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Vulnerability and resilience to food and nutrition insecurity: A review of the literature towards a unified framework

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Abstract. Current approaches to measuring food and nutrition security (FNS) mainly consider past access to food, while assessing vulnerability and resilience to food insecurity requires a dynamic setting and sound predictive models, conditional to the entire set of food-related multiple-scale shocks and stresses as well as households' characteristics. The aim of this work is twofold: i) to review the state of the relevant literature on the conceptualization and the empirical measurement of vulnerability and resilience to food insecurity; ii) to frame the main coordinates of a possible unifying framework aiming at improving ex-ante targeting of policy interventions and resilience-enhancing programs. Our argument is that clarifying the relationships existing between vulnerability and resilience provides a better understanding and a more comprehensive picture of food insecurity that includes higher-order conditional moments and non-linearities. Furthermore, adopting the proposed unified framework, one can derive FNS measures that are: scalable and aggregable into higher-level dimensions (scale axiom); inherently dynamic (time axiom); conditioned to various factors (access axiom); applicable to various measures of food and nutrition as dependent variables (outcomes axiom). Unfortunately, the proposed unified framework shows some limitations. First, estimating conditional moments is highly data-demanding, requiring high-quality and high-frequency micro-level panel data for all the relevant FNS dimensions, not mentioning the difficulty of measuring risks/shocks and their associated probabilities using short panel data. Hence, there is a general issue of applicability of the proposed approach to typically data-scarce environments such as developing contexts. Second, there is an inherent tradeoff between the proposed approach in-sample precision and out-of-sample predictive performance. This is key to implement effective early warning systems and foster resilience-building programs.

Keywords: vulnerability, resilience, food security, nutrition.
JEL Codes: I32, O12, Q12.

1. INTRODUCTION

In an ideal world, agrifood systems would be resilient, inclusive and sustainable, producing sufficient, safe and nutritious food for all, and generating livelihoods that guarantee people's economic access to that food (FAO *et*

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al., 2021). In stark reality, agrifood systems fail to keep about 10 percent of the world's population free from hunger (FAO *et al.*, 2022) and agrifood supply chains and livelihoods are increasingly exposed to multiple stressors: droughts, floods, armed conflict, food price hikes, and long-term stresses, including climate change and environmental degradation (FAO, 2021).

This challenges the received wisdom on food and nutrition security (FNS) measurement, analysis and policymaking. In fact, current approaches to measuring FNS mainly consider past access to food, failing to provide policymakers with forward-looking information and a good understanding of the wider risks that households face (Capaldo *et al.*, 2010). Conversely, assessing vulnerability and resilience to food insecurity requires a dynamic setting and sound predictive models, conditional to the entire set of food-related multiple-scale shocks and stresses as well as households' characteristics (Upton *et al.*, 2016; Ibok *et al.*, 2019).

The aim of this work is twofold: i) to review the state of the relevant literature on the conceptualization and the empirical measurement of vulnerability and resilience to food insecurity; ii) to frame the main coordinates of a possible unifying framework between vulnerability and resilience – and the related concept of poverty trap – aiming at improving ex-ante targeting of policy interventions and resilience-enhancing programs.

Our argument is that clarifying the relationships existing between vulnerability, poverty traps and resilience allows getting a better understanding and more comprehensive picture of FNS, that is able to satisfy all the relevant axioms to FNS measurement as highlighted by Upton *et al.* (2016). Specifically, one can derive FNS measures that are: scalable and aggregable into higher-level dimensions (scale axiom); inherently dynamic (time axiom); conditioned to various factors (access axiom); applicable to various measures of "active and healthy life" as dependent variables (outcomes axiom). Unfortunately, as reported more in detail in this review, the proposed unified framework requires some pre-conditions: first, it is computationally intensive, thus it requires high-quality and high-frequency micro-level panel data for all the relevant dimensions to FNS, not to mention the difficulty of measuring risks/shocks (and their self-reported proxies) and their associated probabilities using short panel data. Hence, there is a general issue of how to combine this unifying measurement approach with the typical data-scarce environments that are common in developing contexts. Second, although there are specific situations where these measures could be effectively implemented, there is an inherent tradeoff between their in-sample precision and out-of-sample predictive performance.[1] This is key if the aim is implementing effective early warning systems and resilience-building programs in the most fragile agri-food systems. In this respect a promising route could be improving the interoperability of traditional survey data with non-conventional data sources (big data, crowdsourced data, citizen-generated information, etc.), although many technical and institutional challenges remain (Carletto, 2021).

The rest of the work is organized as follows: Sections 2 and 3 review the relevant literature on vulnerability and resilience, respectively, by addressing conceptualization, measurement issues and empirical evidence; Section 4 depicts the state of the art of the analysis of both vulnerability and resilience as applied to food insecurity; Section 5 describes a possible unifying framework; Section 6 concludes and provides some key recommendations for future research.

2. Vulnerability

2.1. The emergence of vulnerability concept

The concept of vulnerability to poverty aims at answering a simple but crucial question: what is the likelihood that an individual or a household will be poor in the next future? Unfortunately, providing an answer to this question is not an easy task. First, we need to agree on a common social norm in terms of welfare (e.g., consumption), and on a common benchmark (e.g., the poverty line). Second, although vulnerability is strictly linked to poverty, the two concepts are different. Current poverty is an ex-post status referring to the static situation in which the individual lives at the very same moment it is observed and measured, whereas vulnerability means predicting future poverty (Chaudhuri *et al.*, 2002). Indeed, the concept of vulnerability, which is an inherently forward-looking construct of the expected outcomes (Alwang *et al.*, 2001), is neither directly observable nor linked to the actual manifestation of shocks (Imai *et al.*, 2011; Magrini *et al.*, 2018). As a result, poor households ex-post are not necessarily so ex-ante and correlates of vulnerability may differ from those of poverty. This distinction plays a crucial role when designing policies: targeting only the currently poor could exclude a significant group of individuals that risk experiencing a welfare loss, i.e., the vulnerable groups. Along with pro-poor policies (policies directly targeting poor people), we also need to carry out pre-

[1] This is the traditional issue of "overfitting" in data driven approaches. In fact, these approaches tend to learn too well the training data to the extent that it negatively impacts the out-of-sample predictive performance (Hastie *et al.*, 2009).

ventative strategies directly targeting the vulnerable ones (Montalbano, 2011). Third, vulnerability is a complex subject not identified by a single, easily measurable construct. All individuals, households, communities and even nations face multiple risks, natural or man-made, idiosyncratic and covariate, from different sources. Hence, as emphasized by Hoddinott and Quisumbing (2003), there is a wide consensus on what vulnerability means in general terms but, when we attempt to analyze it in detail, the concept tends to blur and become subsumed in the haze of the multifarious situations of vulnerability, giving only context-specific interpretations. As a result, a proliferation of methodologies, terminology and approaches to vulnerability analysis have been applied to a broad range of topics (e.g., food security, natural disasters, conflict prevention, economic fragility, etc.). Scholars, research centers, multilateral and bilateral organizations and agencies have developed their own definitions and methods to analyze vulnerability. It is notable that not all these definitions include the same key elements and they also use slightly different terminology. Hence, practitioners from different disciplines use different meanings and concepts of vulnerability (Alwang *et al.*, 2001).

2.2. Vulnerability approaches

Different approaches to vulnerability also lead to different methods of estimation. Along with a set of more holistic approaches, such as the traditional sustainable livelihood approach (Chambers and Conway, 1992), that looks at the capacity of communities to sustainably maintain their own livelihoods,[2] there are analyses of vulnerability that typically express welfare in terms of consumption and focus on consumption variability as a proxy for economic instability. Among the latter, the earliest efforts attempt to measure vulnerability simply as the negative impact on household's consumption from exposure to a set of observed risks (the so-called *Vulnerability Exposure to Risk*, see Glewwe and Hall, 1998; Dercon and Krishnan, 2000). Later efforts measure vulnerability as loss in expected welfare in an uncertain environment (Chaudhuri, 2001 and 2003; Ligon and Schechter, 2003; Calvo and Dercon, 2013). Various reviews of the literature (Hoddinott and Quisumbing, 2003; Povel, 2015; Gallardo, 2018) consistently grouped these most recent monetary methods into the following broad categories: *Vulnerability to Expected Poverty* (Chaudhuri, 2001 and 2003; Chaudhuri *et al.*, 2002; Pritchett *et al.*, 2000); *Vulnerability as low Expected Utility* (Ligon and Schechter, 2003 and 2004); *Vulnerability as the Threat of Future Poverty* (Calvo and Dercon, 2003 and 2013). Each of these vulnerability approaches presents its own strengths and weaknesses. Here below, we present the main characteristics of each of them.

