CREATIVITY AND MOTIVATIONS

ECONOMIC RESEARCH CENTER

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DEPARTMENT OF ECONOMICS AND LAW

Measuring economic vulnerability
A Structural Equation Modeling approach

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CreaM- Working Paper Series Nr. 1/2018

ISBN: 2421-4264

Creativity and Motivation Economic Research Series
Working paper series
Editor: Nadia Cuffaro
e-mail: cuffaro@unicas.it

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Measuring economic vulnerability: a Structural Equation Modeling approach

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January 15, 2018

Abstract:
The aim of this paper is to use a multivariate approach to improve the methodology for measuring the economic vulnerability of developing countries. The official index used by the United Nations, the Economic Vulnerability Index (EVI), is a composite indicator defined as the weighted average of a set of variables measuring i) the exposure to exogenous shocks and ii) the consequences of such shocks. We propose to extend the EVI model in order to include variables measuring resilience, i.e. the ability of a country to recover after a shock has occurred, and we evaluate the Structural Equation Model approach to compute a general vulnerability index. Since we analyse data covering 98 countries and 19 years we propose a strategy for dealing with repeated SEM results.

JEL codes: C33, F68, I32

Keywords: vulnerability, resilience, partial least squares, structural equation models

1. Introduction

In the ongoing discussion on how to measure well-being and poverty, especially in relation to the allocation of international aid, the concept of vulnerability has emerged as potentially more useful than measures of poverty.

Vulnerability and resilience are defined by the United Nations International Strategy for Disaster Reduction (UNISDR, 2009) as "the characteristics and circumstances of a community, system or asset that make it susceptible to the damaging effects of a hazard" and "the ability of a system, community or society exposed to hazards to resist, absorb, accommodate to and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions" respectively.

Several measures of vulnerability are used in the literature: they are mainly defined as composite indicators, typically computed as weighted averages of a set of indicators, where all indicators are assumed to have arbitrary (mostly equal) weights and to be uncorrelated to each other (i.e. correlation among them is ignored).

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In order to identify countries that are eligible to enter or leave the Least developed Countries category the United Nations refers, among other measures, to the Economic Vulnerability Index (EVI, Guillamont, 2009)

The EVI is computed as the simple average of 2 sub-indices: an Exposure Index and a Shock Index, which are weighted averages of 5 and 3 variables respectively. As such, the EVI focuses on risk, but neglects measures of resilience.

We start our analysis from all EVI variables, observed on 145 developing countries between 1990 and 2013. Our contribution moves along two dimensions:

1. we propose to enlarge the EVI model, in order to include additional variables affecting resilience;
2. keeping this conceptual structure, we use a Structural Equation Model (SEM) to estimate the vulnerability as a composite indicator based on a weighting system deduced from the data and where the correlation among variables plays its role in determining the vulnerability score.

In the next section we briefly provide the main references to the major measures of vulnerability available from the literature. In section 3 we discuss the main features of the existing EVI, and present our proposal for an extended measure of vulnerability. In section 4 we introduce the key features of the Partial Least Squares Path Modeling (PLS-PM) approach for estimating a Structural Equation Model (SEM), and in the following section 5 we present our results for estimating vulnerability over time with the PLS- SEM approach. Section 6 concludes.

2. The literature on macroeconomic vulnerability[1]

The UN definition of vulnerability, reported above, makes it clear that it depends on several aspects: the probability of facing an hazard, that could be labeled "exposure", and the ability to recover minimizing damages once a shock has occurred, or "resilience". In principle, vulnerability is the outcome of a complex interaction between shocks and resilience: a country can have a high exposure to external shocks, but it might have created adequate institutions to cope with such shocks, so to achieve a low level of vulnerability. Resilience may therefore also depend, dynamically, on the degree of exposure, and a measure of vulnerability obtained by a linear combination of the determinants of exposure (and resilience) may not take properly into account such complex interactions.

