in the data can be exploited to describe how the variability in income changes according to some characteristics. This is the strategy used by Chaudhuri (2003) who estimates the parameters of the specified model through a three-step feasible generalized least squares (FGLS) procedure, suggested by Amemiya (1977).

$$\hat{v}_{h,t} = \hat{pr}(lny_{h,t+1} < lnz \mid \hat{\mu}_{lny_{h,t+1}}, \hat{\sigma}_{lny_{h,t+1}}) = \Theta\left(\frac{lnz - \hat{\mu}_{lny_{h,t+1}}}{\hat{\sigma}_{lny_{h,t+1}}}\right) \tag{14}$$

It must be noticed that using cross-sectional data forces to assume that households with similar characteristics are subjected to the same variability in income, while panel analysis can give a more idiosyncratic idea of shocks, the more correct is the model and the longer the dataset. In both cross-sectional and panel analysis, normality is assumed to compute probabilities, therefore we will have 14, where $\Theta(\cdot)$ denotes the cumulative density of the standard normal, $\hat{\mu}$ and $\hat{\sigma}$ are respectively the estimated expected equivalized disposable income at $t+1$ and the standard deviation.

[9] In his consumption generating function, Chaudhuri (2003) assumes that the elements of $X_{h,t}$ are contemporaneously uncorrelated with $e_{h,t}$ but allows for potential correlation between $X_{h,t}$ and lagged consumption shocks. If this is the case, the standard within-estimator cannot be used, that is the reason why Chaudhuri (2003) uses first differences of consumption and instruments the changes in the predetermined variables using lagged changes and levels of the same variables. In this case, if income is used rather than consumption, the correlation between $X_{h,t}$ and lagged shocks should not be an issue.

Figure 1. The ROC curve



For the FGT version of vulnerability to poverty (Hoddinott and Quisumbing, 2003), for Calvo and Dercon (2005) and Dutta *et al.* (2011) that do not explicitly define an income generating function as in the previous cases, I decided to use as possible income values those already experienced by the household in the past, assuming that the data are informative about all the possible idiosyncratic shocks. The probabilities attached to each income drops below the poverty line is given by $1/d$, where d is the number of observations for each household.

In order to understand which vulnerability measure can detect with more precision poor individuals in advance, I use Receiver Operating Characteristic curve (ROC), which can provide a summary of the degree to which vulnerability acts as a signal for poverty. This method was originally used in the field of engineering or disease diagnosis, to measure the extent to which a given signal can detect an underlying condition. This approach has been then proposed by several authors, among others Madden (2008), also to assess the degree of overlapping between dimensions in the multidimensional poverty framework.

In this context the underlying condition is income poverty in the last year observed, $t+1$, while the vulnerability indexes, computed on information up to time t, are the *symptoms* of poverty; by analyzing the ROC curves of each vulnerability measure is therefore possible to understand which index is the most reliable signal of poverty.

To draw the ROC curve, I first define *poor* those households with equivalized disposable income in the last period observed lower than the traditional relative poverty threshold (60% of the median equivalized income) and *non-poor* otherwise. Given the two groups, it is possible to understand, for each index, to what extent the distinction between *vulnerable* and *non-vulnerable* households produces the *same* partition of the poverty status. For each vulnerability threshold, those individuals that are poor in income and vulnerable are called true positive (TP), those who are classified as non-poor and non-vulnerable are called true negative (TN). If the vulnerability threshold identifies as vulnerable someone who is not poor according to income, he or she will be a false positive (FP), while false negative (FN) is someone poor in income but non-vulnerable. The ROC curve exploits this classification to plot, on the vertical axis, the sensitivity or TP rate, TP/(TP+FN), against 1-the specificity or TN rate, 1-TN/(FP+TN), on the horizontal axis, for all possible values of the vulnerability threshold. The more correlated are vulnerability and poverty, the higher will be the sensitivity and the specificity, the more vulnerability acts as a signal of poverty and, in graphical terms (Fig. 1), the nearer will be the curve to the point (0,1). For a more intuitive summary of the extent to which vulnerability is correlated with income poverty, in the sense of identifying the poor, the area under the ROC curve is reported: the higher is this area the better the signaling.

Even if the area under the ROC curve is a measure of association specifically designed to deal with dichotomous variables, to assess the signaling power, other two alternative criteria are used: the Pearson and the Spearman correlation coefficients.