Vulnerability as Expected Poverty

The Vulnerability as Expected Poverty (VEP) approach is the most controversial but commonly applied method (Christiaensen and Boisvert, 2000; Pritchett *et al.*, 2000; Chaudhuri, 2001 and 2003; Chaudhuri *et al.*, 2002; Christiaensen and Subbarao, 2005). It assesses vulnerability simply as the expected value of the standard Foster-Greer-Thorbecke (FGT) class of decomposable poverty measures (Foster *et al.*, 1984) as follows:

$$VEP_{h,t} = F(z)\int_0^z \left(max\left\{0, \frac{z-c_{h,t+1}}{z}\right\}\right)^\alpha \frac{f(c_{h,t+1})}{F(z)} dc_{h,t+1} \qquad (1)$$

where $c_{h,t+1}$ is household's consumption in the near future; z is the standard poverty line; $\alpha \geq 0$ is the "poverty aversion" parameter; $F(\cdot)$ and $f(\cdot)$ indicate, respectively, the cumulative distribution and the density function. Eq. 1 measures the probability of households falling below the poverty line, multiplied by a conditional probability-weighted function of the shortfall below it (Christiaensen and Boisvert, 2000). The parameter α in Eq. 1 sets the degree of sensitivity of the vulnerability measure to the distance from the poverty line.[3] When $\alpha=0$, VEP measure reduces to the probability that the household will experience poverty, i.e $V=F(z)$.[4] The distribution f is taken as given and reflects both the households' exposure to shocks (idiosyncratic or covariant) and its ability to cope with them.

Empirically, on the assumption that consumption is log-normally distributed, setting the consumption poverty threshold, z, and a threshold probability value above

[2] The sustainable livelihood approach looks at vulnerability as a general concept capturing two main aspects: (i) insecurity in the wellbeing of individuals, households, and communities because of changes in their external environment, and (ii) lack of ability and means to cope because of an internal defenselessness (Serrat, 2017).

[3] This is the key parameter in FGT class of poverty measures (Foster *et al.*, 1984). The case $\alpha=0$ yields a distribution of individual poverty levels in which each poor person counts 1; the ratio of the total poor count to the entire population is simply the poverty headcount ratio. The case $\alpha=1$ uses the normalized gap as a poor person's poverty level, thereby differentiating among the poor according to their relative distance from the poverty line. The case $\alpha=2$ squares the normalized gap and thus weights the gaps by the gaps. As α tends to infinity, the condition of the poorest poor is all that matters.

[4] Most works (Christiaensen and Boisvert, 2000; Pritchett *et al.*, 2000; Chaudhuri and Datt, 2001; Chaudhuri *et al.*, 2002) rely on this choice indeed, but there are also some VEP applications which look at the depth of the poverty ($\alpha=1$) and at the spread of its distribution ($\alpha=2$).

an accepted norm at which a household is considered vulnerable (e.g., Pr > 0.5), it is possible to estimate vulnerability to expected poverty as the probability at time t of a household with characteristics X_h to fall below the poverty line in the near future using the estimated expected mean ($\widehat{c_h}$) and variance ($\widehat{\sigma_h^2}$) of its log consumption, as follows:

$$VEP_{h,t}=Pr(\log c_{h,t}<\log z \mid X_{h,t})=\Phi\left(\frac{\log z-\log \widehat{c_{h,t}}}{\sqrt{\widehat{\sigma_{h,t}^2}}}\right) \tag{2}$$

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

The main assumption of the VEP approach is that environment is stationary and the variance of the residuals in cross-sectional consumption regressions (i.e. the unexplained part of household consumption) is not simply a measurement error and is not equal across households. It rather captures the impact of both idiosyncratic and covariate shocks on consumption, which can be explained by a set of observable household characteristics. The main advantage of the VEP method follows directly from this assumption: vulnerability can be assessed using only a single round of cross-sectional data. This is also the source of its main limitation: cross-sectional variability proxies inter-temporal variance in consumption (hence, it does not consider the impact of household-invariant but time-variant shocks). Furthermore, the distribution of shocks to consumption is independent normal, which contrasts with the empirical evidence on the relatively higher risk aversion of the poor. Finally, the standard version of the approach is not able to differentiate between the impact of idiosyncratic shocks and the impact of covariate shocks.

Acknowledging the latter caveat, Sarris and Karfakis (2006) and Gunther and Harttgen (2009) present different methods to disentangle VEP measures assessing separately the impact of covariate shocks at the community level and the idiosyncratic ones at the household level. More specifically, Gunther and Harttgen (2009) acknowledge the hierarchical structure of community and household variables by applying a multilevel analysis. Hence, they decompose the unexplained variance in households' consumption into a lower-level (i.e., household) and a higher-level (i.e., community) component. On top of that, the VEP method essentially lacks a solid theoretical background and displays a somewhat perverse feature relating to the measure of the welfare consequences of risks: it implies a reduction of vulnerability by increasing the variability of consumption around the poverty line, which is in sharp contrast to the poor being risk averse (Hoddinott and Quisumbing, 2003).[5]

Vulnerability as Low Expected Utility

The Vulnerability as Low Expected Utility (VEU) model tries to counteract the weak theoretical background of the VEP class of measures by proposing a risk-sensitive measure of vulnerability based on expected utility (Ligon and Schechter, 2003 and 2004). According to this approach, the vulnerability of household h is measured as the difference between the utility derived from some level of certainty-equivalent consumption, z_{ce}, above which the household would not be considered vulnerable (i.e., something analogous to a poverty line in the standard ex-post poverty analysis), and the expected utility of future consumption as follows:

$$VEU_h=U_h(z_{ce})-EU_h(c_{h,t}) \tag{3}$$

where U_h is a weakly concave, strictly increasing function. In addition, the VEU method enables the decomposition of vulnerability into two distinct components: vulnerability to poverty, that is, low expected consumption, and vulnerability to risk, that is, high volatility of consumption, as follows:

$$VEU_h=[U_h(z_{ce})-U_h(Ec_{h,t})]+[U_h(Ec_{h,t})-EU_h(c_{h,t})] \tag{4}$$

where the first bracketed term (i.e. the difference in utility at z_{ce} compared to the utility of households' expected consumption) is a measure of vulnerability to poverty and involves no random variables, while the second term, according to the ordinal measures of risk proposed by Rothschild and Stiglitz (1970), measures vulnerability to risk.[6] Moreover, the risk component can be further

[5] To clarify this point, Hoddinott and Quisumbing (2003) provide the following example. Consider two scenarios. In the first scenario, a risk-averse household is certain that its expected consumption in period t+1 will be just below the poverty line. In this case, its computed VEP is accurately equal to 1. In the second scenario, the mean expected consumption remains unchanged, but the household faces a small amount of variability in consumption such that there is a 50% chance of having consumption just above or just below the poverty line. As poor households are risk averse, this second scenario implies a decrease in welfare (as the household would prefer a certain level of consumption over a fluctuating expected consumption). However, the VEP measure – which registers the fluctuation as a 50% chance of escaping poverty – will decrease from 1 to 0.5. This leads to a perverse policy implication, as using VEP a policymaker aiming to reduce vulnerability should actually introduce new sources of risk.

[6] This is the natural counterpart, measured in utility units, of the risk premium the household would be willing to pay in order to eliminate the risk. It can be measured, starting from a (weakly) concave utility

decomposed into covariate and idiosyncratic components. Let $EU_h(x_{h,t})$ be the expected value of consumption conditional on a vector of covariant variables $x_{h,t}$, then we can rewrite the VEU measure as follows:

$$VEU_h=[U_h(z_{ce})-U_h(Ec_{h,t})]+[U_h(Ec_{h,t})-EU_h(c_{h,t}|x_{h,t})]+ [EU_h(c_{h,t}|x_{h,t})-EU_h(c_{h,t})] \quad (5)$$

where the first bracketed component is again vulnerability to poverty, but the second and third components break down vulnerability to risk into two sub-components: vulnerability to covariate risks and vulnerability to idiosyncratic risks. To avoid confusion between the measurement error and idiosyncratic risk, Ligon and Schechter (2003) further decompose their measure of idiosyncratic risk into the risk that can be attributed to a set of distinct, observed, time-varying characteristics. The advantage of this measure is that it can be conveniently adapted to assess vulnerability related to a set of possible sources of risks. For instance, Ligon (2006) and Magrini *et al.* (2018) propose similar measures of vulnerability able to decompose country-level and "meso" risks, respectively, from aggregate ones, by further decomposing the risk component of the VEU measure as follows:

$$\begin{aligned}(VEU_h=&[U_h(z_{ce})-U_h(Ec_{h,t})] + && \text{[poverty]}\\ &[U_h(Ec_{h,t})-EU_h(c_{h,t}|\mu_k)] + && \text{[meso risk]}\\ &[EU_h(c_{h,t})|\mu_k)-EU_h(c_{h,t}|\mu_k,\mu_t)] + && \text{[aggregate risk]} \quad (6)\\ &[EU_h(c_{h,t}|\mu_k,\mu_t)-EU_h(c_{h,t}|\mu_k,\mu_t,x_{h,})] + && \text{[idiosyncratic risk]}\\ &[EU_h(c_{h,t}|\mu_k,\mu_t,x_{h,t})-EU_h(c_{h,t})] && \text{[unexplained risk/ measurement error]}\end{aligned}$$

where μ_k represents a risk term which varies across k clusters of units characterized by heterogeneity in their exposure to global risks, whereas μ_t is an aggregate risk term, common to all units, which may vary over dates and (aggregate) states of nature.