While the general concept of vulnerability is relatively easy to define, its measurement for a given country needs to address several empirical and theoretical problems:

[1] This section is largely based on Altimari (2014), ch.1

1. Restricting our analysis to the vulnerability of a country, which kind of hazards should be considered? In other words, vulnerability *to what*?
2. Should our measure be a predictor of vulnerability, focusing on ex-ante indicators that do not depend on the consequences of a shock? Or should we rely on ex-post measures of how a country has coped with a given shock? Or a combination of both?
3. Since exposure, resilience and vulnerability are abstract, unobservable concepts – what statisticians call *latent variables* – how can we measure them through observable variables? And what roles do the determinants of vulnerability play? Or, to put it differently, if we measure vulnerability through a combination of variables, is there a way to determine the optimal weight for each variable?

In the literature, some measures of vulnerability focus on risk ex-ante assessment, other measures focus on ex-post evaluation of transmission channels. Studies adopting the former approach construct Early Warning Indicators (EWI): see Berg et al. (2000), Reinhart et al. (2000), Berg et al. (2005), IMF-FSB (2010), Dabla-Norris & Bal Gündüz (2012), Hermansen, Mikkel, & Oliver Röhn (2017) among others.

Studies adopting the latter approach include Briguglio (1995), who proposed a Vulnerability and Resilience Index (VRI), extended in Briguglio and Galea (2003) first, and in Briguglio et al. (2006), focusing on an index of resilience. This index was updated in Briguglio et al. (2009)

Other approaches include the Vulnerability Impact Index: see Easter (1999), focusing on Small Island Developing States (SIDS). However, it was soon recognized – Guillamont (1999), CDP (2008) - that vulnerability was potentially relevant to identify the least developed countries (LDCs). Currently the United Nations Committee for Development Policy (CDP) uses three criteria to identify LDCs: Gross national income (GNI) per capita; the human asset index (HAI) and the economic vulnerability index (EVI) (CDP & UNDESA, 2015). The EVI was proposed in Guillamont (1999, 2001, 2009), and updated in Guillamont and Cairolle (2011) and Cairolle (2011), and more recently in Feindouno & Goujon (2016).

Bates et al. (2014) and Angeon – Bates (2015) move along lines similar to ours, but adopting graph theory for exploring extended measures of vulnerability.

Our proposed new indices will be compared to the EVI, and the next section will present its characteristics, along with our proposals for extensions.

3. Measures of vulnerability

The Economic Vulnerability Index (EVI) focuses on the determinants of what we labeled as "Exposure", but which are treated separately in the EVI as "Shock" and "Exposure" – Feindouno & Goujon (2016). More in detail[2], "exposure" is determined by:

1. Population size (POP): smallness – measured in terms of population – increases exposure;
2. Remoteness from world markets (REMOTE): trade-weighted minimum average distance to reach 50% of the world markets. Economic isolation from world markets is considered to increase exposure;
3. Export concentration (EXPCON): measured through an export concentration index. Less diversification in trade increases exposure;
4. Share of agriculture, forestry and fisheries in GDP (AGRSH): measured on a 3-year average of the share of agriculture in GDP. A higher share in the primary sector increases exposure;
5. Share of population living in low elevated coastal zone (COAST): measured by the share of the population that lives in areas contiguous to the coast below a certain elevation threshold. The higher this share, the more likely is that a natural disaster affects the population and the economy.

What Guillamont labels as the "shock" component of the EVI depends upon:

1. Victims of natural disasters (VICTIMS): average share of the population hurt by natural disasters;

2. Instability of agricultural production (AGRINST): deviations between observed and estimated agricultural production;

3. Exports instability (EXPINST): deviations between observed and estimated exports values.

All these variables are measured so that a higher value implies higher vulnerability, and the EVI is obtained from a weighted average of its eight components.[3]

The EVI uses variables which are available for a large number of countries, and an extended period of time: annual data are available from 1995. It is a mix of ex-ante indicators, grouped in the "exposure" sub-index, and ex-post measures, grouped in the "shock" sub-index. The purpose of the EVI is not to evaluate resilience, which is nevertheless a relevant determinant of vulnerability.