While the ROC curve is appropriate for binary variables, the correlation coefficients reflect the correlation between individuals across the complete distribution of vulnerability and income. Especially, the Pearson coefficient assumes a linear relation-

Table 2. Vulnerability to poverty

UK - BHPS (1991-2004)				
Author(s)	**PC**	**C**	**FGT** $\alpha = 1$	**FGT** $\alpha = 2$
Mean	0.134	0.125	0.047	0.024
Std Dev.	0.205	0.176	0.095	0.066
Poor (1)	0.230	0.260	0.142	0.072
Non-poor (2)	0.115	0.098	0.029	0.015
(1)/(2)	2.000	2.653	4.896	4.800
Author(s)	**CD rel.**	**CD abs.**	**DFM1**	**DFM2**
Mean	0.174	0.042	$8.8 \cdot 10^5$	$4.6 \cdot 10^8$
Std Dev.	0.105	0.087	$2.6 \cdot 10^6$	$7.3 \cdot 10^9$
Poor (1)	0.245	0.125	$10.5 \cdot 10^5$	$20.5 \cdot 10^8$
Non-poor (2)	0.160	0.025	$8.5 \cdot 10^5$	$1.44 \cdot 10^8$
(1)/(2)	1.531	5.000	1.235	14.236

Germany - SOEP (1991-2004)				
Author(s)	**PC**	**C**	**FGT** $\alpha = 1$	**FGT** $\alpha = 2$
Mean	0.04693	0.0718	0.0243	0.0088
Std Dev.	0.1049	0.1546	0.0641	0.0300
Poor (1)	0.1100	0.1873	0.1120	0.0412
Non-poor (2)	0.0362	0.0522	0.0094	0.0033
(1)/(2)	3.0387	3.5881	11.9042	12.4848
Author(s)	**CD relative**	**CD abs.**	**DFM1**	**DFM2**
Mean	0.1722	0.0206	$2.79 \cdot 10^6$	$6.81 \cdot 10^7$
Std Dev.	0.0845	0.0554	$12.6 \cdot 10^6$	$284.4 \cdot 10^6$
Poor (1)	0.2229	0.0948	$4.41 \cdot 10^6$	$21 \cdot 10^7$
Non-poor (2)	0.1636	0.0080	$2.51 \cdot 10^6$	$4.4 \cdot 10^7$
(1)/(2)	1.3625	11.8500	1.7522	4.7623

Notes: PC = Prittchett, Suryahadi and Sumarto (2000) and Chaudhuri (2003); C = Chaudhuri (2003); FGT = Foster, Greer and Thorbecke (2008); CD=Calvo and Dercon (2005); DFM = Dutta, Foster and Mishra (2010). Square root of household size as equivalence scale.

ship between two variables and estimates their linear dependence, while the Spearman correlation coefficient is a non-parametric measure of statistical dependence and valuates how well the relation between two variables can be described using a monotonic function. The latter is different from the former coefficient, because less sensitive to strong outliers that are in the tails of both samples.

V. Results

Before looking at the vulnerability measures, I ensured that the samples are representative for the poverty phenomenon in the countries analyzed. The poverty headcount ratio is computed for the UK and Germany in the year 2005 and for Italy in 2004 and then compared with the official data. According to Brewer *et al.* (2006), I find that about 16% of the households are poor in 2005 in the United Kingdom if the relative poverty line is set to the 60% of the median equivalized disposable income, for Germany the percentage of poor households in 2005 is about 12% and for Italy in 2004 the 19% of households is poor as the official Eurostat statistics report.[10] Moreover, since vulnerables include also the *permanently* poor, that are those who stay poor over long periods of time, it is useful also to have an idea of the permanent poverty phenomenon, in this case those households that are poor in both years considered. In Italy among those that are poor in 2004, the 60% of them were poor also in 2002, while in the UK this percentage is 63%, in Germany the persistence of poverty is the highest compared to the other two countries, about 73% of households poor in 2004 remain in the same condition the next year.

In Table 2 a summary of the discussed vulnerability indexes is reported: the mean value, the standard deviation, the average vulnerability for the two categories of households, poor or not, and also the ratio between the mean value of the these two groups.

Starting from the UK and Germany and focusing on the estimated indexes of

[10] As in Brandolini *et al.* (2010), if the 50% of the median equivalized disposable income poverty threshold is used, I find for Italy that about the 12% of households is poor.

