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by

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Abstract

This paper investigates vulnerability to poverty in Haiti. Research in vulnerability in developing countries has been scarce due to the high data requirements of vulnerability studies (e.g. panel or long series of cross-sections). The methodology adopted here allows the assessment of vulnerability to poverty by exploiting the short panel structure of nested data at different levels. The decomposition method reveals that vulnerability in Haiti is largely a rural phenomenon and that schooling correlates negatively with vulnerability. Most importantly, among the different shocks affecting household's income, it is found that meso-level shocks are in general far more important than covariate shocks. This finding points to some interesting policy implications in decentralizing policies to alleviate vulnerability to poverty.

Keywords: vulnerability, poverty, hierarchical model, Republic of Haiti.
JEL classification: C19, C11, I39, R20.

1. Introduction

Albeit the *ex-post facto* explanations of an event may help us understand the underlying factors triggering such event, when it comes to assessing poverty or the risk of falling into it an *ex-ante* analysis, in view of devising forward-looking anti-poverty policies, is the best approach to dealing with that issue. In that vein, the 2000/2001 World Bank Development Report may represent a turning point in poverty assessment. Virtually, research on poverty hitherto had been static in their approach.[1] Meanwhile, a non-poverty status reported by a household or an individual in a given time period may be hiatal and is often the consequence of situations beyond their command. In such a case, a one time picture may not be mirroring individual fundamental circumstances (e.g. stock of productive assets they command (Carter and Barrett, 2004)). This makes a forward-looking assessment of poverty far more desirable than a standard static approach.

It has now become widely recognized that movements in and out of poverty are very common, particularly in the context of developing countries. The design of policies aimed at combating poverty thus ought to focus not only on those presently poor but also those facing the risk of moving into poverty and those trapped into it. These last two embody the concept of vulnerability to poverty.

Many definitions have been proposed in the literature to define and characterize vulnerability to poverty. In line with these definitions, a plethora of approaches to measuring it have also been put forth (see among others, Pritchett, Suryahadi, and Sumarto (2000); Chaudhuri, Jalan, and Suryahadi (2002); Kamanou and Morduch (2002); Tesliuc and Lindert (2002); Ligon and Schechter (2003); Calvo and Dercon (2005); Christiaensen and Subbarao (2005)). Hoddinott and Quisumbing (2003a) give a fair account of the state of the art by saying that research in vulnerability is at a phase of ‘let a hundred flowers bloom’, where a collection of papers propose different approaches to measuring vulnerability and using slightly different conceptual framework.

[1] There are some exceptions. For instance a few early researches before this to adopt a more dynamic approach to analyzing poverty and addressing vulnerability are Ravallion (1988); Morduch (1994); Townsend (1994); Glewwe and Hall (1998); Amin, Rai, and Topa, (1999).

The many definitions and measures of vulnerability to poverty notwithstanding, their common thread is the concern for downside risks. All definitions and measures focus on the measurement of welfare in a world in which welfare reflects, in part, the interplay between the realization of stochastic events or shocks and the ability to anticipate and respond to them (Hodinnott and Quisumbing, 2008).

In this research we propose to investigate vulnerability to poverty in the Republic of Haiti from a microeconometric perspective. We use hierarchical modeling method to allow the estimation of vulnerability to poverty in the entire income distribution using a single cross-section. Specifically, it permits dissecting vulnerability into its different sources at the time that how different shocks at different levels affect households' income can be easily evaluated. To our knowledge no previous work has addressed in a systematic manner the vulnerability issue in the Republic of Haiti, so the present empirical research may be seen as a primer in that respect.[2] The paper is structured as follows. Section 2 presents a survey of the theoretical literature. In Section 3 a brief account of the empirical literature, with focus on developing countries, is presented.[3] Section 4 deals with the hierarchical modelling issue and discuss the results. In Section 5 some final remarks are presented and caveats discussed.

2. Review of the theoretical literature

According to Alwang, Siegel and Jorgensen (2001b), there are five principles a vulnerability concept should abide by: 1) it is forward-looking and could be defined as

[2] The UNDP 2004 human development report on Haiti presents some anecdotal evidence complemented with a summary measure of vulnerability proposed by Jadotte and Rouzier. In their approach the authors focus only on the non-poor to assess a 'subjective' probability of becoming poor.

[3] There is a load full of researches on vulnerability to poverty for developed countries (e.g. Japelli and Pistaferri (2006) and Meghir and Pistaferri (2004) for Italy; Bandyopadhyay and Cowell (2007), Cappellari and Jenkins (2002), and Banks, Blundell, and Brugiavini (2001) for the UK; Hong and Pandey (2007) for the US; Cantó, del Río, and Gradín (2006) for Spain, or Ayllón and Ramos (2008) for Catalonia-Spain; Whelan and Maître (2007) for various European countries. Most of these authors carry out their analysis using panel data and generally under the assumption of complete markets, including insurance market. Such an assumption is not relevant in a developing country context.

the probability of experiencing a future loss relative to some benchmark of welfare; 2) vulnerability is caused by uncertain events; 3) the degree of vulnerability depends on the characteristics of risks involved and household ability to respond to them; 4) vulnerability depends on the time horizon; and 5) both the poor and non-poor could be vulnerable because of their limited access to assets and abilities to respond to risks.

In the microeconometric literature approaches to assessing vulnerability can be divided in three broad categories. The first one construes vulnerability as expected poverty (VEP). Along this line are authors like, Pritchett, Suryahadi, and Sumarto (2000), Chaudhuri, Jalan, and Suryahadi (2002), Christiansen and Subbarao (2005). Pritchett, Suryahadi and Sumarto (2000) understand vulnerability to poverty as having experienced poverty during a certain period of time *t*, over a relevant span $t = -\infty, ..., -2, -1, 0$, or the probability of experiencing poverty in the near future. For Chaudhuri, Jalan and Suryahadi (2002), vulnerability to poverty is the probability to become or remain poor at time $t + 1$, given certain socio-economic characteristics at time *t*. In turn, Kühl's (2003) perception of vulnerability to poverty is the absence of households' resilience to shocks that can bring welfare below a threshold deemed acceptable by society. The latter two definitions are admittedly more forward looking. In any case, the most commonly adopted definition in the academia is the probability of an individual or household to fall into poverty. While knowing the probability to fall into poverty may be preferable to a mere static assessment of poverty, it is arguably desirable that a vulnerability measure provide a complete picture to discern between those facing the risk of falling into poverty, those with the ability to move out of poverty, and the ones with so weak fundamental circumstances that they are trapped into poverty.

Formally, and letting V_{it} be the probability of expected poverty of household *i* at time *t*, then one functional form to represent vulnerability, as is given in Chaudhuri, Jalan, and Suryahadi (2002), can be posited according to [1]:

$$[1] \qquad V_{it} = \int_{\beta_{t+1}} \left(\int^{z} dF\left(y_{i,t+1} \mid X_i, \beta_{t+1}, \alpha_i, \varepsilon_{i,t+1} \right) \right) dG\left(\beta_{t+1} \mid \beta_t \right)$$

where $dF(\cdot \mid \cdot)$ is the cumulative density of $y_{i,t+1}$ conditional on $\left(X_i, \beta_{t+1}, \alpha_i, \varepsilon_{i,t+1}\right)$ and $dG(\cdot \mid \cdot)$ is the cumulative density of β_{t+1} conditional on $\beta_{t.}$ Equation [1] can be written in a much more empirically implementable fashion as in [2]:

$$[2] \qquad V_{it} = \Pr\left(y_{i,t+1} = y\left(X_i, \beta_{t+1}, \alpha_i, \varepsilon_{i,t+1}\right) \le z \mid X_i, \beta_t, \alpha_i, \varepsilon_{it}\right)$$

where y is a welfare measure (either consumption or income), and z is the societal benchmark (the poverty line). X_i contains vectors of household characteristics, β_t is a vector of parameters, α_i an atemporal unobservable household effect, and ε_i the error term. Therefore, Equation [2] is the probability that a household will be poor in period $t + 1$ given her fundamental circumstances in period t. An extension of [2] to account for more than one period had been proposed by Pritchett, Suryahadi, and Sumarto (2000). For n periods, $\forall n \in \mathbb{N}^* = \{1\} \cup \mathbb{N}^+$, and $\forall z \in \left[z^-, z^+\right]$ with $z^- > 0$ and $z^+ \le \infty$, vulnerability (or, as denoted by the authors, the risk of household *i,* represented by $R(\cdot)$) is the probability that at least in one spell household's welfare will be below the societal benchmark. This can be expressed as follows:

$$[3] \qquad R_i(n,z) = 1 - \left\{\left[\left(1-\Pr\left(y_{i,t+1}\right) < z\right), .., \left(1-\Pr\left(y_{i,t+n-1}\right) < z\right), \left(1-\Pr\left(y_{i,t+n}\right) < z\right)\right]\right\}$$

where y_{t+i}, $i = 1, 2, ..., n-1, n,$ are measured in constant terms throughout the n periods. Equation [3] implies that the degree of vulnerability of household i is equal to 1 minus the probability of no episodes of poverty. Now, given a probability threshold (set exogenously), p, the authors determine a household to be vulnerable if the probability she faces is greater than p during n periods. Formally this can be represented in the following manner:

$$[4] \qquad V_{it}(z,n;p) = I\left[R_{it}(z,n) > p\right]$$

with $I[\cdot]$ being an indicator function equal to 1 if the condition in the right hand side of [4] is true, and zero otherwise. Results based on this approach and related ones can lead to very odd conclusions. As Ligon and Schechter (2003) put it, a mean preserving spread at the lower tail of the distribution, increasing therefore risk exposure for households in that section of the distribution, makes vulnerability, when construed as expected poverty, decline.[4] To remedy such a drawback the authors make use of an expected utility approach to defining vulnerability as low expected utility (VEU).