We have therefore chosen to extend the EVI by including additional indicators that (a) are available for a large enough number of (developing) countries, and (b) can account for the ability of each country to cope with the consequences of a shock.

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[2] For a detailed description of variables, including data sources, see Appendix 1.

[3] The maintainers of the EVI have set up a useful tool to evaluate the impact on the index of different weights, available at http://byind.ferdi.fr/

We have chosen the following variables to complement the measure of exposure:

1. Surface area (SURFACE): total area, including areas under inland bodies of water and some coastal waterways. This is an alternative measure of smallness, which is intended to complement the existing measure based on population size. The two measures are obviously correlated (simple correlation for 2013 is 0.8) but do not represent the same information. In addition, results from the PLS method - that we will describe later – will improve when determinants of latent variables are correlated. As for population size, exposure is assumed to decrease with surface extension;
2. Import concentration (IMPCON): standardized Herfindahl-Hirschmann index published by UNCTAD. When imports are concentrated, the risk of suffering from an external shock to import prices increases;
3. Foreign direct investment (FDI): net inflows of investment to acquire a lasting management interest (10% or more of voting stock) in an enterprise operating in an economy other than that of the investor, scaled by GDP. On the one hand, FDI may contribute to economic development, when they imply job creation, technological transfers, and when they contribute to providing foreign reserves. On the other hand, reliance on FDI increases the risk of a sudden stop in investment and economic activity, should FDI be stopped. We therefore assume that a larger share of net FDI on GDP increases exposure. In the PLS estimate, we also include an inverse measure of FDI as a determinant of resilience.
4. Net official development assistance and official aid, in percent of GDP (AID). Aid from the rest of the world should improve resilience, but a sudden stop to such funds may itself be an adverse shock. We therefore use this indicator both as a determinant of exposure, and as a determinant of resilience, in the PLS estimate. In our weighted average measure, we assume that AID only affects exposure.

All new variables have been standardized in the same way as for the EVI indicators: they have been scaled in the 0-100 interval, so that a higher value of the indicator implies higher vulnerability (so that, for instance, the country with the smallest surface will have a SURFACE value of 100). In addition, we adopted upper and lower bounds, as the EVI does for its component variables – see Feindouno – Goujon (2016).

In addition, we selected the following variables as determinants of resilience[4]:

1. Net flows on external public and publicly guaranteed debt, in percent of GDP (FDEBT). A higher level of foreign debt – and therefore of flows associated to such debt – relative to national income reduces the room for maneuver of the government, and therefore the ability to cope with an adverse shock;

[4] For more details, see Appendix 1, and the companion web site at http://gennaro.zezza.it/files/abz

2. Debt service on external debt, in percent of GDP (DEBTS). In a similar way, the largest the share of national income which flows abroad to service the debt, the lower the ability of the country to cope with an adverse shock. In practice, DEBTS includes principal repayments, which are excluded from the FDEBT measure: we notice that the correlation between the two measures is low, so that adding DEBTS produces additional information on vulnerability;
3. Gross fixed capital formation, in percent of GDP (GFCF). A higher level of productive capital should increase resilience;
4. Net FDI and net official development assistance and official aid. See above.

As additional determinants of resilience, we use the World Bank's Worldwide Governance Indicators:

5. Control of Corruption (CC)
6. Government Effectiveness (GE)
7. Political Stability and Absence of Violence/Terrorism (PS)
8. Regulatory Quality (RQ)
9. Rule of Law (RL)
10. Voice and Accountability (VA)

Governance indicators should have a strong impact on resilience. The drawback in adding these variables is that they are only available from 1996, and therefore their inclusion does not allow to estimate backward the extended index of vulnerability to years before 1996.[5]

A number of other indicators have been analyzed, but discarded because they were not available for a sufficient number of countries over an extended period of time. They include several measures of human capital (school enrolment at different stages); additional measures of private or total foreign external debt, both as stocks to GDP or as flows on foreign debt to GDP; other measures of trade openness and trade composition (openness gap, share of commodity exports/extractive industry exports/manufacturing exports on total exports, cost to exports); imports concentration or volatility (instability of imports; imports of energy/fules/food in percent of GDP or consumption); other measures of the fiscal stance (public expenditure) or of the structure of production (share of services on GDP).