Table 3. Vulnerability to poverty and Income poverty correlation

UK - BHPS (1991-2005)				
Index	**Area under the ROC (SE)**	**95% Conf. Interval**	**Pearson coefficient**	**Spearman coefficient**
PC	0.6758 (0.0093)	0.6576-0.6940	-0.2429	-0.3724
C	0.7480 (0.0088)	0.7307-0.7652	-0.3653	-0.5433
FGT $\alpha = 1$	0.8272 (0.0072)	0.8130-0.8413	-0.3192	-0.5537
FGT $\alpha = 2$	0.8147 (0.0072)	0.8006-0.8289	-0.2284	-0.5398
CD (rel.)	0.7118 (0.0092)	0.6938-0.7298	-0.2411	-0.3066
CD (abs.)	0.8256 (0.0072)	0.8114-0.8397	-0.3063	-0.5518
DFM1	0.6809 (0.0078)	0.6656-0.6961	0.0458	-0.3172
DFM2	0.8432 (0.0072)	0.8291-0.8573	-0.0679	-0.5977

Germany - SOEP (1991-2005)				
Index	**Area under the ROC (SE)**	**95% Conf. Interval**	**Pearson coefficient**	**Spearman coefficient**
PC	0.6933 (0.0080)	0.6776-0.7089	-0.1449	-0.2723
C	0.7702 (0.0067)	0.7571-0.7832	-0.2490	-0.5255
FGT $\alpha = 1$	0.8883 (0.0050)	0.8784-0.8981	-0.2850	-0.5598
FGT $\alpha = 2$	0.8826 (0.0051)	0.8727-0.8925	-0.2234	-0.5547
CD (rel.)	0.6762 (0.0081)	0.6603-0.6920	0.0163	-0.0736
CD (abs.)	0.8878 (0.0050)	0.8779-0.8977	-0.2793	-0.5593
DFM1	0.7624 (0.0056)	0.7516-0.7733	0.0089	-0.3796
DFM2	0.8937 (0.0052)	0.8835-0.9038	-0.0169	-0.5925

Notes: PC = Prittchett, Suryahadi and Sumarto (2000) and Chaudhuri (2003); C = Chaudhuri (2003); FGT = Foster, Greer and Thorbecke (2008); CD=Calvo and Dercon (2005); DFM = Dutta, Foster and Mishra (2010). Square root of household size as equivalence scale.

vulnerability, it is possible to notice that those households poor in 2005 are, on average, more vulnerable than those non poor and this for each measure. The ratio of vulnerability between the two categories is different among indexes and depends also on their functional form. For instance in the UK, according to Pritchett *et al.* (2000)'s index, those households poor in 2005 are twice more vulnerable, in terms of probability, than those who turned out to be non poor, while for the index proposed by Dutta *et al.* (2011), when the low current living standard exacerbates the potential drops in welfare, this ratio is seven times higher.

In order to assess which index is the best signal of poverty, I focus on the area under the ROC curve reported in Table 3 as precision criterion.

Comparing the UK and Germany, it is possible to distinguish in both countries two groups of measures, those with an area larger than 0.8, that can be labelled *high-performers*, and those with lower values (*low-performers*). According to the ROC area point estimates, the indexes that belong to the high-performers group, in both countries, are the FGT version of vulnerability, regardless of the alpha value, the Calvo and Dercon's index that accounts for the absolute risk sensitivity, and the second version of Dutta *et al.* (2011)'s measure of poverty risk. In Appendix it is shown that these results are insensitive also using different equivalence scales.

Ranking further the indexes of vulnerability is not so straightforward, looking at the 95% confidence intervals it is possible to notice in fact that they always overlap, meaning that it is not sure that the estimated areas are statistically different among them; a possible strategy that could help in distinguishing the most precise index of vulnerability could be testing the equality among areas, in order to understand if the difference in terms of point estimates is really significant or if, on the contrary, we are dealing with measures of poverty risk equally precise.

I use therefore a non-parametric comparison of the ares under correlated ROC curves proposed by DeLong *et al.* (1988) that exploits the theory on generalized U-statistics to generate an estimated covariance matrix and a test statistic with an asymptotically chi-square distribution. In Table 4 the tests for the following null hypothesis are reported: equality among the ROC areas of the high-performer indexes and pairwise equality between each high-performer index with that one which records the highest area (for the UK and Germany the highest value is estimated for the

Table 4. Equality tests among areas under the ROC curves

UK - BHPS (1991-2005)			
Index	**Area under the ROC**	**Std. Err.**	**95% Conf. Interval**
FGT $\alpha = 1$	0.8272	0.0072	0.81304-0.84131
FGT $\alpha = 2$	0.8147	0.0072	0.80060-0.82888
CD (abs.)	0.8256	0.0072	0.81145-0.83972
DFM2	0.8432	0.0072	0.82910-0.85734
H_0: area(FGT $\alpha = 1$) = area(FGT $\alpha = 2$) = area(CD (abs.)) = area(DFM2)			
chi2(3) = 220.79		Prob>chi2 = 0.0000 ***	
H_0: area(FGT $\alpha = 1$) = area(DFM2)			
chi2(1) = 31.64		Prob>chi2 = 0.0000 ***	
H_0: area(FGT $\alpha = 2$) = area(DFM2)			
chi2(1) = 89.84		Prob>chi2 = 0.0000 ***	
H_0: area(CD (abs.)) = area(DFM2)			
chi2(1) = 38.11		Prob>chi2 = 0.0000 ***	