Defining U_i as a strictly increasing and weakly concave utility function, Ligon and Schechter (2003) posit the vulnerability of household *i* as follows:

$$[5] \qquad V_i = U_i\left(y^e\right) - EU_i\left(y_i\right)$$

where y^e (which is in fact a poverty line) is defined by the authors as a certainty equivalent income level above which a household would be considered non vulnerable. y^e is set in such a way that inequality among individuals is zero. That is, it is the expected income realization homogenized by some convenient equivalence scale. *E* stands for expectation. [5] can be rewritten as follows:

$$[6] \qquad V_i = \left[U_i\left(y^e\right) - U_i\left(Ey_i\right)\right] + \left[U_i\left(Ey_i\right) - EU_i\left(y_i\right)\right]$$

where the first term in the right hand side is a utility gap measure (i.e. poverty) and has all the properties of the FGT_α class of poverty measures. In turn, the second term represents the risk (shock) faced by household *i*. This latter term can be decomposed into idiosyncratic and covariate risks, as is captured by [7]:

$$[7] \qquad V_i = \underbrace{\left[U_i\left(y^e\right) - U\left(Ey_i\right)\right]}_{\text{Poverty}} + \underbrace{\left\{\left[EU_i\left(Ey_i \mid \overline{\mathrm{x}}\right) - EU_i\left(y_i\right)\right]\right\}}_{\text{Idyosincratic risk}} + \underbrace{\left\{U_i\left(Ey_i\right) - EU_i\left[E\left(y_i \mid \overline{\mathrm{x}}\right)\right]\right\}}_{\text{Covariate risk}}$$

[4] But as Chaudhuri (2003) sustains, if one is not interested in quantifying the contribution of risk to vulnerability, then there should not be much concern in that respect.

The authors further decompose to account for possible measurement error that would otherwise bias idiosyncratic risk to yield equation [8]:

$$V_i = \underbrace{\left[U_i\left(y^e\right) - U\left(Ey_i\right)\right]}_{\text{Poverty}} + \underbrace{\left\{EU_i\left[E\left(y_{it} \mid \bar{\mathrm{x}}_{\mathrm{t}}\right)\right] - EU_i\left[\mathrm{E}\left(y_{it} \mid \bar{\mathrm{x}}_{\mathrm{t}}, \mathrm{x}_{\mathrm{it}}\right)\right]\right\}}_{\text{Idyosincratic risk}} + \tag{8}$$
$$+ \underbrace{\left\{U_i\left(Ey_{it}\right) - EU_i\left[E\left(y_{it} \mid \bar{\mathrm{x}}_{\mathrm{t}}\right)\right]\right\}}_{\text{Covariate risk}} + \underbrace{\left\{EU_i\left[E\left(y_{it} \mid \bar{\mathrm{x}}_{\mathrm{t}}, \mathrm{x}_{\mathrm{it}}\right)\right] - EU_i\left(y_{it}\right)\right\}}_{\text{Measurement error and unexplained risk}}$$

After adequately choosing a functional form for U_i and a way to estimate the conditional expectations,[5] regressing each part of the Equation [8] on household and community characteristics leads to the correlates of vulnerability.

Christiansen and Subbarao (2005) criticize this approach to measuring vulnerability as expected utility on the grounds that it puts individual risk preferences at the forefront of vulnerability assessment. Admittedly, adverting to risk attitudes in vulnerability assessment may in a way be against the very principle of equality of opportunity. Adopting such an approach implies that risky individuals who are affected adversely by some shock inherent with their choices would be treated favorably when policies are designed to help those that are identified as vulnerable.

The third approach construes vulnerability as uninsured exposure to risk-VER (Glewwe and Hall (1998); Amin, Rai, and Topa (1999); Dercon and Krishnan (2000); Tesliuc and Lindert (2002). Under this framework vulnerability is defined as the inability to smooth consumption over time, given the presence of shocks. In such a case, no specific vulnerability measure is estimated. Many different models to measure vulnerability as uninsured exposure to risk can be found in the literature but the general form adopted is the following:

[5] As is standard in the literature, the functional form for U_i adopted by the authors is the constant relative risk aversion (CCRA), which can be represented by: $U_i\left(y\right) = y_i^{1-\rho} / 1-\rho$, where $\alpha > 0$ is a risk aversion parameter, which renders U_i more sensitive to both risk and inequality as α increases.

[9] $$\Delta \ln y_{it} = \beta X_i + \sum \gamma s_t + \sum \delta S_t + \sum \lambda D + \Delta \varepsilon_{it}$$

where $\Delta \ln y$ in the income growth rate, *s* and *S* are idiosyncratic and covariate shock respectively.[6] *D* is a set of administrative region dummies, and ε is an error term. Finally, β, γ, δ, and λ are parameters to be estimated. It is straightforward that the income generating process of a household not subject to shocks can be represented by [10]:

[10] $$\Delta \ln y_{it} = \beta X_i + \sum \lambda D + \Delta \varepsilon_{it}$$

So, the net effect of idiosyncratic and covariate shock, as is captured by γ and δ, is given by subtracting [10] from [9] (Tesliuc and Lindert, 2002).

The shortcoming with such an approach is that, when fluctuations in the lower tail of the distribution are low, which is often the case, poor households may not be considered vulnerable (Christiansen and Subbarao, 2005). By the same token, non-poor households with risky assets (e.g. investment in the stock market) may be counted as vulnerable due to the high probability of adverse shocks their wealth is subject to. Chaudhuri (2003) also sustains that vulnerability measures that focus on consumption smoothing ability ignore the asymmetry of shocks, while Ligon and Schechter (2002) contend that vulnerability to shocks does not depend directly on household income (or consumption) level under this approach. The methodology adopted for this research follows Chaudhuri, Jalan, and Suryahadi (2002) and and Günther and Harttgen (2009). The model is developed in Section 4 below.

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[6] Idiosyncratic shock may include shocks like the illness or death of the bread-winner, while covariate shocks are those typically those that affect the region, the community where the household resides, or the entire country e.g. droughts, terms of trade shocks.

3. Review of the empirical literature

This section highlights the main findings for idiosyncratic and covariate shocks focusing on developing countries. According to Fafchamps, Udry and Czukas (1998), possession of livestock (small or large) seems not to be a good insurance instrument against drought shocks in West Africa, while Ligon and Schechter (2003) determine that rural households in Bulgaria who possess livestock are less vulnerable.[7] Droughts also have consequences on the long term for growth in Ethiopia (Dercon, 2004b). In the same vein, Sarris and Karfakis (2006) found that in two rural areas of Tanzania, Kilimanjaro and Ruvuma, covariate shocks, particularly weather-induced fluctuations in production and terms of trade shocks, are the main drivers of increased vulnerability of farm households. Results from Tesliuc and Lindert (2002) for Guatemala also go along this line; the authors found that poor households are much more exposed to natural disasters and agricultural-related shocks, while the non-poor are found to be more vulnerable to economic shocks specific to the formal economy. The same applies to Malawi where subsistence farmers record high level of vulnerability due to droughts (Makoka and Kaplan, 2005). Hoddinott (2006) reports the depletion of assets of Zimbabwean households due to drought shocks, with serious long term consequences on the health of women and children (as measured by the body mass index – BMI).

Ramachandran, Kumar, and Viswanathan (2006) used the latter conceptualization (i.e. BMI) to center the vulnerability debate. They use BMI as a proxy of health status and posit that a low health status is tantamount to being exposed to high risk or vulnerability.[8] Health-related complications are the main reason for households to descend into poverty throughout Uttar Pradesh-India. The inexistence of health insurance schemes force villagers to incur debt to defray healthcare expenses. The debt is generally

[7] There seems to be a well established literature on the ineffectiveness of large livestock (cattle) to cope with drought shocks and smooth consumption, particularly when asset markets are not well integrated. However, small livestock (e.g. pigs and goats), because they are more liquid, are in general better instruments to smooth consumption in the face of this covariate shock.

[8] Being health a component of human capital, which is negatively correlated with vulnerability (or positively correlated with ex-post risk coping ability), the enjoyment of good health is assumed to have a positive impact on the standard of living prospects of an individual.

contracted from lenders whom they have to pay back at usurious interest rate.[9] Bali-Swain and Floro (2008) also found for India that self-helped microfinance group is a key factor in reducing vulnerability to poverty. Zaman (1999) reached the same conclusion with respect to the role of micro-credit in reducing vulnerability of women in Bengladesh.