In Table 1 we report the simple correlation coefficients among the original EVI index, real GDP per capita, and the newly added variables. As it is obvious, correlation is not causation, so that the positive correlation between all governance indicators and real GDP may imply that – as the country gets richer –

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[5] Since all other variables were available for 1995, we set the 1995 value for all governance variables to their 1996 value, not to completely loose one year. See gennaro.zezza.it/files/abz fore more details.

the ability to improve governance increases, rather than the other way round. In any case, simple correlations are informative to evaluate how much our variables are related to each other, and to the original EVI.

Table 1. Simple correlation among new variables and the EVI

	EVI	GDPPC	FDEBT	DEBTS	GFCF	AID
EVI	1.000					
GDPPC	-0.544	1.000				
FDEBT	0.201	-0.164	1.000			
DEBTS	-0.039	0.128	-0.251	1.000		
GFCF	-0.165	0.209	0.196	-0.004	1.000	
AID	0.527	-0.490	0.119	0.052	-0.116	1.000
CC	-0.133	0.352	0.112	0.076	0.278	-0.109
GE	-0.395	0.543	0.077	0.115	0.319	-0.317
PS	0.159	0.220	0.157	0.027	0.253	-0.073
RQ	-0.376	0.440	0.040	0.094	0.168	-0.291
RL	-0.180	0.383	0.083	0.086	0.296	-0.194
VA	-0.087	0.277	0.021	0.137	0.042	-0.092

	CC	GE	PS	RQ	RL	VA
CC	1.000					
GE	0.788	1.000				
PS	0.573	0.471	1.000			
RQ	0.656	0.819	0.409	1.000		
RL	0.846	0.834	0.631	0.758	1.000	
VA	0.599	0.586	0.462	0.664	0.681	1.000

As a first step, we computed an extended EVI, that we label EVI-E, as a weighted average of all of the variables, with equal weights, in order to compare our results – and our rankings – to those of the EVI, without changing the statistical procedure to compute the index.

[FIGURE 1 ABOUT HERE]

In Figure 1 we report a scatter diagram plotting our weighted average, EVI-E, against the original EVI. It is apparent that the two measures are highly correlated, as expected, but the EVI-E has a smaller number of observations with high values of vulnerability. This is confirmed by the frequency distribution of the two indices, reported in Figure 2.

[FIGURE 2 ABOUT HERE]

The extended EVI is more symmetrically distributed, with a smaller variance than the EVI. We can therefore expect the EVI to identify a smaller number of countries in a “very vulnerable” state, against the EVI-E.

Checking the two measures over time reveals that EVI and EVI-E share the same trends and turning points for most – but not all – countries: see Figure 3. Casual inspection also reveals that the EVI-E is somewhat more volatile over time for individual countries than the EVI.

[FIGURE 3 ABOUT HERE]

Comparing the rankings for the most vulnerable countries according to the EVI and the EVI-E provides useful results (Table 2): countries with a high vulnerability according to the EVI, which have a lower rank according to the EVI-E, are those with good values for the governance indicator, and are therefore expected to be more resilient. This is the case, for instance, for Tonga and St. Kitts and Nevis.

Table 2. Highest EVI rank in 2013

Country	EVI-Rank	EVI-E-Rank
Gambia, The	1	2
Eritrea	2	1
Tonga	3	21
St. Kitts and Nevis	4	62
Sudan	5	3
Burundi	6	5
Chad	7	4
Guyana	8	15
Sierra Leone	9	8
Solomon Islands	10	11

Our analysis has also shown a potential weakness in one of the sub-indices of the EVI. The "remoteness" sub-index measures the distance of each country from global markets. In Figure 4 we plot the change in the index over time for all countries in our sample.