Germany - SOEP (1991-2005)			
Index	**Area under the ROC**	**Std. Err.**	**95% Conf. Interval**
FGT $\alpha = 1$	0.8883	0.005	0.8784-0.8981
FGT $\alpha = 2$	0.8826	0.005	0.8727-0.8925
CD (abs.)	0.8878	0.005	0.8779-0.8977
DFM2	0.8937	0.005	0.8835-0.9038
H_0: area(FGT $\alpha = 1$) = area(FGT $\alpha = 2$) = area(CD (abs.)) = area(DFM2)			
chi2(3) = 201.33		Prob>chi2 = 0.0000 ***	
H_0: area(FGT $\alpha = 1$) = area(DFM2)			
chi2(1) = 5.95		Prob>chi2 = 0.0147 **	
H_0: area(FGT $\alpha = 2$) = area(DFM2)			
chi2(1) = 23.76		Prob>chi2 = 0.0000 ***	
H_0: area(CD (abs.)) = area(DFM2)			
chi2(1) = 7.06		Prob>chi2 = 0.0079 ***	

*Notes: FGT = Foster, Greer and Thorbecke (2008); CD=Calvo and Dercon (2005); DFM = Dutta, Foster and Mishra (2010). Square root of household size as equivalence scale. Confidence levels are reported with the following notation: p-value *** $\leq$ 0.01, ** $\leq$ 0.05, * $\leq$ 0.1.*

Table 5. Specificity for given values of sensitivity (85%, 80%, 75%)

UK - BHPS (1991-2005)						
Sensitivity	85%		80%		75%	
	Specificity	Rank	Specificity	Rank	Specificity	Rank
PC	37.69	6	44.92	7	51.27	8
C	48.02	5	58.40	5	65.57	5
FGT $\alpha = 1$	70.27	2	74.86	3	78.00	2
FGT $\alpha = 2$	70.14	3	73.86	4	76.83	4
CD (rel.)	34.79	7	41.35	8	54.43	7
CD (abs.)	70.27	2	75.05	2	77.94	3
DFM1	50.54	4	54.16	6	57.86	6
DFM2	72.77	1	78.21	1	82.16	1

Germany - SOEP (1991-2005)						
Sensitivity	85%		80%		75%	
	Specificity	Rank	Specificity	Rank	Specificity	Rank
PC	66.18	5	43.36	7	52.94	7
C	52.89	7	61.08	6	66.19	6
FGT $\alpha = 1$	83.70	3	86.79	3	89.32	2
FGT $\alpha = 2$	83.52	4	86.52	4	88.52	4
CD (rel.)	32.61	8	37.64	8	40.25	8
CD (abs.)	83.75	2	86.80	2	89.29	3
DFM1	63.68	6	66.97	5	69.20	5
DFM2	86.87	1	89.48	1	92.14	1

Notes: PC = Prittchett, Suryahadi and Sumarto (2000) and Chaudhuri (2003); C = Chaudhuri (2003); FGT = Foster, Greer and Thorbecke (2008); CD=Calvo and Dercon (2005); DFM = Dutta, Foster and Mishra (2010). Square root of household size as equivalence scale.

second version of Dutta *et al.* (2011)'s measure of poverty risk).

Focusing on the UK, the equality in all cases can be strongly rejected, among all the areas and for each pairwise test, meaning that the estimated ROC areas are statistically different. These results lead to the conclusion that the second version of the index proposed by Dutta *et al.* (2011) can be considered the best signal of poverty if the identification of poors is the concern. The same tests are repeated for Germany with the same results, rejection of equality in all cases.

The area under the ROC curve can be seen as a criterion of the overall signal precision: all the false positive-false negative combinations are choosen by varying the threshold that divides vulnerable and non vulnerable households. But in this context the two types of errors that can be made could have a different relevance for assessing the signal precision: identifying as non-vulnerable households that will be poor is worse than defining as vulnerable someone who will not be poor.

Both errors anyhow cannot be reduced at the same time: if few false negatives are prefererred, a higher error in terms of false positive have to be tollerated and viceversa. What can be done, for taking into account the different weight attached to the two types of errors, is to choose a specific, high and fixed level of sensitivity (that means few false negative cases) and classify the measure in terms of specificity: the raking will give an idea of identification precision when we tolerate only a certain percentage of false negatives. The overall rank based on the area under the ROC curve may not be the same if we focus only on a specific partition of vulnerables.