The VEU measure of vulnerability raises three main and interrelated concerns too: first, the obvious circumstance that the choice of a specific form of the utility function directly affects the magnitude of the phenomenon; second, the difficulty to transform VEU measures of vulnerability, expressed in utility units, into actual economic policy targets (Hoddinott and Quisumbing, 2003); third, the fact that it does not satisfy the so-called "focus axiom" ensuring that the vulnerability measure should be exclusively sensitive to negative future outcomes whereas positive future outcomes should be not reflected in the measure (Calvo and Dercon, 2013).[7]

Vulnerability as the Threat of Poverty

The Vulnerability as the Threat of Poverty (VTP) class of vulnerability measures tries to overcome some of the weaknesses of both VEP and VEU methods (Calvo and Dercon, 2003; Calvo 2008; Calvo and Dercon, 2013; Povel, 2015). Starting from the assumption that people suffer and are wary of the future if their knowledge of what it holds is uncertain, VTP measures associate vulnerability to the extent that poverty cannot be safely ruled out as any of the possible future scenarios (Calvo, 2008). Specifically, the VTP approach measures vulnerability as a probability-weighted average of future indices of deprivation in different states of the world as follows (Calvo and Dercon, 2013):[8]

$$VTP_{h,t}=1-E[x^{\alpha}_{h,t}] \quad (7)$$

where $x_{h,t}$ is an index of deprivation, i.e., represents the rate of coverage of basic needs, which is derived for each state of the world as $x_{h,t}=\frac{\tilde{y}_{h,t}}{z}$, where $\tilde{y}_{h,t}(y_{h,t}); z)$ is censored at z; $y_{h,t}$ is the consumption level (after all consumption smoothing efforts have been deployed); z is the standard poverty line; and $0<\alpha<1$ represents risk sensitivity[9] as when α increases to 1, the household approaches risk-neutrality.

This measurement combines households' exposure to risks with deprivation and shortfalls in welfare indicators. In this respect, the VTP measure represents an improvement of both VEP and VEU. VTP is risk-sensitive and satisfies the so-called focus axiom, according to which the burden of future poverty will not be compensated by possible future positive outcomes. This means that uncertainty/risk not related to poverty in any state of the world does not enter this measure of vulnerability. Furthermore, VTP is not affected by outcome changes above the poverty line. However, two main caveats apply to the use of the VTP measure as well. Firstly, for those facing no uncertainty with known $x_i=x^*<1$ for all i, then $VTP>0$. In other words, being poor is the dominant threat in terms of vulnerability. However, there is no agreement on this in the literature that traditionally

function, as the difference between the utility of consuming the expected consumption with certainty and the expected utility from consuming c_h.

[7] Calvo and Dercon (2003) clarify this providing the following example. Consider a poor that buys each week a state lottery ticket. She spends a very small sum of money, but 'you never know', and there is a 0.001 percent chance of winning the top prize of $10,000. If the focus axiom was not applied, it would be sufficient to increase the top prize to make her less vulnerable. Again, a kind of perverse policy implication can be derived by applying this vulnerability measure.

[8] A multidimensional extension of VTP has been proposed by Calvo (2008) using data from Peru (1998–2002).

[9] The parameter α is not only an index of risk aversion but it is also comparable to the from the Foster-Greer-Thorbecke measure of poverty in so far it measures the severity of possible future poverty.

distinguishes the determinants of poverty from those of vulnerability. Secondly, the empirical strategy of VTP implies the use of lengthy panel data to retrieve predictions of the rate of coverage of basic needs and the distribution of random idiosyncratic shocks looming for households in the future in various states of the world (Calvo, 2008). This is not only subject to misspecifications and measurement errors but assumes a time-invariant discrete uniform distribution of shocks, which is indeed an assumption as strong as proxying inter-temporal variance with cross-sectional variability, as made by the VEP method.[10] Although VTP surely constitutes a generous effort of building an axiomatic approach to vulnerability,[11] it lacks robust empirical analyses capable of providing a clear added value to its common alternative measures.

Recent attempts to adapt vulnerability to the field of food insecurity have been implemented by Bogale (2012), Sileshi *et al.* (2019) and Ibok *et al.* (2019). In this framework, we can distinguish two main strands of vulnerability analysis: (i) tentative adaptations to food insecurity of households' probability to fall below the food poverty line, mainly in cross-sectional settings (Capaldo *et al.*, 2010; Sileshi *et al.*, 2019; Gattone at al., 2022); (ii) the elaboration of multidimensional indices to measure household's food insecurity and contextual vulnerability as a latent variable (Ibok *et al.*, 2019). Although multidimensional indices cannot capture the forward-looking aspect of vulnerability, they can be used to develop vulnerability maps of FNS, i.e., hotspots reflecting locations with high exposure and sensitivity but low adaptive capacity (de Sherbinin, 2014).

To measure contextual vulnerability, Ibok *et al.*, (2019) compute a vulnerability to food insecurity index (VFII) that includes three main components, that are the exposure index (E_h), the sensitivity index (S_h) and the adaptive capacity index (AC_h), as follows:

$$VFII_h=\sum AC_h-(\sum E_h+\sum S_h). \tag{8}$$

Exposure refers to food-related shocks that affect the household access to safe and nutritious food and is widely defined as the degree to which a system faces risk, shock or hazard. The sensitivity component measures the previous or cumulative experience of food insecurity, such as stunting, child mortality, and hunger within the household. Adaptive capacity is the ability of households to successfully adjust to the effect of food-related shocks through coping mechanisms (Engle, 2011).

2.3. Empirical evidence

By using a set of Monte Carlo experiments, Ligon and Schechter (2004) explore the performance of the above vulnerability measures and estimators. They find that estimating vulnerability from cross-sectional data (such as in the case of VEP) leads to estimates which are even inferior to simple static poverty measures, essentially because they lack control for risk sensitivity. Conversely, panel data with a longitudinal dimension as short as two years for a few thousand units (roughly the size of the typical World Bank's Living Standard Measurement Survey datasets) allow estimating vulnerability almost close to its limiting values. However, this holds for short stationary panel. Elbers and Gunning (2003) offer an elegant solution to the non-stationarity issue in long panels, using a structural dynamic model to derive simulation-based estimates of vulnerability that incorporate both risks and predictable variation in consumption over time. Thanks to their dynamic exercise they demonstrate that much of the effect of risk on the mean of the ergodic distribution of consumption reflects the ex-ante effect, that is a household can be chronically poor because its response to risk lowers average consumption permanently. This implies that mean consumption is not independent of risk as implicitly assumed by the standard vulnerability measures. As a result, by ignoring any behavioral response to risk (e.g., consumption smoothing) all the above vulnerability measures underestimate the overall effect of risk in measuring vulnerability. Elbers and Gunning (2003) argue that, using simple regression-based methods, one could accurately identify vulnerable households provided that asset data are included as regressors to proxy such ex-ante behavioral responses to risk.[12]

A key feature is thus the risk sensitivity of the applied vulnerability measures. Ligon and Schechter (2003) and Magrini *et al.* (2018) looking at differ-

[10] Think, for instance, at the unprecedented change in the frequency and severity of shocks brought about by climate change.

[11] Apart from the aforementioned "focus axiom", Calvo and Dercon (2007) propose an additional set of axioms to be satisfied by their vulnerability measure: "symmetry over states" (i.e., the only relevant difference between two states of the world i and j should be the difference in their outcomes and probabilities; "continuity and differentiability" of the vulnerability function; "scale invariance" (i.e., vulnerability measure should not depend on the unit of the measure of outcomes); "normalization" to impose boundaries for reasons of comparability; "probability-dependent effect" of outcomes (i.e., vulnerability should be sensitive to the likelihood of that particular state of the world); "probability transfer" (i.e., if y_j is greater than or at least equal to y_i, then vulnerability cannot increase as a result of a probability transfer from state j to state i); "risk sensitivity" (i.e., greater risk should increase vulnerability); "constant relative risk sensitivity" (i.e., risk sensitivity remains constant if all state specific outcomes increase proportionally).

[12] This is important empirical evidence supporting section 5 arguments.

ent samples of Bulgarian and Vietnamese households, respectively, consistently demonstrate that the average welfare under risk is lower than it would be in a certainty-equivalent scenario and that this was not necessarily linked to the actual manifestation of shocks. Klasen and Waibel (2013) and Povel (2015) reach a similar conclusion, showing that rural households in Vietnam (and to a lesser extent in Thailand thanks to higher opportunities for diversification) were vulnerable because more exposed to downside risks amid local reforms.

Capaldo *et al.* (2010) were the first to estimate vulnerability to food insecurity. They computed it as the normal probability that the individual minimum dietary energy requirement under light physical activity is lower than the expected individual dietary energy consumption (measured in kilocalories). They apply the standard VEP measure (Eq. 1) by simply substituting a measure of household's expected dietary energy consumption for consumption expenditure. In a similar effort, Gattone *et al.* (2022) use as outcome variable both raw and standardized scores of the Food Insecurity Experience Scale (FIES).[13] These authors also exploit machine learning algorithms to select the most predictive combinations of household characteristics thus getting pure stochastic residuals.

Thanks to the availability of panel data, Letta *et al.* (2022) adapt VTP to food insecurity following the extension proposed by Povel (2015). Using information about the occurrence of the shocks and estimating the related loss of income, Letta *et al.* (2022) predict the deprivation indexes associated to all the different states of the world that are given by the different combinations of shocks the household might face, by applying the following ex-ante measure of household vulnerability:

$$VTP_h=\sum_{j=1}^{N_i}\left(p_{hj} \times x_{hj}^{\alpha}\right) \tag{9}$$

where $N_i=\sum_{k=0}^{K_i}\frac{K_i!}{(K_i-k)!k!}$ represents the number of possible states of the world; p_{hj} represents the probability of the state of the world j to occur (it ranges between zero and one); x_{hj}^{α} denotes the deprivation index, namely the loss of income in the state of the world j, measured as $x_{hj}=\sum_{q=1}^{Q_{hj}}\frac{s_{hjq}}{y_h}$, where s_{hjq} represents the severity of the shock q and y_h is the household income. To distinguish between households vulnerable to income losses but not experiencing food insecurity, Letta *et al.* (2022) also use FIES data.