As is generally established, education provides individuals with greater ex-post risk coping ability and the findings from different studies confirm such a view. In that sense, Chaudhuri, Jalan and Suryahadi (2002) determined for Indonesia a negative correlation between schooling and vulnerability. Interestingly, their results also disclose that vulnerability of rural households with no formal schooling stems from low mean of consumption prospects. Meanwhile, vulnerability for their urban counterparts is volatility determined, that is, with greater variance. Results for Brazil (Ribas and Machado, 2007) and Nigeria (Alayande and Alayande, 2004) go along the same line. On the contrary, Mckenzie (2003) showed that less educated heads (particularly in the rural area) exhibited higher degree of resilience to the 1982 debt crisis and the 1994 peso crisis in Mexico. The same thing is observed during the Mexican Tequila crisis by Cunningham and Maloney (2000).

As to the sex divide, Jha and Dang (2008) interestingly found for a group of selected countries in Central Asia (Azerbaijan, Kazakhstan, Kyrgyzstan, and Tajikistan) that female-headed households are much less vulnerable than their male counterparts. Christiaensen and Boisvert’s (2000) study in the Northern part of Mali also points to the same direction, in that female-headed households show higher expected average consumption along with a lower variance. This also applies to Brazil, despite the fact that women in this country are in general poorer than men (*supra)*.

In standard poverty analysis rural areas always fare worse than urban and the conclusion is not different in vulnerability assessment. In that spirit, Günther and Harttgen (2009) estimate vulnerability to be much higher in rural than in urban areas in

[9] For further evidence in India see Dilip and Duggal (2002).

Madagascar. The authors sustain that vulnerability in the rural area is explained mainly by a low expected mean consumption and idiosyncratic shock, while in the urban area high volatility in consumption and covariate shocks explain in great part vulnerability. Similar conclusions are reached for Indonesia (Chaudhuri, Jalan, and Suryahadi, 2002) and Kenya (Christiansen and Subbarao, 2005). Calvo (2008) in turn reveals fairly the same degree of idiosyncratic risk (as measured by consumption variability) between rural and urban households in Peru.[10] For Ecuador, Ligon (2008) stresses that it is the relatively low level of inequality among urban households (understood as being closer to average expenditure, but not necessarily enjoying less disparity among them) that results in lower vulnerability and risk of urban dwellers compared with the rest of the country.

In general, the common denominator in these researches is that rural households' vulnerability stems from low endowments, which are translated into low average living standards, while urban households' vulnerability is largely explained by high volatility in living standards.

4. Analytical framework

The different approaches to measuring vulnerability outlined in Equations [1] through [9] above make very high data requirements. In the absence of panel data, long time series of similar sampling units must be available to construct pseudo-panel and conduct vulnerability analysis based on those approaches. The restriction with which we are faced in terms of data calls for a model that permits vulnerability assessment using a single cross-section. We shall start from the benchmark model that allows vulnerability assessment using a single cross-section (Chaudhuri, Jalan, and Suryahadi (2002)) and then build on Günther and Harttgen (2009) to develop our framework for vulnerability to poverty. Chaudhuri, Jalan, and Suryahadi (2002) demonstrated that under certain conditions and very strong assumptions, the individual welfare standard distribution can

[10] It is worth mentioning that the database used by the author is not nationally representative since it only covers 272 household over five spells.

be estimated to arrive, after some manipulations, at a probability of expected poverty using the first and the second moment of the income distribution. For a one point observation on households across regions the income generating process (IGP) can be expressed as in [10]:

$$[10] \quad \ln y_i = \beta X_i + \varepsilon_i$$

If the IGP in [10] is correct, then Chaudhuri, Jalan, and Suryahadi (2002) demonstrated that using the estimates of the first and the second moment of income after applying a feasible generalized least squares (FGLS) estimation procedure,

$$[11] \quad \hat{E}\left(\ln y_i \mid X_i\right) = X_i \hat{\beta} \qquad \text{(estimated mean)}$$

$$[12] \quad \hat{V}ar\left(\ln y_i \mid X_i\right) = \hat{\sigma}^2_{\varepsilon,i} = X_i \hat{\theta} \quad \text{(estimated variance)}$$

and assuming log-Normality of income, then a vulnerability level $\hat{v}$ can be estimated for household *i* using the following expression:

$$[13] \quad \hat{v}_i = \Pr\left(\ln y_i < \ln z\right) = \Phi\left(\frac{\ln z - X_i \hat{\beta}}{\sqrt{X_i \hat{\theta}}}\right)$$

where $\Phi(\cdot)$ denotes the cumulative distribution function. Vulnerability in such a case would be explained by the idiosyncratic random component of [10], i.e ε_i.

The assumption of log-Normality is crucial for estimating vulnerability as is given in [13]. As is demonstrated in Singh and Maddala (1976) log-Normal distribution models better the poor in the distribution of income while Pareto does so for the very rich.[11] Accordingly, for a vulnerability study, albeit not just the poor may be vulnerable, the log-

[11] See Shorrocks and Wan (2008) and Zhang and Wan (2008) for recent contributions under this approach.

normal assumption of the distribution of income is more sensible and is therefore warranted.

With respect to the dataset, albeit a cross-section, the design of the data permits a hierarchical modeling; and the nesting made at more than one level makes our dataset share certain features of a short panel (see Cameron and Trivedi, 2005: 845-847). In the ECVH-2001 clustering is made on the primary sampling units (PSU) in the data. So, households are nested into clusters (in our case PSU, which are communal sections), which in turn are nested into strata (in our case administrative regions or *Départements*). This gives rise to observations nested at two levels, i.e a three-level hierarchy. This feature is common in developing countries' living standards measurement surveys-LSMS (see Chander, Grootaert, and Pyatt, 1980) and the ECVH-2001 can be classified as such.

Cognizant of the fact that shocks at various levels affect households differently, estimating a one-level model to assess vulnerability would most likely inflate the impact of idiosyncratic shocks on vulnerability. Most importantly, shocks taking place at lower levels are more likely to exert a much greater impact on individuals' vulnerability degree, implying therefore the concentric nature of shocks. Consequently, insufficient disaggregation would amplify the importance of the variance of the latest level component while taking no heed of shocks occurring at higher levels. This would evidently underestimate the importance of overall shocks on vulnerability. Therefore, unraveling shocks to analyze how at different levels they impact households' income may be crucial for policy design as this can better inform different levels of government (e.g. local, regional, federal level) on the most appropriate measures to be implemented to provide people with the mechanisms to cope with shocks and their associated risks. In that respect, to exploit the full structure of the dataset, we will use a three-level hierarchical model. The greatest benefit of the hierarchical specification in vulnerability analysis may lie in its ability to control for possible downward bias of localized shocks on estimated mean income.[12]

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[12] In light of what has been established in the inequality decomposition analysis, this could be the case for *Nord-Est* and *Nord-Ouest* administrative regions given their very low relative income.

Hierarchical models have been widely used in social sciences, particularly in educational (e.g. Burstein, Fischer, and Miller, 1986; Goldstein et al., 1993) and health research (eg. Goldman and Rodriguez, 2001). To our knowledge the first study to apply hierarchical modeling in the vulnerability to poverty literature is that of Günther and Harttgen (2009). These authors have recourse to a two-level hierarchical model using maximum likelihood (ML) technique in their estimation. In this paper, building on Chaudhuri, Jalan, and Suryahadi's (2002) idea to assess vulnerability from a single cross-section, we expand Günther and Harttgen (2009) and propose a three-level hierarchical variance-components model. Additionally, and contrary to the latter paper that resorts to ML, the estimation procedure adopted here is a (partially Bayesian) restricted maximum likelihood-REML.

ML is asymptotically more efficient than FGLS although the latter is more robust when the Normality assumption is untrue (Amemiya, 1977). Moreover, ML parameter estimates are consistent and asymptotically unbiased. The consistency and asymptotic unbiasedness of ML estimates are large sample properties though. So, ML estimates fail to comply with such properties when higher level units (i.e. observations in levels higher than level-1) are small (Raudenbush and Bryk, 2002:13-14). In small samples ML overestimates the model precision for not taking into account the uncertainty associated with the estimates of the random parameters arising from the hierarchical modeling, and this would lead to overly liberal hypothesis tests (Goldstein, 1995: 23) because of artificially short confidence interval (op. cit. p.53). And as the data structure shows in Table 1 in annex of chapter 1, except for *Département de l'Ouest*, all clusters nested within strata (level-3) have far lower than 100 observations and they are unbalanced. The basic structure of a three-level hierarchical model can be posited as follows:

$$[14] \quad \begin{cases} [14a] \quad \ln y_{ics} = \alpha_{0cs} + \beta X_{ics} + \varepsilon_{ics} & \rightarrow \quad \text{Household level-1} \\ [14b] \quad \alpha_{0cs} = \beta_{00s} + u_{0cs} & \rightarrow \quad \text{Cluster level-2} \\ [14c] \quad \beta_{00s} = \gamma_{000} + u_{00s} & \rightarrow \quad \text{Stratum level-3} \end{cases}$$

where the indices i, c, s in that case respectively denote households, clusters, and stratum are:

i	$= 1,2,\ldots, n_{cs}$	households within cluster c in stratum s,
c	$= 1, 2, \ldots, C_s$	clusters within stratum s,
s	$= 1, 2, \ldots, S$	strata.