Table 5 reports for given values of sensitivity (85%, 80%, 75%)[11] the corresponding specificity that allows to rank the measures: the higher the specificity, for a certain sensitivity level, the lower the fraction of false posivites and the better the signal.

The results show how the second version of Dutta *et al.* (2011)'s index of vulnerability minimizes the false positives for each sensitivity value both in the UK and Germany, this allows to say that also controlling for a specific type of error DFM2 remains the most precise.

The Italian case is only partly comparable with the other two countries and this is due to the data available: the information in the SHIW for each household is different

[11] The corresponding false negatives are respectively 15%, 20% and 25%.

Table 6. Vulnerability to poverty

Italy - SHIW (1989-2002)				
Author(s)	**PC**	**C**	**FGT** $\alpha = 1$	**FGT** $\alpha = 2$
Mean	0.0765	0.1305	0.0395	0.0193
Std Dev.	0.1169	0.2223	0.0957	0.0643
Poor (1)	0.1487	0.3626	0.1456	0.0754
Non-poor (2)	0.0602	0.0784	0.0156	0.0067
(1)/(2)	2.4701	4.6250	9.333	11.2573
Author(s)	**CD rel.**	**CD abs.**	**DFM1**	**DFM2**
Mean	0.2564	0.0346	$9.7 \cdot 10^5$	$1.1 \cdot 10^9$
Std Dev.	0.1015	0.0872	$28.4 \cdot 10^5$	$2.39 \cdot 10^{10}$
Poor (1)	0.3318	0.1285	$15.7 \cdot 10^5$	$45.1 \cdot 10^8$
Non-poor (2)	0.2395	0.0135	$8.4 \cdot 10^5$	$3.28 \cdot 10^8$
(1)/(2)	1.3854	9.5185	1.87	14.09

Notes: PC = Prittchett, Suryahadi and Sumarto (2000) and Chaudhuri (2003); C = Chaudhuri (2003); FGT = Foster, Greer and Thorbecke (2008); CD=Calvo and Dercon (2005); DFM = Dutta, Foster and Mishra (2010). Square root of household size as equivalence scale.

Table 7. Vulnerability to poverty and Income poverty correlation

Italy - SHIW (1989-2004)								
Index	**Area under the ROC (SE)**	**95% Conf. Interval**	**Pearson coeff.**	**Spearman coeff.**	Se = 0.8		Se = 0.7	
					Sp	Rank	Sp	Rank
PC	0.6996 (0.0138)	0.6725-0.7267	-0.1530	-0.3097	45.11	7	61.01	8
C	0.8298 (0.0104)	0.8096-0.8501	-0.2510	-0.6117	69.18	5	79.87	5
FGT $\alpha = 1$	0.8551 (0.0101)	0.8353-0.8749	-0.2540	-0.5882	84.83	2	87.85	2
FGT $\alpha = 2$	0.8510 (0.0101)	0.8312-0.8708	-0.1962	-0.5842	84.05	4	87.21	4
CD (rel.)	0.7294 (0.0138)	0.7024-0.7564	-0.1394	-0.2728	40.01	8	68.16	7
CD (abs.)	0.8546 (0.0101)	0.8348-0.8745	-0.2461	-0.5878	84.78	3	87.75	3
DFM1	0.7606 (0.0105)	0.7400-0.7811	-0.0620	-0.4156	66.60	6	71.03	6
DFM2	0.8507 (0.0104)	0.8302-0.8711	-0.0336	-0.5922	85.66	1	89.30	1

Notes: PC = Prittchett et al. (2000) and Chaudhuri (2003); C = Chaudhuri (2003); FGT = Foster, Greer and Thorbecke (2008); CD=Calvo and Dercon(2005); DFM=Dutta,Foster and Mishra (2010). Square root of household size as equivalence scale. Sp=Specificity, Se=Sensitivity.

compared to the BHPS and SOEP in terms of frequency of observations and freshness. In fact while in the UK and Germany I aim to forecast the poverty status in the next year (from 2004 to 2005), in the Italian case I aim to anticipate poverty two years later (from 2002 to 2004), therefore the performance of indexes may change. For instance those based on the *current living standard* could be penalized by not so up-to-date information about income in terms of forecasting power.