[13] These scores have been implemented under FAO's project Voices of the Hungry and represent a subjective survey-based experiential measure of FNS aimed at overcoming the lack of multidimensionality of the traditional measures of food insecurity vulnerability, like food consumption or per capita food intake (Cafiero *et al.*, 2018).

3. RESILIENCE

3.1. The emergence of resilience concept

The concept of resilience has been used in fields as different as engineering, psychology, ecology and epidemiology since long ago. Mechanical and civil engineers were probably the first to use this concept back in nineteenth century as the capacity of different materials to absorb loads (McAslan, 2010). Psychologists began referring to resilience in the 1970s (Rutter, 2012) as the overcoming of a stress or adversity, or a relatively good outcome despite risk experiences. In the same years, ecologists developed different notions of resilience such as the amount of disturbance an ecosystem can absorb before shifting into an alternative state (Holling, 1973) or the speed of return to a pre-existing equilibrium following a perturbation or shock (Pimm, 1984). More recently, the literature on socio-ecological systems (Gunderson *et al.*, 1997; Levin *et al.*, 1998; Reyers *et al.*, 2018) emphasized resilience as "the ability of people, communities, societies, and cultures to live and develop with change, with ever-changing environments" (Folke, 2016: 3). In this literature, the concept of resilience has been used to inform analysis of change in economic and ecological systems, suggesting the advantages of analyzing change in the system as a Markov process, with the transition probabilities between states offering a natural measure of the resilience of the system in such states (Perrings, 1998 and 2006).[14]

The emergence of the resilience concept in economics and FNS analysis is relatively recent and basically related to the emphasis put by humanitarian and development agencies on the need to integrate humanitarian (i.e., short-run, emergency) interventions and development (i.e., long-run) intervention. The Hyogo Framework for Action, that represents the most important result of the World Conference on Disaster Reduction (UNISDR, 2005), and more recently the UN World Humanitarian Summit (UN, 2016), identified the so-called human-development-peace nexus as a key principle informing the operations of multilateral as well as bilateral cooperation agencies[15]. As emphasized by the multi-agency

[14] At the best of our knowledge, Perrings (1998) was the first modelling the economy-environment systems dynamics as a Markov process and defining resilience as transition probabilities between different future states. This intuition is also crucial for modelling resilience in a conditional moment-based framework (Barrett and Constas, 2014; see below the section on resilience as a normative condition approach). In section 5, we will argue this is the most appropriate theoretical framework to model resilience to food and nutrition insecurity.

[15] For example, the UN and the World Bank set up the "New way of working" to deliver the nexus approach. The OECD has made the nexus a priority and members of OECD's Development Assistance Committee

Resilience Measurement Technical Working Group, "In a world where conventional approaches to dealing with humanitarian aid and development assistance have been questioned, resilience has captured the attention of many audiences because it provides a new perspective on how to effectively plan for and analyze the effects of shocks and stressors that threaten the wellbeing of vulnerable populations" (Constas *et al.*, 2014a: 4). According to this literature, the idea of resilience holds appeal as (i) it provides a unified response to shocks resulting from catastrophic events and crises, and to the stressors associated with the ongoing exposure to risks that threaten wellbeing, and (ii) it carries the meaning of a generalized ability to respond to an array of threats that have become more difficult to predict (Constas *et al.*, 2014b).

However, there is considerable debate and ambiguity over the nature of resilience (e.g., a state, a capacity, or a condition), its location (e.g., in individuals, communities, or institutions) and the time frame of resilience-relevant responses (e.g., short- or long-term). As a result, typologies of resilience and "shopping lists" of resilience properties abound (Watts, 2016: 263). Even focusing just on the literature specifically dealing with resilience in developing contexts, that is the capacity of an individual or a household to avoid long-lasting negative consequences in terms of wellbeing, we can find different conceptualizations and definitions that highlight theoretical heterogeneity and lead to different measurement methods. In the next section we will focus exclusively of these approaches.

3.2 Resilience approaches

In a recent scoping review, Barrett *et al.* (2021) identify at least three different definitions relevant for the so-called "development resilience" that drive different approaches, namely resilience as *capacity*, resilience as a *return to equilibrium*, and resilience as a *normative condition*[16].

Resilience as capacity

The most common conceptual approach treats resilience as an ex-ante capacity that limits the adverse effects of risk exposure (i.e., stressors) and/or the near- or longer-term consequences of shocks on individual/household wellbeing. This approach, proposed by FAO within the so-called Resilience Indicators for Measurement and Analysis (RIMA) framework (FAO, 2016), sees resilience as the "capacity that ensures stressors and shocks do not have long-lasting adverse development consequences" (Constas *et al.*, 2014a: 4). Being unobservable, resilience is estimated as a latent variable through the so-called resilience capacity index (RCI), that captures the effects of some combination of observable and unobservable attributes – of an individual, household, community, or more aggregate unit – in a two-step procedure (Alinovi *et al.*, 2008, 2010; d'Errico *et al.*, 2018). In the first step, factor analysis is used to identify the attributes – called "pillars" in the RIMA framework: Access to Basic Services (ABS), Assets (AST), Social Safety Nets (SSN) and Adaptive Capacity (AC) – that contribute to household resilience, starting from observed variables.[17] The factors considered as contributors to each pillar were only those able to explain at least 95% of the variance. In the second step, a Multiple Indicators Multiple Causes model (Bollen *et al.*, 2010) was used, specifying the relationships between the unobservable latent variable (RCI), a set of outcome indicators (FNS indicators,) and the attributes (pillars):

$$RCI=[\beta_1,\beta_2,\ldots,\beta_n]\cdot[ABS,AST,SSN,AC]+\varepsilon_1 \quad (10)$$

and

$$[W_1,W_2,\ldots,W_n]=[\alpha_1,\alpha_2,\ldots,\alpha_n]\cdot RCI\cdot[\varepsilon_2,\varepsilon_3,\ldots,\varepsilon_n] \quad (11)$$

where ε_i are error terms.

The approach proposed by TANGO International (Smith and Frankenberger, 2018) is similar to FAO's in so far it operationalizes resilience as a latent capacity through reduction of a multidimensional set of variables to a resilience index by means of data reduction methods. This approach estimates a RCI based on factor analysis on a wide range of indicators to estimate three latent variables: absorptive, adaptive, and transformative capacities. Absorptive capacities seek to mitigate the impact of shocks and include the availability of assets

are showing some signs of changing how they fund programs. It also has strong relevance to the UN Development System Reform. All UN agencies and many donors and multi-mandated NGOs are supportive of this approach.

[16] A fourth definition is resilience as transformation as emphasized in the literature on socio-ecological systems (Walker *et al.*, 2004; Reyers *et al.*, 2018) that views transformability as a key feature of resilience reflecting the capacity to create a fundamentally new system when ecological, economic, or social structures make the existing system untenable.

[17] Informed by previous research on resilience, vulnerability and food security, RIMA also proposes the set of variables comprised in each pillar, such as: (i) schools, health centers, markets, water, electric grid for access to basic services (ABS); (ii) productive (e.g. land, livestock, agricultural equipment,, etc.) or non-productive (e.g. house, other real estate properties) assets (AST); (iii) transfers (e.g. cash or in-kind), formal and informal insurance mechanisms, etc. for social safety nets (SSN); and (iv) access to institutions and networks, diversification of livelihood sources, etc. for adaptive capacity (AC).

and savings. Adaptive capacities spread risk by diversifying livelihoods and relying on social safety nets. Transformative capacities seek to change the underlying dynamics, for example, by improving governance, improving access to markets or empowering women.

As self-evident from the above formalization, the resilience capacity is treated as an explanatory variable of the final outcome (e.g., FNS). Specifically, RCI is a variable that helps explaining variations in the wellbeing outcome, that is a proxy that mediates the negative impact of shocks and stressors rather than an outcome per se. This is important because the many interventions that aim to build resilience necessitate a conceptualization and measure of resilience that can serve as an outcome, in order to evaluate whether resilience is indeed increasing among beneficiaries of a given intervention.