Now working backwards by replacing [14c] into [14b] and the resultant into [14a], yields:

[15] $$\ln y_{ics} = \gamma_{000} + \beta X_{ics} + u_{0cs} + u_{00s} + \varepsilon_{ics}$$

which can be rewritten as:

[15a] $$\ln y_{ics} = \underbrace{\left(\gamma_{000} + \beta X_{ics}\right)}_{\text{Fixed part}} + \underbrace{\left(\varepsilon_{ics} + u_{0cs} + u_{00s}\right)}_{\text{Random part}}$$

Equation [15] is the reduced form three-level hierarchical (or variance-components) model unconditional at levels 2 and 3. The outcomes and parameters in [14] and [15] are defined as:

$\ln y_{ics}$ = log_income of household i in cluster (village or community) c and stratum s.

α_{0cs} = Mean log_income of cluster c in stratum s (in our case administrative region or *Département*).

ε_{ics} = Deviation of household ics's log_income from cluster mean (i.e. the common raw residual error term, but in that case of the fixed part of the estimation).

β_{00s} = Mean log_income in stratum s.

u_{0cs} = Deviation of cluster cs's mean log_income from the stratum mean (i.e. the random intercept at level-2).

γ_{000} = Grand mean, which is the typical β_0 in a one-level model.

u_{00s} = Deviation of stratum s's mean log_income from the grand mean (i.e. the random intercept at level-3).

For clarity, we will henceforth refer to the clusters as communes[13] and the strata as regions. Now, good estimates of the random part of the estimation should yield u_{0cs}, $u_{00s} > 0$ and $u_{0cs} > u_{00s}$, as far as their coefficients are concerned. As to the vulnerability assessment, the variance of u_{00s} $\hat{\sigma}^2_{u00s}$, which is the between regions variance (i.e. variability in β_{00s}, is construed as the covariate shock taking place at the region (stratum) or national level, while we will refer to the variance of u_{0cs} $\hat{\sigma}^2_{u0cs}$, which is the between communes within region variance (i.e. the variability in α_{0cs}), as a meso-level (intermediate) shock occurring at the commune (cluster) level. Finally, idiosyncratic shocks would be captured by the variance of ε_{ics} at the household level $\hat{\sigma}^2_{\varepsilon ics}$, which, in line with our nomenclature, is defined as between-households within-commune within-region variance (i.e. the variability in γ_{000}). So, the total residual is the sum of the raw residuals plus the random parameters: $\varepsilon_{ics} + u_{0cs} + u_{00s}$. This implies that, for our linear random intercepts model, the variance of $\ln y_{ics}$ would be the sum of the three variances (i.e. $\mathrm{Var}(\ln y_{ics}) = \hat{\sigma}^2_{\varepsilon,ics} + \hat{\sigma}^2_{u,0cs} + \hat{\sigma}^2_{u,00s} = \hat{\sigma}^2_{\varepsilon,ics+u,0cs+u,00s} = \hat{\sigma}^2_{total}$). It is also clear that for the previous condition to hold the random parameters u_{0cs} and u_{00s} should not only be mutually independent (i.e. $\mathrm{Cov}(u_{0cs}, u_{00s}) = 0$), but also respectively independent from the raw residuals ε_{ics} (i.e. $\mathrm{Cov}(u_{0cs}, \varepsilon_{ics}) = 0$, $\mathrm{Cov}(u_{00s}, \varepsilon_{ics}) = 0$).

The model sketched above is very trivial in the sense that no predictors are introduced at level-2 and level-3 and therefore no cross-level or variation effects are captured (i.e. how variables at one level affect the outcome or the behavior of other variables at another). We do so just to convey the crux of the model and focus on a linear random-intercept model [14]at this stage. Besides, introducing cross-variation makes the calculation of the variances at each level quickly cumbersome and not too malleable.[15]

[13] In fact they should be referred to as 'communal sections' to reflect the administrative division of the country because it is divided into 140 communes, but for short we use the word 'communes'.

[14] A model with more complex variance covariance structure will be explored in future research. For illustrative purpose, a simple three-level model with covariates at level 2 and 3 is presented in annex A.

[15] For instance, with just one covariate at level 3, it can be shown that now total variance would be given by: $Var\left(\ln y_{ics} \mid X_{ics}, u_{00s}, u_{0cs}\right) = \sigma^2_{\varepsilon,ics} + \sigma^2_{u,0cs} + 2Cov\left(u_{00s}, u_{0cs}\right) X_{ics} + \sigma^2_{u,00s} X^2_{ics}$, with $Cov\left(u_{00s}, u_{0cs}\right) > 0$. And more covariates at each level add exponentially to the complexity of the variances calculation.

Subsumed in the model specification is the allowance for free heteroskedastic disturbance terms (i.e. Cov(X_{kics}, ε_{ics}) $\neq 0$, for some X_k), which would capture unobserved characteristics and shocks at different levels that contribute to different households' income with otherwise similar observed traits. This is opposite to what is generally considered in hierarchical modeling with respect to the disturbance term at level 1, and what is usually assumed in poverty analysis (i.e. homoskedastic variance of the error term).[16] Chaudhuri (2003) contends that in economic term the heteroskedastic error is to be interpreted as the inter-temporal variance of logarithm of income. Not allowing for heteroskedastic errors is tantamount to imposing households with low mean income to never experience higher income variability than those with higher average income (supra). If it makes more sense to hypothesize that households with low mean income will tend to exhibit higher consumption variability than those with high income, the former may or may not have lower income variability than the latter. So, under this framework the first and the second moment of living standard need not be monotonically related across households. In that respect, the flexible heteroskedastic specification allows the marginal effects of the regressors on the ex-ante mean and variance of future consumption to differ in sign (Just and Pope, 1979). Risk coping ability or income (consumption) smoothing is easily captured by this flexibility (supra).

In light of the above discussion it is good to emphasize that REML estimates the random intercepts variance accounting for the loss of degrees of freedom from the estimation of the grand mean while ML does not (see Rabe-Hesketh and Skondral, 2005:16). In addition, when the data design is unbalanced (i.e. uneven distribution of

[16]Homoskedasticity in this case is often rationalized in terms of measurement error of some unobserved event that determines the income (or consumption) process and affect all households equally.

lower level observations nested into higher level units[17]) REML estimates are more trustworthy.[18]

Now, in light of our three-level hierarchical model Equations [11] and [12] for the estimated mean and variance should be accordingly amended to account for the random intercepts. Therefore, for the estimated mean and estimated variance, we now have:

[16] $$\hat{E}\left(\ln y_{ics} \mid X_{ics}, u_{0sc}, u_{00s}\right) = X_{ics}\hat{\beta} + \hat{u}_{0sc} + \hat{u}_{00s}$$

[17] $$\hat{V}ar\left(\ln y_{ics} \mid Z_{ics}\right) = \hat{\sigma}^2_{\varepsilon,ics} = \exp\left(Z_{ics}\kappa\right)$$

with $Z_{ics}\kappa$ being the skedasticity function, and the elements of *Z* and *X* overlap. Equation [17] is estimated accounting for the contribution of the variances of the random intercepts. Moreover, to avoid the possibility of negative variances, we model [17] as a non-linear function of *Z*.

As far as the assignment of values to the random intercepts in [16], we resort to an empirical Bayes procedure using a shrinkage (or reliability) factor that, inter alia, due to the unbalanced structure of the data, will downplay the influence of uninformative communes (i.e. communes within which the number of observations is very small) while bolstering the strength of large ones (Rabe-Hesketh and Skrondal, 2005:22). The empirical Bayes predictor of the level-2 random intercept is given by:

[18] $$\hat{u}^{EB}_{0cs} = \hat{\lambda}_{\alpha,0cs}\hat{u}^{REML}_{0cs}$$

[17] In the dataset used unequal number of households is allocated to each cluster (which will be our level-2), and unequal number of clusters are nested into the strata (which will be our level-3). This makes the design of the data unbalanced a both level-2 and level-3, which in our context can formally be posited as: $n_{cs} \neq n, \forall c$ and $m_s \neq m, \forall s,$ where n_{cs} is the number of observations in commune *c* and m_s the number of observations in region *s*.

[18] Yet another alternative is to apply a bootstrap procedure to REML, but as noted by Goldstein (1995: 60) bootstrapping the random parameters will give rise to unstable estimators for the residuals since each residual associated to a higher level uses the corresponding value of the cross-product matrix of the raw residuals.

where $\hat{\lambda}_{\alpha,0cs}$, which is the reliability of communes sample mean in assessing the difference among communes within the same region (i.e. a shrinkage factor), is given by:

$$[18a] \quad \hat{\lambda}_{\alpha,0cs} = \hat{\lambda}_{cs} = \frac{\hat{\sigma}^2_{\alpha,0cs}}{\left(\hat{\sigma}^2_{\alpha,0cs} + \frac{\hat{\sigma}^2_{\varepsilon,ics}}{n_{cs}}\right)}$$

n_{cs} is defined as before, i.e. the number of households per commune *c* in region *s*. Likewise, the level-3 empirical Bayes random intercept is given by the expression:

$$[19] \quad \hat{u}^{EB}_{00s} = \hat{\lambda}_{\beta,00s}\hat{u}^{REML}_{00s} = \frac{\hat{\sigma}^2_{\beta,00s}}{\hat{\sigma}^2_{\beta,00s} + \left[\sum\left(+\hat{\sigma}^2_{\alpha,0cs} + \frac{\hat{\sigma}^2_{\varepsilon,ics}}{n_{cs}}\right)^{-1}\right]^{-1}} \cdot \hat{u}^{REML}_{00s}$$

where $\hat{\lambda}_{\beta,00s}$, which is the reliability of region's sample mean as an estimate of its true mean is given by:

$$[19a] \quad \hat{\lambda}_{\beta,00s} = \hat{\lambda}_{s} = \frac{\hat{\sigma}^2_{\beta,00s}}{\hat{\sigma}^2_{\beta,00s} + \left[\sum\left(+\hat{\sigma}^2_{\alpha,0cs} + \frac{\hat{\sigma}^2_{\varepsilon,ics}}{n_{cs}}\right)^{-1}\right]^{-1}}$$

Moreover, since the hierarchical model estimated is unconditional at levels 2 and 3 the associated variances of the random intercepts are calculated directly and later scaled down by their corresponding shrinkage factor estimated above to arrive at the empirical Bayes version of their variance. We assume, as understated at the outset, that they respectively represent shocks at meso and covariate (macro) level affecting households' income.