[FIGURE 4 ABOUT HERE]

The chart shows that the value of the index changes in the same direction for most countries, with an upward movement in 2003, and a downward movement in 2010-2012. This is interpreted in the EVI as increase in vulnerability for each country – in the former case – and reduced vulnerability, in the latter case. However, synchronicity over countries suggest that it is the definition of "global markets" that is shifting, possibly with reduced trade with less developed countries in 2003, and increased trade in 2010-2012. This cast some doubts on the usefulness of this sub-index for computing macroeconomic vulnerability of each individual country.

In the following we extend our analysis by adopting a different statistical methodology, namely the Partial-Least Squares – Structural Equation Model (PLS-SEM). In the next section we provide a brief overview of this approach, and in the next section we apply the method to our measures of vulnerability.

4. The PLS approach to Structural Equation Models

The term Structural Equation Modeling (SEM) refers to the set of statistical multivariate data analysis techniques incorporating unobserved, or *latent*, variables measured through indicator variables.

Given a data matrix *X*, partitioned by column in J blocks, a *path diagram* (Figure 5) is the typical representation of a causal model where each block Xj (j = 1, …, J) is a set of manifest variables related to a latent variable ξj.

In such a diagram, rectangles represent manifest variables (MV), ellipses latent variables (LV) and the arrows the relations between them, which are supposed to be linear.

[FIGURE 5 ABOUT HERE]

Two models are combined in the path diagram: the *measurement model* (also called outer model), including the relations between each manifest variable and corresponding latent variable, and the *structural model* (also called inner or path model) including the relations among latent variables.

The directions of the arrows describe different model specifications on both levels:

- the measurement model can be *reflective* (mode A), when the manifest variables are a reflection of the latent variable (independent LV – dependent MV) or *formative* (mode B), when the manifest variables have an effect on the latent variable (independent MV – dependent LV);
- the structural model includes *exogenous* latent variables, i.e. latent variables which do not depend on other latent variables, and *endogenous* latent variables, i.e. latent variables which depend on other latent variables.

Sometimes the specification of the causal relation between a manifest and a latent variable may be not as clear-cut as it seems, as most often they are rather correlated each other than dependent one another. In such situations two auxiliary criteria may partially help, either in combination or as alternatives:

- to distinguish *unidimensional* blocks of manifest variables, necessary condition for a reflective measurement model, from *non-unidimensional* blocks of manifest variable, which must be formative;
- to consider the role that variables/blocks play within the model as a whole (i.e. symmetrical versus non-symmetrical approach).

The SEM estimation can be based on the two alternative approaches which define the two classes of the *covariance-based* (mostly confirmative) and the *component-based* (mostly exploratory/predictive) methods.

The main representatives of these approaches are the covariance-based LISREL (Jöreskog, 1979) and the component-based Patial Least Square (PLS) approach to SEM (PLS-SEM), or PLS Path Modeling (PLS-

PM)[6], that is often preferred to the LISREL as it is free from distributional assumptions and thanks to its ability to overcome convergence issues, as well as to avoid improper solutions.

We adopt PLS-PM in our analysis.

4.1 The PLS-PM algorithm

The PLS-PM is an iterative algorithm aimed at estimating latent variables scores through alternated simple and multiple linear regressions, aiming at estimating 3 sets of parameters:

- the individual scores of latent variables;
- the outer (or external) weights of the measurement model;
- the inner (or internal) weights of the structural model.

and is based on alternating, until convergence, an external and internal estimate of the LV, based on OLS regressions, according to the following steps:

Step 1 – Outer estimation of latent variables: is the external estimation v_j of the latent variable ξ_j given by a linear combination of its p_j manifest variables, i.e. the j-th block $\mathbf{X}_j$ of the data matrix $\mathbf{X}$.

$$\mathbf{v}_j \propto \pm\left(\sum_{k=1}^{p_j} \mathbf{w}_{kj}\mathbf{X}_{kj}\right) \qquad 1$$

The symbol $\propto$ means that each latent variable estimation is standardized.