Resilience as return to equilibrium

A second approach conceptualizes resilience as return to equilibrium, that is it assesses whether households have the capacity to recover, sometimes how fast is the speed of recovery, from a shock (Pimm, 1984; Constas *et al.* 2014a; Knippenberg *et al.*, 2019). It describes a condition, i.e. ex-post recovery from shocks, of a wellbeing variable of interest rather than attempting to explicitly model the various capacities that result in rapid recovery. Following Knippenberger *et al.* (2019) notation, let's denote two states $Z^s_{i,t} \in \{0,1\}$ reflecting whether household *i* is experiencing the adverse effects of a shock *s* that hit the household in period *t*-1, with $Z^s_{i,t}=1$ if it has not recovered and $Z^s_{i,t}=0$ if it has fully recovered. Given these two states, i.e. experiencing and not experiencing shock *s*, the probability of passing from state *k* to state *j* is a Markov process: $Pr(Z^s_{i,t-1}=j|Z^s_{i,t}=k)=p_{i,kj}$ where $k,j \in \{0,1\}$. To estimate shock persistence, an auto-regressive linear probability model with one lag can be used:

$$Z^s_{i,t} = \gamma_0 + \gamma^s_1 Z^s_{i,t-1} + \gamma^s_t \left(Z^s_{i,t-1}\delta_t\right) + \delta_t + \mu^s_i + \delta\varepsilon_{i,t} \quad (12)$$

where γ^s_1 conditions the perceived shock, *s*, on previously experiencing shocks, γ^s_t allows this persistence to vary by periods, δ_t is a time fixed effect and μ^s_i is a household fixed effect.

This conceptualization of resilience is closer to the concept of resilience as used in ecology[18] and engineering that emphasize the capacity to bounce back to the initial state. Differently from the RCI methods, it describes a condition, i.e. ex-post recovery from shocks, of a wellbeing variable of interest rather than attempting to explicitly model the various capacities that eventually result in recovery from the shocks. However, this may not be enough for the use of resilience in development practice, where scholars and practitioners usually deal with undesirable initial states such as poverty or food insecurity. In other words, "development resilience"[19] should not be seen just as a mere return to a pre-shock equilibrium without considering whether that ex-ante state was desirable or not.

Resilience as a normative condition

The fact that development resilience needs to address a normatively undesirable initial state is explicitly considered by the third approach that conceptualizes resilience as a construct measured with reference to a normative wellbeing anchoring (Barrett and Constas, 2014), that is a condition that reflects one's capacity to avoid adverse wellbeing states, rather than a capacity itself. Cissé and Barrett (2018) translate this conceptualization into an econometric strategy that estimates resilience as a conditional probability of satisfying some normative standard of living, such as a minimum herd size, per capita expenditures level, food consumption score, etc. This is done in a three-step procedure, as follows:

a) first, the household-specific conditional mean of a wellbeing indicator (e.g., the food consumption score, FCS) is estimated through a multivariate regression:

$$W_{i,t} = \sum_k \alpha_k W^k_{i,t-1} + \gamma \boldsymbol{X}_{i,t} + \theta \boldsymbol{S}_{i,t} + \varepsilon_{i,t} \quad (13)$$

where, the superscript *k* indicates the polynomial order to allow for possible non-linear dynamics under a first-order Markov process assumption as in the poverty trap literature (Carter and Barrett, 2006; Barrett and Carter, 2013); $\boldsymbol{X}$ is a vector of time-varying household and community characteristics; $\boldsymbol{S}$ is a vector of shocks or stressors (e.g., climate, price, health, etc.), and $\varepsilon_{i,t}$ are residuals;

[18] In the sense of Pimm (1984) that captures the speed of return to equilibrium following perturbation, but not in Holling's (1973) formulation that conceptualizes resilience as the size of a disturbance needed to dislodge a system from its stability domain.

[19] As clearly stated by Barrett and Constas (2014: 2): "Unlike the term's use in engineering or ecology, where resilience refers to properties of objects or systems and is neither good nor bad, it is merely descriptive, development resilience has clear normative foundations: More is better. Conceptualized in this way, development resilience concerns the stochastic dynamics of human wellbeing and is a worthy goal for development agencies because it varies inversely with the likelihood of being and remaining poor."

b) then, using the residuals of Eq. 13, and regressing them on the same or potentially other regressors, the household-specific conditional variance of the same wellbeing indicator is estimated:

$$\varepsilon_{i,t}^2 = \sum_k \beta_k W_{i,t-1}^k + \delta \boldsymbol{X}_{i,t} + \vartheta \boldsymbol{S}_{i,t} + u_{i,t} \quad (14)$$

where, $u_{i,t}$ are residuals;

c) finally, using the above conditional moment estimates and assuming a two-parameter distribution (e.g., beta, exponential, gamma, normal, etc.) the conditional probability of satisfying some normative wellbeing standard $\underline{W}$ (e.g., at least a non-poor FCS level) in any n time period in the future, called "resilience score" by Cissé and Barrett (2018), is estimated:

$$\rho_{i,n} \equiv Pr(W_{i,n-1}, X_{i,n}, S_{i,n}) = F(\underline{W}, \widehat{W}_{i,n}(W_{i,n-1}, X_{i,n}, S_{i,n}), \hat{\varepsilon}_{i,n}^2(W_{i,n-1}, X_{i,n}, S_{i,n})) \quad (15)$$

where, $F(\cdot)$ is the assumed two-parameter inverse cumulative density function.

Studies that conceptualize resilience as a normative condition treat the resulting measure as an outcome. This has made it popular among academics doing impact evaluation (Phadera *et al.*, 2019; Premand and Stoeffler, 2020) or trying to describe the resilience of distinct populations as the estimated measure provides clear insights on resilience change, makes possible comparisons across sub-populations, and can be aggregated from individual or household level into community, region, or national resilience indicators.[20]

3.3. Empirical evidence

Being a relatively novel field of study, it is no wonder that most of the empirical literature on resilience has developed over the last years, with half of them published from 2016 on (Barrett *et al.*, 2021). Focusing on studies providing quantitative estimates of household resilience to food insecurity[21], the previous section highlights how different definitions drive devising different estimation methods. Some of them, such as the ones based on the conceptualization of resilience as capacity, use ad hoc empirical estimation strategies that are not well-rooted in theory. More generally, almost all studies do not employ credible causal identification methods.

In terms of the contents of the empirical applications, generally most studies aim at illustrating the properties of the resilience measure and findings about the population under study. However, the differences in the approaches – e.g., resilience as capacity vs. resilience as a normative condition – imply different objectives and results of the empirical applications. For instance, the studies adopting the resilience as capacity approaches generally show that households with higher resilience capacity tend to have less child malnutrition and better food security status (Ansah *et al.*, 2019). Furthermore, some studies adopting the resilience as capacity approach (d'Errico *et al.*, 2018; Smith and Frankenberger, 2018; Brück *et al.*, 2019) estimate the RCI and then test its association with the period-on-period change in the FNS indicators. They generally found that a higher RCI is associated with lower near-term impacts of shocks and higher levels of future food consumption. Specifically, d'Errico *et al.* (2018) found that household RCI is positively related to future household FNS outcomes, decreasing the probability of suffering a future FNS loss and facilitating the recovery after the occurrence of a loss in Tanzania and Uganda,[22] whereas d'Errico *et al.* (2019) identify critical heterogeneous resilience thresholds to temperature anomalies in Tanzania based on RCI. Smith and Frankenberger (2018) found suggestive evidence that social and human capital, exposure to information, asset holdings, livelihood diversity, safety nets, access to markets and services, women's empowerment, governance, and psycho-social capabilities such as aspirations and confidence to adapt, all contribute to reduce the negative impact of flooding on household food security in Bangladesh.

Vice versa, the studies adopting the conditional moment-based approach are more interested in assessing the impact of specific conditions of population groups or interventions to targeted populations on their own resilience level. Being highly data-demanding, this approach has only recently been applied to a few countries in Sub-Saharan Africa (Cissé and Barrett, 2018; Knippenberg *et al.*, 2019; Phadera *et al.*, 2019; Premand and Stoeffler, 2020; Abay *et al.*, 2022), proving to be able to predict the individual's probability of not meeting a normatively-established threshold in the future, being decomposable among groups, and suitable to inform targeting adjusting between exclusion and inclusion errors. From the viewpoint of policy implications, most of these studies focuses on the relationship between social protection programs and resilience. In particular, Phadera *et al.* (2019) show that an asset transfer program in Zambia

[20] See Cissé and Barrett (2018) for details.

[21] The resilience literature provides examples of both quantitative and qualitative studies, roughly equally divided among the two categories. Barrett *et al.* (2021) in their scoping review of the development resilience literature, briefly reviewed also qualitative studies.

[22] These results are robust to various model specifications and valid for both analyzed countries.

was able to increase mean assets and decrease variance, signaling an upward shift in households' conditional asset distributions. Similarly, Premand and Stoeffler (2020) found that a cash transfer program targeting poor households in Niger was able to foster resilience by facilitating savings and income smoothing. More recently, Abay *et al.* (2022) show that productive safety net program in Ethiopia is positively associated with resilience the higher and the longer the transfers to households. Furthermore, combining safety nets with income generating or asset building initiatives increases the effectiveness of the interventions. However, short-term (consumption) and longer-term (resilience) outcomes are likely to be driven by different factors, suggesting that optimizing intervention designs for improving short-term welfare may not necessarily improve households' resilience, and vice versa.

Considering strengths and weaknesses of all proposed approaches, the conditional moment-based approach (Cissé and Barrett, 2018) shows clear advantages from the theoretical viewpoint vis-à-vis the other resilience approaches. In fact, the resilience score estimated using the moments-based approach is normatively anchored, it is easy to interpret being a probability, it can be aggregated across / decomposed between sub-populations (such as the well-known Foster-Greer-Thorbecke poverty measures) and it offers the possibility to set different thresholds (e.g. low probability to be above a high threshold vs. high probability to be below a low threshold) thus providing useful information for minimizing the exclusion or the inclusion error in targeting interventions.