Thus, the estimated vulnerability level of household *ics* should now consequently be:

$$[20] \qquad \hat{v}_{ics} = \Pr\left(\ln y_{ics} < \ln z\right) = \Phi\left(\frac{\ln z - X_{ics}\hat{\beta} - \hat{u}_{0cs}^{EB} - \hat{u}_{00s}^{EB}}{\sqrt{Z_{ics}\hat{\kappa}}}\right)$$

It is clear from [20] that under this approach not accounting for the random intercepts would inflate estimated mean vulnerability, and possibly the vulnerability rate. Under the previous functional forms, non-linear poverty dynamics and the possibility of poverty traps are implicitly built in (Chaudhuri, Jalan, and Suryahadi, 2002). Consequently, it is evident that structural or chronic poverty could be exacerbated or downplayed if the random coefficients were not accounted for.[19]

The specification used here does not include strata fixed effects and other information on community characteristics. This evidently has its drawbacks but has also two benefits. Firstly, it avoids possible downward bias of localized shocks on estimated mean income,[20] A very strong assumption made by this model to allow the estimation of vulnerability from a single cross-section is that cross-sectional variation is a good proxy of inter-temporal variation. Kamanou and Morduch (2002) proposed a non-parametric model based on Monte Carlo and bootstrapping to simulate future consumption and estimate vulnerability. Their method assumes that households consumption shocks are drawn from the same distribution. That is, the households face the same risks and shocks and have access to the same coping mechanism. Therefore, the method does not allow for heteroskedasticity (Chaudhuri, 2003).

[19] In this context, we define the structural or chronic poor as those that are poverty trapped. That is, household whose both observed and estimated income fall below the poverty line. Formally, the structural poor (or chronic or poverty trapped) comply the condition: $\ln y_{ics} < \ln z$ and $\hat{E}\left[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}\right] < \ln z$.

[20] In light of what has been established in the inequality decomposition analysis, this could be the case for *Nord-Est* and *Nord-Ouest* administrative regions given their very low relative income.

4.1 Results and discussion

We use the Haiti Living Conditions Survey (ECVH-2001) for the application of this research. Table A1 presents some descriptive statistics of the variables used in the regression analysis. The variables retained show very high significance and in general the expected signs. Lagrange multiplier test strongly supports the heteroskedasticity hypothesis of the level 1 variance $\left(\chi^2_{15} = n \cdot \bar{R}^2 = 1947.4,\ \Pr > \chi^2 = 0.0000\right)$.The regression results are presented below in Table 1. Discussion of the parameter coefficient is beyond the purview of the present research, but some results are worth pointing out.

As expected, schooling shows the usual positive and sheepskin effect on household income. The robustness of lower welfare level for households headed by female is confirmed while being a domestic migrant household means higher income level. The latter result is in line with standard economic theory on domestic migration.[21] Also, households from all institutional sectors generate, as we expected, higher income than the unemployed albeit, as will later be shown, the vulnerability status of the latter is not necessarily higher. Livestock possession (both small and large[22]) has a positive impact on household's income, with the latter being more important. The interaction of a bad weather shock and livestock reveals however that large livestock do not seem to provide protection against income drop under the presence of a shock (in that case meso-level) as small livestock do.[23] This highlights the higher productivity of large livestock than small ones, but also reveals the illiquidity of the former compared with the latter, and the possibility of the non-existence of an integrated livestock market.[24] Again, access to land and basic infrastructure provides greater income streams to households. Working in the non-farm sector appears to be more productive as it bestows greater level of

[21] It should however be kept in mind the imbalances that internal migration can cause when there is a giant city, in that case Port-au-Prince, that absorbs the bulk of migrants and jobs, infrastructure, and public services not being created and supplied at the same rate this urban population is increasing (for more discussion see Todaro and Smith, 2006: 335-346).

[22] In our definition small livestock include pigs, goats, sheep, and poultry, while large livestock makes reference to cattle (e.g. cows, buffalos). They are all measured in levels, i.e. the quantity possessed.

[23] For the idiosyncratic shock "death of a household member" we found the opposite signs on those predictors, but they were not statistically significant from zero therefore they were dropped.

[24] Similar results are found by Christiansen and Subbarao (2005) for Kenya.

income. Finally, remittances from abroad act as a real cushion against the idiosyncratic shock of “death of a household member”.

Table 1. Regression results of Restricted Maximum Likelihood. Depvar. Log of per adult equivalent income

Fixed	Coefficient	Std. Err.	z		
Reference: no formal schooling					
Primary	0.2840***	0.0315	9.02		
Secondary	0.5579***	0.0431	12.94		
University or higher	1.2234***	0.1225	9.99		
Sex (1 if head is female)	-0.0685**	0.0263	-2.61		
Age	-0.0183***	0.0041	-4.49		
Age squared	0.0002***	0.0000	5.57		
Dependency ratio	-0.1908***	0.0128	-14.93		
Migrant (1 if household head is internal migrant)	0.0572*	0.0343	1.67		
Reference: unemployed					
Private	0.3339***	0.0660	5.06		
NGO & Others	0.7004***	0.1042	6.72		
Public	0.1573	0.1129	1.39		
Family enterprise aid	0.3777**	0.1356	2.78		
Domestic worker	0.1671	0.4309	0.39		
Self-employed	0.2577***	0.0316	8.16		
Non farm	0.0766**	0.0369	2.08		
Small livestock	0.0095***	0.0018	5.38		
Large livestock	0.0489***	0.0079	6.21		
Shock_small_livestock	0.0158***	0.0048	3.29		
Shock_large_livestock	-0.0844***	0.0243	-3.48		
Agricultural land	0.0671*	0.0384	1.75		
Technology_land	0.3280***	0.1034	3.17		
Electricity	0.3075***	0.0480	6.40		
Landline	0.5764***	0.0839	6.87		
Piped_water	0.2556***	0.0515	4.96		
Sealed road	0.0889**	0.0424	2.09		
Death	0.4437***	0.0925	4.80		
Death_noremit	-0.6038***	0.0990	-6.10		
Intercept	7.7099***	0.1708	45.15		
Random-effect parameters	Estimate			*% variance explained*	*No. Obs.*
Region	0.1489*	0.0793		10.33	9
Commune	0.2865***	0.0250		19.89	496
Household	1.0054***	0.0175		69.78	7157

LR test for adequacy of the three-level model (H0: variance of Region is on the parameter boundary space), $\chi^2(01)$= 123.17 Prob > χ^2 = 0.0000.

LR test vs. linear regression $\chi^2(2)$ = 1343.82 Prob > χ^2 = 0.0000.

*, **, and ***, imply significance at 0.1, 0.05 and 0.01 per cent level, respectively.

Some prefatory points are in order before delving into the discussion of vulnerability profiles. Contrary to the specification in Equation [1] regarding the poverty line, we deem that an exogenous poverty line adjusted to take into consideration possible price changes in the next period should be used to reflect societal benchmark. In that respect, the poverty line is set as in Jadotte (2006). The idea of setting the poverty line exogenously and adjusting it for possible price variation is perfectly compatible with the assumption of stability of the β_S and μ_K (i.e. no structural change in the economy) stated above. Moreover, an arbitrary threshold of 0.5 (standard in the literature) at and above which a household is considered vulnerable is chosen. Finally, we define the poverty trapped (chronic or structural poor) as households whose both observed income and estimated mean income lie below the poverty line. Vulnerability for this group of households is fundamentally poverty driven,[25] albeit their low income streams may be a corollary of their risk aversion. Households who are risk averse will tend to engage in activities that can guarantee them an amount of income with certainty, however low that amount that amount may be. We call the transient poor those households with observed income below the poverty line but estimated income above the poverty line. These are households with potential upward mobility. On the other hand, households with weak fundamentals, i.e. with observed income above the poverty line but with estimated income below that threshold, face potential downward mobility. Finally, given a vulnerability threshold of 0.25, we call the risk driven vulnerable those households with estimated income above the poverty line but with vulnerability degree above 0.25.