Step 2 – Inner estimation of latent variables: each latent variable is re-estimated based on its relation with other latent variables. The internal estimation z_j of ξ_j is given by:

$$\mathbf{z}_j \propto \sum_{j'} \mathrm{e}_{jj'}\mathbf{v}_{j'} \qquad 2$$

where $e_{jj'}$ are the internal weights and can be set equal to the sign of the correlation coefficient between the outer estimates of the j -th and the j'-th LVs (Centroid scheme), or to their correlation coefficient (Factor scheme), or to the regression coefficient (Path scheme).

Step 3 – Computation of the outer weights: it differs between reflective and formative schemes.

In the reflective scheme each manifest variables depends on the latent one, so that each outer weight can be estimated as a simple regression coefficient of the model:

$$\mathbf{x}_{ij} = w_i \xi_j + \varepsilon_{ij} \qquad 3$$

i = 1, …, p_j (number of manifest variables in the block j)

Being latent variable standardized, wi it is the covariance between the i-th manifest variable of the block j and the internal estimation of the latent variable, i.e.:

$$w_i = \text{cov}\left(\mathbf{x}_{ij}, \mathbf{z}_j\right) \qquad 4$$

In the formative way, the latent variable depends on its manifest ones, so the outer weights are the multiple regression coefficients of the model:

$$\xi_j = X_j w_{ij} + \delta_j \qquad 5$$

and

$$\mathbf{w}_j = \left(\mathbf{X}_j^{'} \mathbf{X}_j\right)^{-1} \mathbf{X}_j^{'} \mathbf{z}_j \qquad 6$$

Outer weights estimations are used for a new external estimation of the latent variable. The four steps are iterated until convergence between external and internal estimation is reached.

Then, once these three steps converge to a definite estimation of the latent variables, the path-coefficients are determined as coefficients of the system of simple and/or multiple regressions between each endogenous ($\xi_j^{(endo)}$) and its exogenous ($\xi_j^{(exo)}$) latent variables, system specified by the structural model:

$$\xi_j^{(endo)} = \sum_{m=1}^{M} \beta_{jm} \xi_m^{(eso)} + \varepsilon_{jm} \qquad 7$$

m = 1, …, M (number of exogenous latent variables for $\xi_j^{(endo)}$.

4.2 Proposed models

According to a SEM approach, the concepts of Exposure, Shock and Resilience represent as many (exogenous) latent variables, described by all their observed variables and impacting on the Vulnerability (endogenous).

We specify the models for estimating the EVI according to the Hierarchical PLSPM (or Repeated Indicators Approach, or Multi-block analysis; Wold (1975); Tenenhaus & Esposito Vinzi (2005); Tenenhaus & Hanafi (2005), typically used for modeling composite indicators.

In such a model, all manifest variables in each block are put together and used to define a so–called super–block, i.e. an additional latent variable described by the whole set of variables and whose final score can be interpreted like the composite indicator estimation.

In other words, the final index is obtained as a linear combination of the variables where the weights are defined based also on their block structure (i.e. accounting for the correlations within blocks).

Figure 6 shows the two path models describing the base EVI (in white) and the EVI-E (white + grey).

[Figure 6 about here]

We specified the measurement model based on blocks dimensionality, setting the reflective scheme (mode A) for all the blocks except the super-block, which is not unidimensional. The inner estimation was based on the Path-scheme.

5 Results

In order to compare our results to the original EVI, two versions of the index were estimated by PLS-PM:

- the EVI-PLS: PLS-SEM estimation using the 8 base EVI indicators as manifest variables, related to 2 exogenous latent variables (Exposure and Shock) explaining an endogenous super-block (Vulnerabilty);
- the EVI-E-PLS: PLS-SEM estimation using the 21 indicators (8 base + the additional 13) as manifest variables, related to 3 exogenous latent variables (Exposure, Shock and Resilience) explaining the endogenous super-block (Vulnerability).