However, from the practical viewpoint a recent assessment comparing RCI-like measures, such as the ones proposed by FAO (2016) and Tango international (Smith and Frankenberger, 2018), and the resilience score (Cissé and Barrett, 2018) concludes that "none of the measures consistently outperforms the far simpler approach of using the most recent value of the relevant wellbeing measure to predict the future value of that same variable" (Upton *et al.*, 2022: 13). There is still a lot to do in empirical research to improve the modest out-of-sample predictive accuracy of resilience measures as applied to FNS outcomes.

4. VULNERABILITY AND RESILIENCE AS TOOLS FOR FNS ANALYSIS

Despite the attempts mentioned above to adapt the existing measures of resilience/vulnerability to the analysis of FNS, we still lack a unified framework of vulnerability and resilience to FNS. To pursue this objective, we need first to define what FNS is about. This initial step is critically important because it frames the context against which the vulnerability and resilience concepts can be assessed as useful tools for applied analysis, i.e. gauging insights on how to measure FNS, monitoring the impact of its determinants (including different shocks and stressors), assessing progress towards FNS, designing interventions, and targeting policies.

According to FAO, food security exists if and only if "all people at all times have physical, social, and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (World Food Summit, 1996). Analyzing this definition it is clear that "all people" refers to any social group, focusing primarily on the most vulnerable ones (e.g., children, the elderly, pregnant and lactating women, the poor, etc.); "at all times" refers to both short and long-run FNS problems, highlighting the need to reduce food consumption volatility over time; "access" emphasizes that the key dimension ensuring FNS is a relational dimension that links the utilization of food by consumers with the availability of food, that can be impaired by physical (e.g., lack of infrastructure), social (e.g., unequal distribution among and within social groups, including the household), and economic (e.g., poverty) factors; the reference to "dietary needs and food preferences" makes clear that consumer sovereignty and the right to food are key in determining FNS, whose ultimate goal is "an active and healthy life".

There is a vast agreement that this definition can be conceptualized as resting on four dimensions – availability, access, utilization, and stability – that are inherently hierarchical, with availability necessary but not sufficient to ensure access, which is in turn necessary but not sufficient for effective utilization, all of them being necessary but not sufficient for stability (Webb *et al.*, 2006).[23] Although FNS measurement has been substantially expanded in recent decades, there persists significant dissatisfaction with existing measurement systems (Barrett, 2010; Headey and Ecker, 2013). To date, no FNS measure can capture all food security dimensions.[24]

[23] As emphasized by Dasgupta and Ray (1986), the hierarchy can also go the other way around especially for very poor people: very low utilization would imply less access and availability because of a poor health status that will not ensure the capacity to gain a livelihood, leading to a nutrition poverty trap.

[24] For instance, food availability measures enable frequent and geographically broad estimates, but at the expense of neglecting waste and the inevitably unequal distribution and uses of food within a population. Conversely, measures based on higher-cost individual and household surveys can associate measures with targetable individual characteristics, offering depth in measuring two or three of the food security dimensions (e.g., commonly, access and utilization).

In practice, analysts use proxy measures for different aspects of FNS, implying that the choice among indicators necessarily involves tradeoffs as each measure highlights and neglects different food security dimensions.[25] As a result, it is the objective of the specific analysis at hand that drives the choice of an indicator.

Nevertheless, there are some general characteristics that an ideal FNS measure must feature. First and foremost, food availability, access to food and its utilization may change over time with risks (Pangaribowo *et al.*, 2013). In other words, households become food insecure when they are unable to mitigate the negative risks associated to food availability, access, and utilization dimensions. A forward-looking framework is essential to capture this dynamics as explicitly suggested by the "at all times" argument of the Word Food Summit FNS definition and captured by the stability dimension. In short, FNS inherently encompasses risks. Unfortunately, this forward-looking framework has been largely missed by current literature except a few isolated cases (Haddad and Frankenberger 2003; Webb *et al.*, 2006; Løvendal and Knowles, 2007). The proposed distinction between chronic food insecurity - defined as the incapacity to cover minimum food needs over the long term – and transitory food insecurity – defined as a temporary incapacity to cover food needs – appears to be misplaced too (Devereux, 2016). While a chronic status is more proximate to a deterministic path (i.e. the structural determinants of food and nutrition insecurity), a temporary incapacity is more linked to shocks and/or misfortune. The strong risk aversion of the poorer households points rather to the long-term impacts of risks and calls for the incompleteness of FNS analyses that do not look adequately at the comprehensive impacts of risk exposure on FNS, that is the need to look at the second moment of the relationship.

This is where vulnerability and resilience come into the picture. In fact, both are genuinely forward-looking, that is they reflect the probabilities of satisfying a given food consumption norm in the future. Furthermore, an ideal FNS measure should be able to capture the heterogeneity of various groups of population, i.e. it should capture the generating process of different FNS and nutrition outcomes (Barrett, 2002) at different scales of analysis, from national to subnational, community, household and individual levels. In short, as emphasized by Upton *et al.* (2016), an ideal FNS measure metric would satisfy four basic axioms:

1. *Scale*: being able to address both individuals and groups at any scale of aggregation, including geographic regions and political jurisdictions (cf. "all people" in the food security definition);
2. *Time*: encompassing both predictable and unpredictable variability over time capturing the "stability" dimension (cf. "at all times" in the food security definition);
3. *Access*: referring to various notions of individual and collective wellbeing, capturing explicitly the "access" dimension and implicitly also the "availability" dimension as a necessary condition for access (cf. "physical, social and economic access" in the food security definition);
4. *Outcome*: focusing on dietary, health, and/or nutrition outcomes is required to capture the "utilization" dimension of food security. (cf. "an active and healthy life" in the food security definition).

To date, no FNS measure satisfies all four axioms. It is worth emphasizing that virtually all currently used proxy measures are inherently static and most of them do not allow aggregation/decomposition of the involved measure. Furthermore, many of them do not cover the utilization dimension. As a result, these measures poorly reflect food security under the World Food Summit definition.

The key question here is whether and to what extent vulnerability and resilience can do a better job than standard FNS measures in assessing who the food insecure are. To answer this question, we will use the four axioms above to critically assess the capacity of the various vulnerability and resilience approaches to reflect food and nutrition security as defined by FAO (Table 1).

Starting from vulnerability measures, they are of course all inherently forward-looking. However, the most commonly applied measure, namely VEP, does not satisfy the time axiom as it rests on a very heroic assumption, that is the cross-sectional variation of the

Table 1. Assessment of vulnerability and resilience approaches to FNS measurement.

Approaches	FNS security measurement axioms			
	Scale	Time	Access	Outcome
Vulnerability				
Expected poverty	Yes	No	Yes	No
Low expected utility	Yes	Yes	Yes	No
Threat to future poverty	No	Yes	Yes	Yes
Resilience				
Capacity	No	No	Yes	Yes
Return to equilibrium	No	Yes	Yes	No
Normative condition	Yes	Yes	Yes	Yes

[25] Thereby subtly influencing prioritization among FNS interventions.

sampled household's consumption is a good proxy of the variation over time of household-specific consumption. At the same time, it falls short also satisfying the outcome axiom in so far a level of consumption above the poverty line – i.e. not being poor – is a necessary but not a sufficient condition for non-deprivation in key dimensions such as nutrition and health. By shifting the focus from achieving a given level of consumption to a measure of risk premium expressed in utility units, VEU sorts out the time axiom but do not explicitly address the outcome axiom. VTP fares better in so far it is risk sensitive and explicitly considers the rate of coverage of basic needs – including the ex-ante risk of becoming food insecure, even if ex-post consumption below a critical norm does not materialize. This in principle could be more proximate to FNS. However, it does not satisfy the scale axiom. In fact, it explicitly takes into account the many different states of nature a given individual is exposed to, which cannot be aggregated across individuals unless very strong hypotheses are met.

Resilience as a capacity explicitly considers various possible FNS indicators and correlates explaining food access. However, this approach falls short in the other two axioms, being not decomposable/aggregable across sub-populations and being not a forward-looking measure. Resilience as return to an equilibrium is forward-looking and can in principle be conditioned to factors that can make the recover from a shock faster or slower, thus satisfying the time and access axioms, respectively. Unfortunately, it is not decomposable/aggregable across sub-populations (scale axiom) and, more importantly, it falls short of fully addressing any nutritional/health norm, focusing only on the capacity of the household/individual to return to the pre-shock status, thus not satisfying the outcome axiom. The resilience as a normative condition is the only approach that can measure FNS in a way that meets all four of the FNS measurement axioms. In fact, by identifying FNS at the individual or household level, the measure is aggregable into higher-level groups (social groups, regions, etc.), thereby satisfying the scale axiom; the approach is explicitly dynamic and forward-looking, thereby satisfying the time axiom; the analyst can condition the moments of the FNS distribution on any of a host of economic, physical, and social factors, thereby satisfying the access axiom; and by using suitable measures of health or nutritional status as dependent variables, this method satisfies also the outcomes axiom.[26]

5. THE CASE FOR A UNIFYING FRAMEWORK

The analysis carried out above makes clear that vulnerability and resilience share most of the building blocks for an adequate conceptualization of FNS analysis, such as the explicit consideration of risks, stressors and shocks as well as the ability/capacity to detect future and possibly long-lasting adverse welfare consequences, although only the resilience as a normative condition (i.e., the conditional moment-based approach) satisfies all four FNS measurement axioms. On the other hand, it is self-evident that the two concepts, although looking at the same subject – i.e. the effect of risks and shocks on economic agents' wellbeing – and sharing common conceptualization and estimation needs – i.e. the need for a forward-looking analysis in a dynamic stochastic framework – are actually different constructs. Starting from this common ground and keeping in mind the highlighted important differences, we propose a unifying framework able to estimate multiple conditional moments of the same welfare function.