Mean vulnerability is as expected very high in Haiti at about 74 per cent at the national level; this is equal to the poverty rate found in earlier research (Jadotte, 2007) and this figure can somehow corroborate the validity of the estimation procedure adopted above. Vulnerability rate however is above 83 per cent, which, paraphrasing Chaudhuri (2003), makes conspicuous the general underestimation of poverty incidence in standard

[25] Our definition of vulnerable poor is more stringent than Chaudhuri, Jalan, and Suryahadi's, who focus on the estimated mean.

static poverty assessments. This finding is not some sort of self-fulfilling prophecy though since that higher rate of vulnerability than the mean does not apply across all groups and regions in the decomposition analysis as predicted vulnerability will depend on the fundamentals that determine the income generating ability of a household.[26]

Table A2 in annex presents vulnerability estimates by residential area. As can be observed, the rural area fares worst than the MAPAP and the other urban. The former has a mean and incidence of vulnerability of 80 and 93 per cent, respectively. For the MAPaP and the semi-urban area these figures are 42 and 36 per cent, and 76 and 87 per cent, respectively.[27] Also, both the semi-urban and the rural areas have estimated mean income lower than the poverty line, while for the MAPaP that is higher. Among the poor, about 94 per cent of them are trapped into poverty[28] and among the non poor almost 54 per cent face the risk of downward mobility (i.e. to fall into poverty) while upward mobility is at only about 6 per cent. This means that 94 per cent of those already poor will remain poor. These average figures have very different patterns across residential areas, with the rural area showing the highest incidence and the MAPaP the lowest one (see Table A2).

For the different kind of shocks, as measured by the variance at different levels, in general idiosyncratic shocks at 0.95 are far more important than meso-level shocks at 0.17, which in turn are generally more prevalent than covariate shocks at 0.04. By area of residence, rural households show less idiosyncratic income volatility with 0.92 compared to the semi-urban with 0.96 and the MAPaP with 1.07. This lower idiosyncratic volatility in the rural area however cannot be interpreted as if households there were engaging in low risk low return activities. In fact, the vast majority of those employed in the rural area

[26] For instance, the mean vulnerability for university graduates household heads is about 12 per cent (similar to their poverty rate) while their vulnerability incidence is slightly above 4 per cent.

[27] The functional form and variables used here may be understating vulnerability in the MAPaP. Vulnerability to poverty has many facets and should not be confined to its pecuniary aspect. Exposure to political violence is another aspect of vulnerability, and yet people in the MAPaP are much more exposed to political violence than in any other area or region in Haiti. Were this factor to be taken into consideration the gap among the different residential areas would probably dwindle.

[28] This percentage is conditional on being previously poor. The percentage of poverty trapped among the entire population is easily derived by multiplying the poverty trapped among the poor and the poverty rate of the population. In this case, at national level the poverty trapped would be approximately equal to 69 per cent. The same procedure applies within subgroups.

are self-employed or farmers. Self-employment is inherently riskier than other types of employment in terms of stability of income streams, and agriculture is also associated with high income risk due to price fluctuations and the quasi inexistence of any scheme of subsidy or protection in Haiti to farmers. So, this low idiosyncratic variability of income may be indicative of rural households' income streams to be at near subsistence level, which does not leave room for too many fluctuations. This conjecture also applies to the semi-urban area since its productive structure is not very different from that of the rural area.

Meso-level shocks on household income at the semi-urban and rural area levels (0.18 and 0.17, respectively)[29] are more important than in the MAPaP with 0.14. Meso-level institutions or lack thereof may be explaining the greater impact of meso-level shocks on households' income in regions other than the MAPaP. Covariate shocks on the other hand are more important in the MAPaP with 0.1 than in the rural area with 3.40E-02, which in turn are more important than in the other urban area with 2.96E-02. So, covariate shocks are more important in the MAPaP while meso-level shocks are relatively more important in the semi-urban and the rural area. In terms of policy implications, this suggests that decentralizing policies at local government level can have a much greater effect on household's income than policies implemented at the national level, particularly for the semi-urban and rural area.

Decomposition of vulnerability into low-income prospects and high income volatility (measured by the idiosyncratic variance), using as representative household the one with the (estimated) median income and median idiosyncratic variance, also sets clear that households in the MAPaP are vulnerable due to high income volatility, while both semi-urban and rural households face vulnerability because of low income prospects.[30] More than 93 per cent of households in the MAPaP are vulnerable because of high income volatility (risk-induced vulnerability) while less than 13 per cent of them are affected by poverty driven vulnerability (low income prospects vulnerability). For the

[29] There is no statistical difference between the two.
[30] Despite the inherent risk associated with the economic activities and the institutional sector that households in these latter two regions specialize in (namely, agriculture and self-employment).

semi-urban and rural households high volatility vulnerable are, respectively, about 52 and 41 per cent, while poverty driven vulnerability in these two regions is by the order of 62 and 63 per cent, respectively. Those percentages give an idea of the quantity of households that are vulnerable because of both low income prospects and high income volatility and they are overwhelmingly rural with about 71 per cent, followed by semi-urban with approximately 26 per cent. So, only about 3 per cent of MAPaP households are vulnerable both because of low income prospects and high income volatility.

By administrative region (see Table A3), the results also confirm what we have found in early research (Jadotte, 2007). Vulnerability rate is the lowest in *Département de l'Ouest* with a 57.38 per cent incidence while *Nord-Est* is the most severely affected with a 98.51 per cent incidence, followed by *Nord-Ouest* with a 97.67 per cent incidence. Likewise, *Ouest* shows the highest idiosyncratic variance followed by *Nord* and *Nord-Est.* Meso-level shocks in turn are more important in *Artibonite* while *Nord-Est* exhibits not only the highest covariate variance but this is even more important than the meso-level variance in this region. In general, this again highlights the importance of decentralized policies in alleviating vulnerability in the different administrative regions of the country. Noteworthy, the impact of covariate shocks on household's income in *Nord-Est* brings to the fore the general dysfunctions in this region and suggests that action taken at national level could have a greater effect in alleviating vulnerability there.

As Table A2 brings to light the fact that vulnerability in terms of low income prospects is largely a rural phenomenon, a cursory look at Table A4 in annex also reveals that those with no formal education are the ones mostly vulnerable and with the highest poverty incidence. Almost 96 per cent of those with no schooling are vulnerable compared to a 4 and zero per cent for those with university degree. Besides, more than 98 per cent of those belonging to the group with no formal education are chronically poor or trapped into poverty, with expected mean income much lower than the poverty line. These results were in any case expected and confirm the well established hypothesis of the negative correlation between vulnerability and education (Schultz, 1975). Indeed educated people can adapt more easily to changing circumstances, therefore showing greater ex post coping capacity (Christiansen and Subbarao, 2005). As to the sources of vulnerability in this group, even though the vast majority of the poverty driven vulnerable stem from the no schooling group (more than 76 per cent), while basically none of those with university degree are observed in this category, the risk driven vulnerable are also composed in great part by the non educated with an almost 65 per cent. This makes clear that policies that aim at improving and stabilizing household's income streams in the medium and long term would better achieve its goal through accumulation of human capital, specifically education.[31] Another pattern is uncovered when looking at the vulnerability to poverty ratio across educational groups. Vulnerability is more concentrated (i.e. less widespread) at higher levels of schooling.[32]

As can be read from Table A5 in annex, households headed by females also exhibit both higher mean and vulnerability incidence than their male-headed counterparts. About 82 per cent of male-headed households are vulnerable while vulnerability affects 85 per cent of households headed by female. Likewise, female-headed households' vulnerability is induced by low income prospects and higher volatility in greater proportion than their male counterparts. So, despite the lower income prospects of households headed by female the instability of their income streams is also higher. The model breakdown predicts a clear feminization of vulnerability to poverty with a potential downside risk of about 56 per cent for female and about 53 per cent for male-headed households.

Vulnerability by age cohort (see Table A6 in annex) also asserts the inexistence of any welfare related life cycle effect. Contrary to being counterintuitive, these results stand much to reason in the case a developing country like the Republic of Haiti, where the level of education has traditionally been low but is now in a transition where the youth has greater stock of human capital and therefore show an ability to generate higher income than the elderly, even after controlling for remittances from abroad. Vulnerability

[31] It should be mentioned also that those who do not enjoy good health have (naturally) a greater vulnerability incidence.
[32] A vulnerability to poverty ratio less than 1 means higher concentration of vulnerability.

and poverty among the youngest cohorts (15-25 and 26-40) are the lowest and older cohorts, despite being more affected by low income prospects, tend to have higher income volatility. Younger cohorts also show greater resilience to poverty as well as better ability to insulate themselves from it.

Household heads who derive income principally from agriculture and its sidelines also show vey high incidence of vulnerability compared to non-farm worker. Vulnerability incidence for farm workers is almost 96 per cent compared to roughly 80 per cent for non-farm workers (see Table A7 in annex columns 1 and 2). Farmers also face greater downside risk with more than 81 per cent of the non-poor predicted to fall into poverty while roughly 3 per cent can manage to escape poverty. Vulnerability in the non-farm sector is driven principally by high volatility, while those in the farm sector face both low income prospects and high income volatility vulnerability. Undoubtedly, one factor that could help make a difference in farmers' plight is the access to farming production technology.