The summary statistics in Table 6 show how, on average, even if information is not as rich as in the other two countries, those households poor in 2004 were more vulnerable in 2002 than those non poor. According to the area under the ROC it is still possible to notice two groups of measures: among the most precise already mentioned there is also vulnerability computed with cross-sectional data, but the associated area (0.82) remains anyhow lower than 0.85 estimated for all the other high-performers. In this case the estimated precision of the two FGT indexes, the CD (absolute) and DFM2 is very similar, the areas range from 0.8507 to 0.8551 meaning that frequency and freshness of information affect the precision of indexes in terms of equalizing the identification power, especially when current living standard condition plays a role in explaining poverty two periods later. Similar results are obtained also using other equivalence scales (see Appendix).

In order to understand if, in this case, the two FGT indexes, the CD (abs.) and DFM2 are equally precise, the results of the equality test between the FGT index with $\alpha = 1$ and DFM2, the two indexes that register the larger difference in terms of areas point estimates (area larger than 0.85) are reported, if the null hypothesis is accepted, it is possible to conclude that the indexes are equally precise in terms of identification of future poors. As shown in Table 8 the null hypothesis of equality is accepted.

As the overall test of precision based on the area under ROC does not allow to

Table 8. Equality tests among areas under the ROC curves

Italy - SHIW (1989-2004)			
Index	**Area under the ROC**	**Std. Err.**	**95% Conf. Interval**
C	0.8298	0.0104	0.80956-0.85013
FGT $\alpha = 1$	0.8551	0.0101	0.83526-0.87490
FGT $\alpha = 2$	0.8510	0.0101	0.83120-0.87085
CD (abs.)	0.8546	0.0101	0.83482-0.87446
DFM2	0.8507	0.0104	0.83024-0.87114
H_0: area(DFM2) = area(FGT $\alpha = 1$)			
chi2(1) = 1.08		Prob>chi2 = 0.2995	

*Notes: C = Chaudhuri (2003); FGT = Foster, Greer and Thorbecke (2008); CD=Calvo and Dercon (2005); DFM = Dutta, Foster and Mishra (2010). Square root of household size as equivalence scale. Confidence levels are reported with the following notation: p-value *** $\leq$ 0.01, ** $\leq$ 0.05, * $\leq$ 0.1.*

rank the measures in this case, I try to understand, for given values of sensitivity, if there is some index that performs better controlling for a certain type of error. By setting the sensitivity at 80% and 70%, i.e. tolerating respectively 20% and 30% of false negative, it is possible to rank the measures according to the specificity rate. The last columns of Table 7 show that even if the Dutta *et al.* (2011)'s index in general is as precise as some other index of vulnerability, nevertheless it minimizes the false positives when controlling for specific high sensitivity rates.

VI. Conclusions

According to the choosen correlation criterion, the Receiver Operating Characteristic curve, which is specifically designed for binary variables, I found that among those indexes proposed in literature to anticipate poverty risk, some are more precise than other in identifying the future poors, i.e. the FGT indexes of vulnerability independently of the α value, the Calvo and Dercon (2005) version when absolute risk sensitivity is taken into account and the Dutta *et al.* (2011)'s measure, that accounts for the role of the current living standard in mitigating the potential drop in income. These indexes, as more accurate in anticipating the poverty status, can be used as operational measures or *ex ante* information instruments for improving anti-poverty policies design. Moreover, if there is particular interest in limiting a certain type of identification error, i.e. avoiding too much cases in which households labelled as non-vulnerable turn out to be poor, the index proposed by Dutta *et al.* (2011) among the high-performers behaves better than the others, even if frequency of observations and freshness of information are different.

Individual vulnerability assessments can be useful for understanding the characteristics of households that are on average more exposed to income shocks to design better risk-management and anti-poverty policies, but also moving this analysis at the aggregate level could be interesting. Aggregate indexes of vulnerability could be important not only for evaluating the economic performance and the social progress in a country as the Commission on the Measurement of Economic Performance and Social Progress (CMEPSP) suggested, but also in terms of how relevant could be this exposure to risk in case of crisis and financial downturns. We can expect that countries where a larger part of the population is vulnerable could suffer more severe negative consequences in case of aggregate shocks, leading to higher costs not only in terms of welfare drop but also in recovering from such situations. Kamanou and Morduch (2002) took a step towards this direction, proposing a version of aggregate vulnerability: they computed their measure using a statistical method to generate a possible distribution of aggregate poverty indexes. Alternatively it would be also interesting understanding how we can aggregate vulnerability, starting from the individual or household level, and relate this exposure to risk with other macroeconomic variables.

References

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.

Azam, M. and Imai, K. (2009) Vulnerability and Poverty in Bangladesh, the University of Manchester: The School of Economics Discussion Paper Series 0905.

Bandyopadhyay, S. and Cowell, F. (2007) Modelling Vulnerability in the UK, LSE STICERD Research Paper 89.