To begin with, let's discuss why vulnerability and resilience are *not* one the flip side of the other. To clarify this, it is useful to refer to a graph originally proposed by Carter *et al.* (2007) in one of the first empirical studies assessing the role of shocks in the emergence of poverty traps (Figure 1). It shows the likely impact of a shock on asset dynamics for two archetypical wealthy and a poor household, A_w and A_p respectively. Moving from the left to the right different phases of this dynamics are highlighted: (i) the pre-shock period (no shaded background); (ii) the time when shock hits the households (darkest gray background), followed by (iii) the coping phase when the households try to smooth the negative effect of shock on consumption through asset decumulation (intermediate gray background), and (iv) the recovery phase (pale gray background) when the household would hopefully be able to rebuild its own asset stock unless it is caught in a poverty trap.

The households' dynamics in absence of shocks is represented by the solid lines in the pre-shock phase and the dashed lines in the subsequent phases.[27] If the households are not / will not be hit by a shock, then they are not vulnerable (V = 0). They are also resilient (R = 1) as they are not affected by risks or shocks that can drive his wellbeing beneath a given normative threshold. The situation is quite different if a shock hits the households. Specifically, when the shock hits a very poor house-

[26] For an empirical application to Kenyan pastoralist households, using the household dietary diversity score and child mid-upper arm circumference as outcomes, see Upton *et al.* (2016).

[27] The assumption here, consistently with neoclassical growth theory, is that without shocks there could be a convergence process through which the poor household will be able to accumulate faster than the wealthier household thus catching up with the latter.

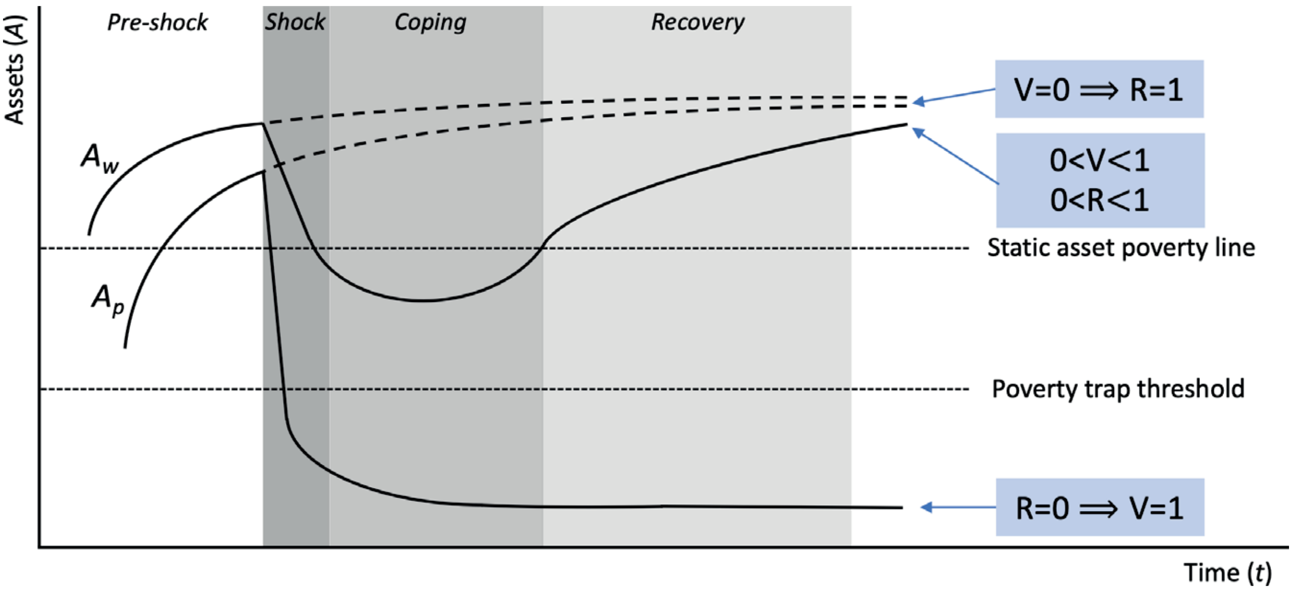

Figure 1. Different household asset dynamics after a shock: vulnerability vs. resilience. Source: Authors' elaboration from Carter *et al.*, 2007.

hold driving it below the poverty trap threshold,[28] this implies the household is not able to recover (R = 0, i.e. it is not resilient) and *a fortiori* this implies that it is vulnerable too (V = 1). However, Figure 1 also shows that there could be intermediate cases where a given household can be both vulnerable and resilient (0 < V < 1 and 0 < R < 1), as shown by the evolution of the asset dynamics of the wealthier household, A_w, that is driven beneath the static asset poverty line by the shock, but is also able to bounce back above the asset poverty line after a period of recovery.[29]

In fact, while vulnerability looks at the probability of an agent's wellbeing falling beneath some normative standard in at least one period in the future, resilience highlights the prospective importance of the non-linear path dynamics. This can be done adopting the poverty traps framework to explore the long-term path of the agent's wellbeing: focusing only on conditional expectations, we can conclude that an agent is expected to be on average dynamically non-poor if she is above the poverty line threshold (i.e., the asset threshold beneath which people fall into a poverty trap, see Carter and Barrett, 2006). However, if instead of looking only at conditional expectation we consider also conditional variance, it might be that the agent would be both vulnerable (e.g., becoming food insecure) and resilient (e.g., because food insecurity is sufficiently low in duration, intensity, and/or likelihood).

To show this, let's look at Figure 2, that represents the reduced form of one possible conditional expectation function of household wellbeing, where today's wellbeing appears on the horizontal axis and tomorrow's expected wellbeing on the vertical axis. The dashed 45° line represents points where standards of living are not expected to change over time (i.e., dynamic equilibria or stable states). Following Barrett and Constas (2014), three distinct regimes (and equilibria) can be identified: (i) a humanitarian emergency area, within which the agent is bound to collapse toward death, D; (ii) a chronic food insecurity area, within which people recover from shocks, either adverse or favorable, to a stable but food and nutrition insecure status, I; and (iii) a food and nutrition security area, within which people are expected to recover from non-catastrophic shocks leading to a food and nutrition secure equilibrium, S. These three

[28] The poverty trap threshold has been dubbed by Zimmerman and Carter (2003) as the "Micawber threshold" (borrowing it from Lipton, 1993), after the Dickens' character who was a perpetually insolvent debtor with whom David Copperfield took up residence, who moves in and out of different jobs and debtor's prison, unable to advance his own standards of living. The Micawber threshold is a *dynamic* asset poverty threshold according to which households whose assets place them above it would be expected to escape poverty over time, while those below it would not.

[29] A consistent outcome can be derived by looking at consumption behavior – that is the flip side of this asset behavior – by adopting a structural framework such as that proposed by Elbers and Gunning (2003). In this framework, resilient but vulnerable households can be identified by looking at the long-term non-linear consumption dynamics under risk, taking simultaneously into account their risk exposure and their consumption smoothing behavior through changes in assets. This allows to compute, for each time period, households' vulnerability as a function of various sources of heterogeneity – primarily, initial assets but also differences in risk exposure – and correctly track a non-poor individual or household with a high second conditional moment in her expected path dynamics as both vulnerable and resilient.

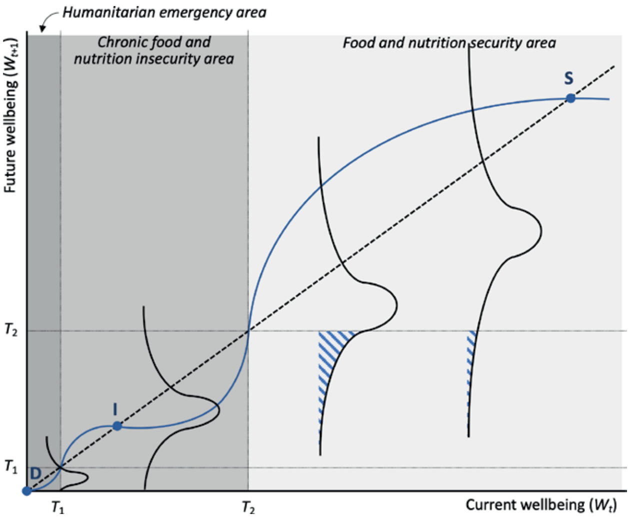

Figure 2. Non-linear expected wellbeing dynamics with conditional transition distributions. Source: Authors' elaboration from Barrett and Constas, 2014.

regimes are separated by two thresholds, T_1 and T_2, that separate the basins of attraction defined with reference to initial period wellbeing levels expected to lead toward a dynamic equilibrium in the relevant range due to agents' expected behaviors. The non-linear expected wellbeing dynamics is represented by the the expected livelihood function (i.e., the curve swinging around the dashed diagonal): it identifies multiple stable states (i.e., death, non-FNS, and FNS equilibria) as well as thresholds separating the different basins of attraction (i.e., T_1 and T_2).