Domestic migration appears to make a difference in households' livelihood. Domestic migrants, although with a higher income volatility, fare much better all across the board than non-migrant ones (see Table A7 columns 3 and 4), a result that seems to be in line with basic economic theory. A breakdown by institutional sector of employment (including employment status) in Table A8 unveils the plight of the unemployed, the domestic workers, and the self-employed. These three groups are the most severely affected with vulnerability incidence well above 80 per cent. Together the unemployed and the self-employed make up 92 per cent of the population, with the self-employed that represent almost 59 per cent of it. Unexpectedly though, the unemployed and the self-employed are virtually similar in terms of vulnerability degree and status.[33] One factor that is probably concealed here is that self-employment in this country is composed to a great extent of workers in the informal sector and in many instances

[33] The explanation may lie in remittances coming from abroad. The unemployed are among the groups that receive more remittances. About 44 per cent of the unemployed are remittance recipient, standing second after those working in the public sector. Meanwhile, only 26 per cent of the self-employed are remittance recipients. Average remittances sent to the unemployed are 165 per cent higher than those received by the self-employed, and this can really make a difference in their vulnerability and poverty status.

informal economic activity is equivalent to disguised unemployment, at least in the Haitian context. NGO and private sector workers record the lowest incidence level with 35 and almost 51 per cent vulnerability rate respectively.

5. Concluding remarks and caveats

In this essay we use a hierarchical modeling approach to assessing vulnerability to poverty in the Republic of Haiti. No previous work has been found to systematically analyze vulnerability to poverty in this country. Results determine clearly that vulnerability to poverty is largely a rural phenomenon and that this is induced mainly by low income prospects, as opposed to the high income volatility that the urban area faces, specifically the Metropolitan Area of Port-au-Prince. The semi-urban area also shares the same characteristics and plight with the rural area in that respect. The modeling techniques adopted helps uncover the role that a different territorial organization and decentralization can play in alleviating vulnerability. Shocks at communal section level (or meso-level shock) have in general a much greater impact on household's income than covariate shock. Therefore, in terms of policy implications, decentralization and power delegation to give more leeway to local governments when designing policies to fight both poverty and vulnerability can be much more efficient.

Also, it is found that, as expected, vulnerability to poverty is negatively associated with education where estimated income increases almost exponentially with educational attainment. Decomposition of vulnerability also discloses that households with no formal schooling are vulnerable both because of low income prospects and high income volatility in greater proportion than those with formal schooling and such difference increases with the level of education. This highlights the importance of education as a key factor in enhancing and stabilizing household's income in the medium and long term. The results by decomposing vulnerability by age cohorts support the previous contention. Younger cohorts, who are endowed with greater human capital stock, are less vulnerable and show greater resilience to vulnerability. Decomposition by sex of household head indicates that female-headed households across the board fare less well than their male counterparts, and again the difference in educational input between the two sexes seems to be the key factor at play. In light of these results, ex-ante prevention measures are best designed around providing more schooling to individuals as a means to combat vulnerability to poverty in both its low income prospects and high volatility facets.

The validity of those points just highlighted hinges upon the plausibility of the model's assumptions. Particularly, we assumed that inter-temporal variability is well proxied by cross-sectional variability. However, given the instability that characterizes Haiti's contemporary macroeconomic environment, the distribution of risks may tend not to be similar over time. Therefore, the plausibility of the cross-sectional variably as a good proxy for inter-temporal variability may be unsteady and such results are therefore to be taken with a grain of salt. A cross-validation exercise would allow a further assessment of the model in its ability to predict vulnerability to poverty, however data unavailability precludes such an endeavor. Additionally, since urban and rural households face different prices particularly for food stuff, and given the preeminence of expenses on food in total household income, not correcting for differences in price across regions may be inflating vulnerability incidence in the rural area. In that respect, a multiple correspondence analysis (MCA) that would eliminate those price differences, as is proposed in Asselin (2002) for poverty analysis, would probably throw a better picture of the poverty and vulnerability issues across regions and residential areas.

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Annex

Three-level variance components model with covariates at level 2 and 3

$$\ln y_i = \beta X_i + \varepsilon_i$$

$$\begin{aligned} \ln y_{ics} &= \alpha_{0cs} + \beta_1 x_{ics} + \varepsilon_{ics} && \rightarrow && \text{Household level-1} \\ \alpha_{0cs} &= \beta_{00s} + \delta_{01} z_{1cs} + u_{0cs} && \rightarrow && \text{Cluster level-2} \\ \beta_{00s} &= \gamma_{000} + \lambda_{001} w_{1s} + u_{00s} && \rightarrow && \text{Stratum level-3} \end{aligned}$$

where z_{1cs} and w_{1s} are covariates at the 2nd and 3rd level respectively, and δ_{01} and λ_{001} their associated coefficients. And again, working backwards by replacing level 3 into level 2 and the resultant into level 1 yields:

$$\text{[A1]} \quad \ln y_{ics} = \underbrace{\left(\gamma_{000} + \beta_1 x_{ics} + \delta_{01} z_{1cs} + \lambda_{001} w_{1s}\right)}_{\text{Fixed part}} + \underbrace{\left(u_{0cs} + u_{00s} + \varepsilon_{ics}\right)}_{\text{Randompart}}$$

or in more general term and in order:

$$\ln y_{ics} = \underbrace{\left(\beta_0 + \beta_1 x_{1,ics} + \beta_2 x_{2,cs} + \beta_3 x_{3,s}\right)}_{\text{Fixed part}} + \underbrace{\left(\varepsilon_{ics} + u_{0cs} + u_{00s}\right)}_{\text{Randompart}}$$

Table A1. Summary Statistics for household characteristics

	MAPaP	Semi-Urban	Rural	National
Schooling (%)				
No formal	20.82	52.12	69.20	58.80
Primary	30.93	29.07	22.15	24.86
Secondary	42.14	17.70	8.30	15.03
University or Higher	6.11	1.11	0.35	1.31
Sex of household Head (%)				
Male	49.95	50.69	54.66	53.15
Female	50.05	49.31	45.34	46.85
Mean age of household head				
	39.46	46.43	47.01	45.86
Dependency				
	0.63	0.96	0.95	0.91
Migrant (%)				
Yes	71.87	25.80	12.86	23.86
No	28.13	74.20	87.14	76.14
Sector of employment of household head (%)				
Unemployed	48.95	37.75	36.01	38.19
Private sector	11.51	5.42	2.31	4.26
Public sector	3.20	2.74	0.89	1.61
NGO and others	2.10	1.18	1.06	1.23
Family enterprise helper	0.50	0.85	0.97	0.88
Domestic worker	0.30	0.07	0.04	0.08
Self-employed	33.43	51.99	58.72	53.75
Posseses agricultural land (%)				
Yes	0.80	56.89	75.38	61.02
No	99.20	43.11	24.62	38.98
Derives principal income from farming activities (%)				
Yes	0.50	30.76	44.33	35.31
No	99.50	69.24	55.67	64.69
Land technology (use of machineries and/or mechanical irrigation system %)				
Yes	12.50	5.28	1.95	2.63
No	88.50	94.72	98.05	97.37
Number of livestock				
Mean	0.24	4.79	6.14	5.03
Min	0.00	0.00	0.00	0.00
Max	36.00	160.00	112.00	160.00
Number of large cattle				
Mean	0.01	0.81	0.93	0.78
Min	0.00	0.00	0.00	0.00
Max	2.00	50.00	54.00	54.00
Bad weather shock that resulted in loss of small livestock (%)				
	0.00	2.33	2.78	2.67
	100.00	97.67	97.22	97.33
Bad weather shock that resulted in loss of cattle (%)				
	0.00	11.11	5.53	6.61
	100.00	89.89	94.47	93.39

Access to electricity (%)				
Yes	91.49	22.47	9.77	23.89
No	8.51	77.53	90.23	76.11
Landline telephone (%)				
Yes	13.81	3.27	0.78	3.13
No	86.19	96.73	99.22	96.87
Access to piped water (%)				
Yes	25.83	12.21	4.63	9.21
No	74.17	87.79	95.37	90.79
Sealed road (%)				
Yes	28.13	18.62	9.68	14.17
No	71.87	81.38	90.32	85.83
Death (if household has one death over the past three months, including the bread winner)				
Yes	5.31	13.59	13.44	12.34
No	94.69	86.41	86.56	87.66
Percentage of households with deceased member and no remittances from family abroad				
	4.00	11.37	11.69	10.55
	96.00	89.63	88.31	89.45

Author's own calculations based on the ECVH-2001, unweighted data.

Table A2.Vulnerability estimates by area of residence

	National	MAPaP	Other Urban	Rural
Population share	*100*	*13.96*	*21.39*	*64.65*
Poverty incidence	73.68	39.74	74.85	80.61
Estimated mean Log income $\hat{\mathrm{E}}\left(\ln y_{ics} \mid X_{ics}, u_{0sc}, u_{00s}\right)$	7.98	9.06	7.86	7.79
% Poverty trapped $\left(\ln y_{ics} < \ln z \text{ and } \hat{E}\left[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}\right] < \ln z\right)$	94.05	62.47	95.64	96.92
% Strong fundamentals $\left(\ln y_{ics} < \ln z \text{ and } \hat{E}\left[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}\right] > \ln z\right)$	5.95	37.53	4.36	3.08
% Weak fundamentals $\left(\ln y_{ics} > \ln z \text{ and } \hat{E}\left[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}\right] < \ln z\right)$	53.98	18.94	60.52	74.69
Mean vulnerability	73.58	41.50	76.28	79.61
Vulnerability incidence ($v_{ics} > 0.5$)	83.50	36.24	86.81	92.61
Vulnerability to poverty ratio	1.13	0.91	1.16	1.15
Idiosyncratic variance	0.95	1.07	0.96	0.92
Meso-level variance	0.17	0.14	0.18	0.17
Covariate variance	0.04	0.10	0.03	0.03