Baulch, B. and Hoddinott, J. (2000) Economic mobility and poverty dynamics in developing countries, *Journal of Development Studies*, **36**, 1–24.

Biagi, F., Giraldo, A. and Rettore, E. (2009) Gli effetti dell'attrito sulla stima della disuguaglianza in Italia, in *Dimensioni della disuguaglianza in Italia: povertà, salute, abitazione* (Eds.) B. A. S. C. and A. Schizzerotto, Il Mulino, Bologna.

Brandolini, A., Magri, S. and Smeeding, T. M. (2010) Asset-based measurement of poverty, bank of Italy, Economic Research Department: Temi di discussione (Economic working papers) 755.

Brewer, M., Goodman, A., Shaw, J. and Sibieta, L. (2006) Poverty and Inequality in Britain: 2006, Institute for Fiscal Studies: IFS Commentary 101.

Calvo, C. and Dercon, S. (2005) Measuring Individual Vulnerability, university of Oxford, Department of Economics: Economics Series Working Papers 229.

Chaudhuri, S. (2003) Assessing household vulnerability to poverty: concepts, empirical methods and illustrative examples, Columbia University. Mimeo.

Chaudhuri, S., Jalan, J. and Suryahadi, A. (2002) Assessing house- hold vulnerability to poverty from cross-sectional data: a methodology and estimates from Indonesia, Columbia University, Department of Economics: Discussion Paper 0102-52.

DeLong, E., DeLong, D. and Clarke-Pearson, D. (1988) Comparing the Areas Under Two or More Correlated Receiver Operating Characteristic Curves: A Nonparametric Approach, *Biometrics*, **44**, 837–845.

Dercon, S. (2006) Vulnerability: a micro perspective, QEH Working Papers QEHWPS149.

Dutta, I., Foster, J. and Mishra, A. (2011) On measuring vulnerability to poverty, *Social Choice and Welfare*, forthcoming.

Foster, J., Greer, J. and Thorbecke, E. (1984) A class of decomposable poverty measures, *Econometrica*, **52**, 761–766.

Gaiha, R. and Imai, K. (2008) Measuring Vulnerability and Poverty: Estimates for Rural India, World Institute for Development Economic Research (UNU-WIDER): Working Papers RP2008/40.

Gaiha, R., Imai, K. and Kang, W. (2011) Vulnerability and poverty dynamics in Vietnam, *Applied Economics*, **43**, 3603–3618.

Gerry, C. and Li, C. (2010) Consumption smoothing and vulnerability in Russia, *Applied Economics*, **42**, 1995–2007.

Hoddinott, J. and Quisumbing, A. R. (2003) Methods for microeconometric risk and vulnerability assessments, The World Bank: Social Protection Discussion Paper Series 0324.

Imai, K., Wang, X. and Kang, W. (2009) Poverty and Vulnerability in Rural China: Effects of Taxation, The University of Manchester, The School of Economics: Discussion Paper Series 0913.

Jalan, J. and Ravaillon, M. (1998) Determinants of Transient and Chronic Poverty: Evidence from Rural China, World Bank Policy Research Working Paper No. 1936.

Jamal, H. (2009) Assessing Vulnerability to Poverty: Evidence from Pakistan, Social Policy and Development Centre (SPDC): Research Report N.80.

Jha, R., Dang, T. and Sharma, K. (2009) Vulnerability to poverty in Fiji, *International Journal of Applied Econometrics and Quantitative Studies*, **6**, 51–68.

Kamanou, G. and Morduch, J. (2002) Measuring Vulnerability to Poverty, World Institute for Development Economic Research: Working Papers UNU-WIDER Research Paper, 2002/58.

Ligon, E. and Schechter, L. (2003) Measuring vulnerability, *Economic Journal*, **113**, C95–C102.

Madden, D. (2008) Health and Income Poverty in Ireland, 2003-2006, University College Dublin, School Of Economics: Working Paper 200815.

Osberg, L. (1998) Economic Insecurity, University of New South Wales, Social Policy Research Centre: SPRC Discussion Paper 88.

Osberg, L. (2010) Measuring Economic Insecurity and Vulnerability as part of Economic Well-being: Concepts and Context, in *IARIW 31st General Conference*, St. Gallen, Switzerland.

Pritchett, L., Suryahadi, A. and Sumarto, S. (2000) Quantifying Vulnerability to Poverty: A proposed Measure Applied to Indonesia, The World Bank: Working Paper WPS 2437.

Skoufias, E. and Quisumbing, A. R. (2003) Consumption Insurance and Vulnerability to Poverty: A Synthesis of the Evidence from Bangladesh, Ethiopia, Mali, Mexico and Russia, International Food Policy Research Institute: FCND Discussion paper 155.