Looking just at conditional expectation, as the poverty trap literature usually does, what counts is just the initial state, W_t, that determines the expected future wellbeing state, W_{t+1}. However, we cannot rule out that a negative shock hitting an agent who is above the poverty trap threshold, even if associate with a very low likelihood (represented in Figure 2 by the dashed areas under the conditional transition distribution functions associated to the conditional expectation function), can bring that agent beneath the normative established threshold (e.g. a certain level of food intake) for some periods t in the future, thus determining a welfare loss (in this case, she will be also recorded as vulnerable). Furthermore, the same shock can modify the process through which stocks of assets (e.g., land) and flows of inputs (e.g. labor) can generate flows of income or other goods or services of value (e.g., farm output, time spent with friends, etc.). That is, the structure of this process (i.e., the shape of the expected livelihood function) can change. This also can determine a welfare loss as compared to the pre-shock situation. Resilience as a normative condition (Cissé and Barrett, 2018) records these potentially non-linear dynamics of shock-induced welfare changes, estimating what is the conditional probability of being at or above a given normative standard at some point t in the future.

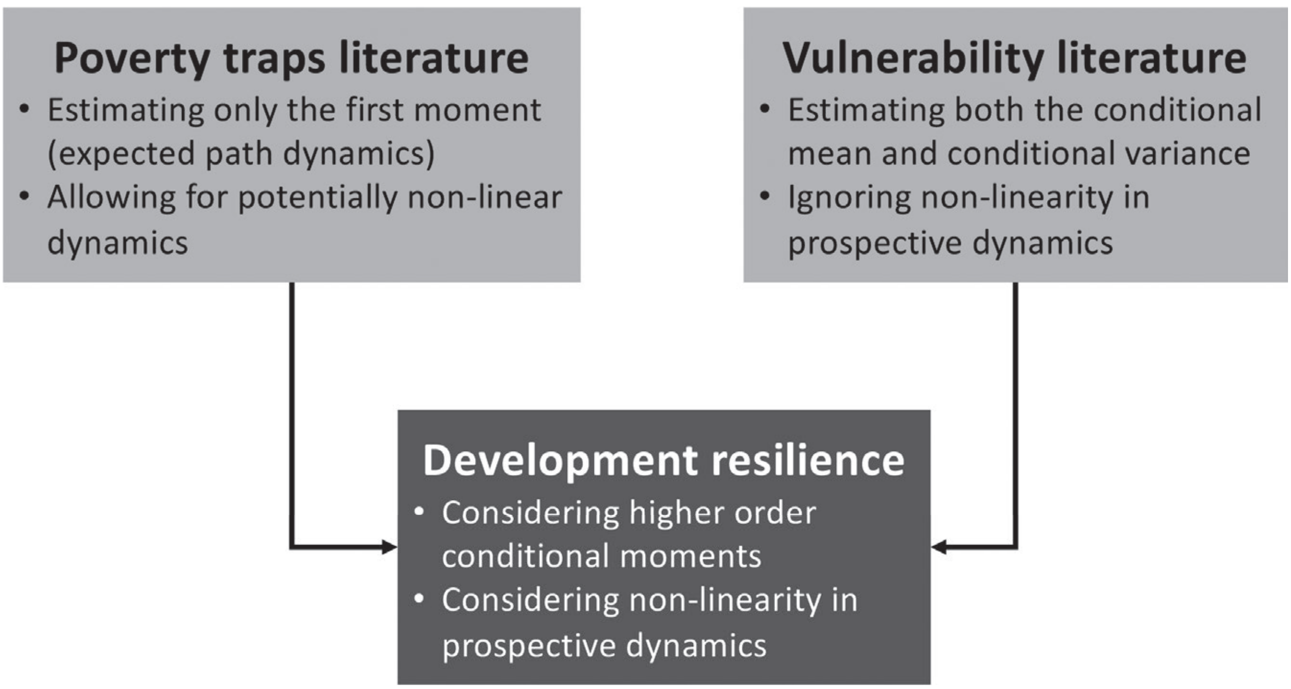

Figure 3. Conditional moments-based resilience as a unifying framework.

If and only if this probability (i.e., the resilience score, see Eq. 15) is higher than a normatively established minimal threshold probability (i.e., an acceptably high level of probability of being food secure), we can classify that agent as resilient. The flip side of this would be a potentially non-linear time-varying measure of vulnerability, using the time sequence of resilience estimates to estimate transition probabilities into or out of poverty conditional on one's characteristics, risk exposure and immediate pre- and post-shock welfare measures.

Unfortunately, the vulnerability literature generally does not allow for such a non-linear dynamics. At the best of our knowledge, the only paper estimating vulnerability in a framework of non-linear dynamics is Elbers and Gunning (2003). They used a stochastic Ramsey model to find the household optimal welfare measuring vulnerability as the shortfall from the welfare attained if the household consumed permanently at the poverty line (see, also, Elbers *et al.*, 2007). Unfortunately, the data needed to estimate such a structural dynamic model are often not available in developing contexts.

All the above emphasizes the need to consider the contributions of different strands of literature to reach a unified framework for a comprehensive, forward-looking analysis of food and nutrition security. Specifically, we need to draw on the poverty traps literature to include potentially non-linear path dynamics and asset-based poverty traps; at the same time, we need to leverage on the vulnerability literature to get a forward-looking, probabilistic measure of wellbeing accounting for both conditional means and conditional variance. In this respect, the resilience conditional moment-based approach proposed by Cissè and Barrett (2018) emerges as a possible unifying concept to effectively and comprehensively assess food and nutrition security (Figure 3): on the one hand, the vulnerability literature emphasizes the need to estimate both the conditional mean and conditional variance, but it ignores non-linearity in prospective dynamics; on the other hand, the poverty trap literature allows for potentially non-linear dynamics but estimates only the first moment (expected path dynamics). The development resilience conceptualization (Barrett and Constas, 2014; Cissé and Barrett, 2018) borrows on both strands of literature considering higher order conditional moments (as vulnerability does) and non-linearity in prospective dynamics (as poverty traps do).

6. CONCLUSIONS AND RECOMMENDATIONS

This paper aims at answering a key research question: how leveraging the existing knowledge to improve ex-ante targeting of households vulnerable to food and nutrition insecurity and to enhance the effectiveness of interventions aiming at building resilience. In order to answer to this question, we reviewed the literature on conceptualization and empirical measurement of vulnerability and resilience with specific reference to food insecurity. Building on these strands of literature, our answer is twofold: first, we need to operationalize a single, unified framework able to estimate multiple conditional moments of the same welfare function, including potentially non-linear path dynamics, to assess forward-looking, probabilistic measures of food insecurity able to satisfy a specific set of axioms (i.e., suited for targeting and program evaluation); second, we need to acknowledge what are the main limitations of current analyses and propose a clear roadmap for improvement.

We argue that clarifying the relationships between vulnerability and resilience helps providing a better suited and more comprehensive framework for FNS analysis as anticipated by Cissé and Barrett (2018) in proposing the so-called "development resilience" framework. In fact, from the conceptual viewpoint, this framework makes possible to integrate some valuable features of the vulnerability and poverty traps concepts into implementable, theory-based resilience measures. It considers higher-order conditional moments (as vulnerability literature does) and non-linearity in prospective dynamics (as poverty traps literature does). From the practical viewpoint, the nature of the resilience allows for the integration into a single framework relief (i.e., humanitarian) as well as development efforts, putting greater emphasis on longer term preventative measures rather than short-term curative responses. This is particularly important taking into account the current discourse on the human-development-peace nexus as an operational principle guiding international organization/agencies interventions (UNRISD, 2005; UN, 2016). This unified framework also meets the four food security measurement axioms as highlighted by Upton *et al.* (2016).

Looking at the limitations of the approach, we acknowledge that estimating these conditional moments is highly data-demanding, as it requires high-frequency, micro level, good quality panel data, ideally at seasonal frequency, including the entire set of possible covariates and idiosyncratic shocks, that are seldom available especially in developing contexts. On top of this, it should be emphasized that the estimated measures exhibit only modest out-of-sample predictive accuracy, generating many false negative and positive (Upton *et al.*, 2022). Those are the actual Achille's heels of the proposed framework and there is still a lot of work to be done to improve resilience measurement. This calls for alternative data generation strategies as well as investing in some applied research priority areas. Referring to the former, integration with non-conventional data sources (e.g., massive, crowdsourced, citizen-generated data, etc.) appear to be a promising route. However, it also needs reaching better quality standards to be properly linked to survey data (Carletto, 2021). As a result, the analysis of the data gaps and the promotion of complementarity and interoperability between old and new data sources is one of the key missing links for the operationalization of a truly unified framework.

In terms of a future applied research agenda, the first recommendation is methodological and calls for producing more accurate measures of vulnerability and resilience to food insecurity increasingly inspired by the depicted common unified framework. A second recommendation refers to expand the geographical coverage as well as the range of shocks and stressors considered, focusing on areas that have been relatively neglected by the studies carried out so far such as the rigorous evaluation of resilience-building interventions impacts (e.g., specific asset transfers vs. provision of public goods such as irrigation schemes or transport infrastructure, etc.), and exploring the relationships between measures at different levels of analysis such as individuals, households, communities and higher geography levels.

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