Table A3. Vulnerability estimates by administrative region

	Ouest	*Sud-Est*	*Nord*	*Nord-Est*	*Artibonite*	*Centre*	*Sud*	*Grande-Anse*	*Nord-Ouest*
Population share	*27.27*	*7.89*	*10.40*	*5.64*	*12.83*	*8.17*	*9.54*	*9.85*	*8.40*
Poverty incidence	54.61	75.40	78.63	91.83	79.08	79.15	82.14	79.15	86.02
Estimated mean Log income $\hat{\mathrm{E}}(\ln y_{ics} \mid X_{ics}, u_{0sc}, u_{00s})$	8.66	8.08	7.8	6.8	7.77	8.03	7.74	7.73	7.59
% Poverty trapped $\left(\ln y_{ics} < \ln z \text{ and } \hat{E}[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}] < \ln z\right)$	80.49	96.48	97.26	99.46	96.42	95.90	98.04	97.85	99.03
% Strong fundamentals $\left(\ln y_{ics} < \ln z \text{ and } \hat{E}[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}] > \ln z\right)$	19.51	3.52	2.74	0.54	3.58	4.10	1.96	2.15	0.97
% Weak fundamentals $\left(\ln y_{ics} > \ln z \text{ and } \hat{E}[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}] < \ln z\right)$	29.57	67.63	67.92	87.88	72.92	68.03	81.97	85.71	89.29
Mean vulnerability	54.04	73.95	79.71	94.36	79.08	76.20	81.62	82.22	84.89
Vulnerability incidence ($v_{ics} > 0.5$)	57.38	89.38	90.99	98.51	91.50	90.09	95.17	95.32	97.67
Vulnerability to poverty ratio	1.05	1.19	1.16	1.07	1.16	1.14	1.16	1.20	1.14
Idiosyncratic variance	1.02	0.89	0.99	0.98	0.92	0.86	0.91	0.91	0.92
Meso-level variance	0.18	0.08	0.11	0.15	0.31	0.06	0.17	0.15	0.22
Covariate variance	0.10	0.03	5.10E-04	0.18	0.01	0.01	4.00E-04	3.36E-03	2.65E-03

Table A4. Vulnerability estimates by educational attainment

	No Schooling	Primary	Secondary	University or Higher
Population share	*58.80*	*24.86*	*15.03*	*1.31*
Poverty incidence	83.39	68.80	49.16	11.70
Estimated mean Log income $\hat{\mathrm{E}}(\ln y_{ics} \mid X_{ics}, u_{0sc}, u_{00s})$	7.67	8.12	8.78	10.28
% Poverty trapped $\left(\ln y_{ics} < \ln z \text{ and } \hat{E}[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}] < \ln z\right)$	98.40	91.75	71.64	36.36
% Strong fundamentals $\left(\ln y_{ics} < \ln z \text{ and } \hat{E}[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}] > \ln z\right)$	1.60	8.25	28.36	63.64
% Weak fundamentals $\left(\ln y_{ics} > \ln z \text{ and } \hat{E}[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}] < \ln z\right)$	81.26	55.32	25.96	0.00
Mean vulnerability	82.50	70.20	49.65	12.17
Vulnerability incidence ($v_{ics} > 0.5$)	95.56	80.38	48.42	4.26
Vulnerability to poverty ratio	1.15	1.17	0.98	0.36
Idiosyncratic variance	0.94	0.94	0.99	1.05
Meso-level variance	0.17	0.16	0.16	0.21
Covariate variance	0.04	0.05	0.06	0.08

Table A5. Vulnerability estimates by sex of household head

	Male	Female
Population share	*53.15*	*46.85*
Poverty incidence	71.29	76.38
Estimated mean Log income $\hat{\mathrm{E}}(\ln y_{ics} \mid X_{ics}, u_{0sc}, u_{00s})$	8.06	7.89
% Poverty trapped $\left(\ln y_{ics} < \ln z \text{ and } \hat{E}[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}] < \ln z\right)$	93.69	94.42
% Strong fundamentals $\left(\ln y_{ics} < \ln z \text{ and } \hat{E}[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}] > \ln z\right)$	6.31	5.58
% Weak fundamentals $\left(\ln y_{ics} > \ln z \text{ and } \hat{E}[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}] < \ln z\right)$	52.84	55.56
Mean vulnerability	71.88	75.51
Vulnerability incidence ($v_{ics} > 0.5$)	81.97	85.24
Vulnerability to poverty ratio	1.15	1.12
Idiosyncratic variance	0.92	0.98
Meso-level variance	0.17	0.16
Covariate variance	0.04	0.05

Table A6. Vulnerability estimates by age cohorts

	15-25	26-40	41-54	55-65	< 65
Population share	*8.45*	*34.97*	*27.85*	*14.92*	*13.80*
Poverty incidence	72.40	72.23	76.42	73.97	72.47
Estimated mean Log income $\hat{\mathrm{E}}\left(\ln y_{ics} \mid X_{ics}, u_{0sc}, u_{00s}\right)$	8.00	8.03	7.94	7.92	8.00
% Poverty trapped $\left(\ln y_{ics} < \ln z \text{ and } \hat{E}\left[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}\right] < \ln z\right)$	89.27	93.75	94.29	95.32	95.53
% Strong fundamentals $\left(\ln y_{ics} < \ln z \text{ and } \hat{E}\left[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}\right] > \ln z\right)$	10.73	6.14	5.71	4.68	4.47
% Weak fundamentals $\left(\ln y_{ics} > \ln z \text{ and } \hat{E}\left[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}\right] < \ln z\right)$	47.90	48.35	51.06	65.11	66.18
Mean vulnerability	71.33	72.89	74.43	74.59	73.89
Vulnerability incidence ($v_{ics} > 0.5$)	77.85	81.14	84.09	87.45	87.45
Vulnerability to poverty ratio	1.08	1.12	1.10	1.18	1.21
Idiosyncratic variance	0.91	0.91	0.92	0.97	1.09
Meso-level variance	0.18	0.17	0.17	0.17	0.16
Covariate variance	0.05	0.05	0.04	0.04	0.04

Table A7. Vulnerability estimates by sector of economic activity and internal migration status

	Farm	Non-farm	Migrant	Non-migrant
Population share	*35.31*	*64.69*	*23.86*	*76.14*
Poverty incidence	83.06	68.55	60.07	77.94
Estimated mean Log income $\hat{\mathrm{E}}\left(\ln y_{ics} \mid X_{ics}, u_{0sc}, u_{00s}\right)$	7.77	8.10	8.37	7.86
% Poverty trapped $\left(\ln y_{ics} < \ln z \text{ and } \hat{E}\left[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}\right] < \ln z\right)$	97.43	91.81	86.74	95.81
% Strong fundamentals $\left(\ln y_{ics} < \ln z \text{ and } \hat{E}\left[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}\right] > \ln z\right)$	2.57	8.19	13.26	4.19
% Weak fundamentals $\left(\ln y_{ics} > \ln z \text{ and } \hat{E}\left[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}\right] < \ln z\right)$	81.26	55.32	25.96	0.00
Mean vulnerability	82.50	70.20	61.54	77.35
Vulnerability incidence ($v_{ics} > 0.5$)	95.56	80.38	66.04	88.97
Vulnerability to poverty ratio	1.14	1.13	1.10	1.14
Idiosyncratic variance	0.82	1.02	1.01	0.93
Meso-level variance	0.19	0.16	0.15	0.17
Covariate variance	0.03	0.05	0.06	0.04

Table A8. Vulnerability estimates by institutional sector

	Unemployed	Private sector	NGO & Others	Public sector	Family enterprise helper	Domestic worker	Self-employed
Population share	*38.19*	*4.26*	*1.61*	*1.23*	*0.88*	*0.08*	*53.75*
Poverty incidence	75.89	49.18	33.91	56.82	82.54	83.33	75.46
Estimated mean Log income $\hat{\mathrm{E}}\left(\ln y_{ics} \mid X_{ics}, u_{0sc}, u_{00s}\right)$	7.82	8.8	9.35	8.37	8.01	8.18	7.98
% Poverty trapped $\left(\ln y_{ics} < \ln z \text{ and } \hat{E}\left[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}\right] < \ln z\right)$	94.94	81.33	58.97	90.00	88.46	100.00	94.70
% Strong fundamentals $\left(\ln y_{ics} < \ln z \text{ and } \hat{E}\left[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}\right] > \ln z\right)$	5.06	18.67	41.03	10.00	11.54	0.00	5.30
% Weak fundamentals $\left(\ln y_{ics} > \ln z \text{ and } \hat{E}\left[\ln y_{ics} \mid X_{ics}, u_{0cs}, u_{00s}\right] < \ln z\right)$	55.24	23.23	19.74	42.11	36.36	0.00	61.65
Mean vulnerability	76.20	50.89	35.09	62.95	73.83	69.26	74.92
Vulnerability incidence ($v_{ics} > 0.5$)	85.36	51.80	33.04	69.32	79.37	83.33	86.59
Vulnerability to poverty ratio	1.12	1.05	0.97	1.22	0.96	1.00	1.15
Idiosyncratic variance	1.07	0.80	0.90	1.06	0.70	1.19	0.87
Meso-level variance	0.16	0.15	0.14	0.16	0.22	0.03	0.18
Covariate variance	0.05	0.06	0.05	0.04	0.04	0.07	0.04

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