The World Bank (2011) Measuring Vulnerability, available at: `http://web.worldbank.org/WBSITE/EXTERNAL/TOPICS/EXTPOVERTY/EXTPA/0,,contentMDK:20238993~menuPK:492141~pagePK:148956~piPK:216618~theSitePK:430367,00.html[2011,February10]`.

Zhang, Y. and Guanghua, W. (2008) Can We Predict Vulnerability to Poverty?, WIDER Research Paper 2008/82.

A. Appendix

Table 9. Vulnerability to poverty and Income poverty correlation

UK - BHPS (1991-2005)				
	OECD equivalence scale		**OECD-modified scale**	
Index	**Area under the ROC (SE)**	**95% Conf. Interval**	**Area under the ROC (SE)**	**95% Conf. Interval**
PC	0.675 (0.0094)	0.6566-0.6935	0.672 (0.0091)	0.6546-0.6902
C	0.743 (0.0089)	0.7255-0.7604	0.749 (0.0088)	0.7323-0.7666
FGT $\alpha = 1$	0.823 (0.0074)	0.8088-0.8378	0.838 (0.0068)	0.8250-0.8518
FGT $\alpha = 2$	0.811 (0.0074)	0.7963-0.8253	0.826 (0.0068)	0.8126-0.8394
CD (rel.)	0.706 (0.0093)	0.6874-0.7240	0.706 (0.0091)	0.6877-0.7236
CD (abs.)	0.822 (0.0074)	0.8072-0.8363	0.837 (0.0068)	0.8235-0.8502
DFM1	0.679 (0.0079)	0.6639-0.6947	0.689 (0.0076)	0.6740-0.7040
DFM2	0.837 (0.0075)	0.8221-0.8513	0.851 (0.0070)	0.8371-0.8643
Germany - SOEP (1991-2005)				
	OECD equivalence scale		**OECD-modified scale**	
Index	**Area under the ROC (SE)**	**95% Conf. Interval**	**Area under the ROC (SE)**	**95% Conf. Interval**
PC	0.705 (0.0078)	0.6897-0.7204	0.690 (0.0081)	0.6744-0.7061
C	0.768 (0.0067)	0.7551-0.7815	0.767 (0.0067)	0.7535-0.7798
FGT $\alpha = 1$	0.874 (0.0056)	0.8626-0.8846	0.881 (0.0054)	0.8705-0.8916
FGT $\alpha = 2$	0.868 (0.0056)	0.8574-0.8794	0.875 (0.0054)	0.8647-0.8858
CD (rel.)	0.646 (0.0084)	0.6295-0.6626	0.664 (0.0083)	0.6482-0.6807
CD (abs.)	0.873 (0.0056)	0.8622-0.8841	0.880 (0.0054)	0.8700-0.8911
DFM1	0.739 (0.0059)	0.7273-0.7505	0.752 (0.0059)	0.7402-0.7632
DFM2	0.884 (0.0056)	0.8734-0.8953	0.883 (0.0056)	0.8721-0.8940
Italy - SHIW (1989-2004)				
	OECD equivalence scale		**OECD-modified scale**	
Index	**Area under the ROC (SE)**	**95% Conf. Interval**	**Area under the ROC (SE)**	**95% Conf. Interval**
PC	0.681 (0.0142)	0.6534-0.7089	0.670 (0.0136)	0.6631-0.7166
C	0.824 (0.0108)	0.8025-0.8447	0.827 (0.0106)	0.8060-0.8474
FGT $\alpha = 1$	0.853 (0.0104)	0.8329-0.8736	0.857 (0.0100)	0.8379-0.8772
FGT $\alpha = 2$	0.849 (0.0104)	0.8291-0.8697	0.854 (0.0100)	0.8344-0.8738
CD (rel.)	0.729 (0.0139)	0.7019-0.7562	0.728 (0.0139)	0.7008-0.7551
CD (abs.)	0.853 (0.0104)	0.8324-0.8731	0.857 (0.0100)	0.8375-0.8768
DFM1	0.756 (0.0108)	0.7382-0.7807	0.764 (0.0107)	0.7433-0.7852
DFM2	0.846 (0.0108)	0.8244-0.8668	0.851 (0.0105)	0.8304-0.8715

Notes: PC = Prittchett, Suryahadi and Sumarto (2000) and Chaudhuri (2003); C = Chaudhuri (2003); FGT = Foster, Greer and Thorbecke (2008); CD=Calvo and Dercon (2005); DFM = Dutta, Foster and Mishra (2010).