We therefore will have a total of four indices, as in Table 3. In Section 2 we explored the similarities between the two indices computed using fixed arbitrary weights, EVI and EVI-E, while we will now be able to investigate what happens when weights are estimated through the PLS-SEM procedure on the same variables, i.e. comparing the EVI index to the EVI-PLS index, and finally what happens when the model is extended, comparing EVI-PLS index to EVI-E-PLS.

Table 3. Comparing our four indices		
	Model specification	
Estimation method	8 variables	8+13=21 variables
Weighted average	EVI	EVI-E
PLS-SEM	EVI-PLS	EVI-E-PLS

Results obtained using different models/estimation methods are compared between each other over time at an empirical level.

Evaluating results is a complex task: since the two models have been estimated 19 times each, we do not focus on classical model reliability/validity or fitting measure, although these aspects have been considered at a general level (classical fitting measures are quite good over all the years), but we will rather point out how the two indices perform in terms of i) the coherence of the results with the underlying theoretical model and ii) capability of the estimated indices to explain real GDP growth, which we chose as a simple aggregate measure of economic performance.

In synthesis, in showing our results we will refer to the following measures:

1. To evaluate the internal coherence of the indices we mainly use some descriptive tools:

- signs and values of the estimated weights and their trend over time;
- trend, correlations and autocorrelations of indices;
- countries' final rankings.

2. We next test the predictive power of the indices by regressing them on real GDP growth.

5.1 Comparing different model specifications

As mentioned above, the main expected consequence of using SEM is to let the index weighting system emerge from the data. In figure 7 the trends of the outer weights of manifest variables on both EVI-PLS and EVI-E-PLS are shown. The basic stability, and/or similar trends, of weights over time can be considered as a strength of choosing the SEM approach.

[FIGURE 7 ABOUT HERE]

On the other hand, the presence of some negative weights for some variables points out that the use of positive (and constant) weights in the classical EVI is not justified by the data (the assumption of positive weights does not rely on positive correlations among variables).

The correlation between EVI and EVI-PLS is low, while they individually show a high autocorrelation from one year to the next, with correlation decreasing with distance in time, proving their strong internal coherence (although autocorrelation in the EVI-PLS and in the EVI-E-PLS are slightly lower than in the original EVI).

In other words, the two indices provide two different measures of vulnerability, each with its own ranking, but both have their own internal coherence.

EVI-E is instead highly correlated to EVI-E-PLS, both for the whole sample and for many countries.

5.2 Does vulnerability help explain growth?

In addition to the comparisons among indices, we have verified which of the proposed models is better able to explain the growth rate in real GDP per–capita, where vulnerability should have a negative impact with growth[6].

In table 4 we report the results of four fixed-effects panel regressions on GDP growth for each of the four indices, adding lagged GDP growth as an additional explanatory variable.

We start from (1) a simple auto-regressive model, and in the next four estimates we introduce one of the vulnerability indices at a time.

Table 4. Fixed-Effects Panel estimation. Dependent variable: real GDP growth per capita

	(1)	(2)	(3)	(4)	(5)
Lagged GDP growth	0.159**	0.157**	0.144**	0.156**	0.153**
EVI		-4.1E-04			
EVI-E			-0.002**		
EVI-PLS				0.1045**	
EVI-E-PLS					-0.011**

[6] We are aware that this analysis cannot rule out the possibility that GDP growth has an impact on vulnerability, and that therefore our explanatory variables may not be weakly exogenous

Intercept	0.203**	0.034**	0.092**	0.021**	0.020**
N	1706	1706	1706	1706	1706
Adj. R2	0.147	0.146	0.155	0.148	0.153

The original EVI is not significant, in model (2), and its PLS-SEM version, in model (4), has the "wrong" sign. On the contrary, the EVI-E and EVI-E-PLS indices, in models (3) and (5) respectively, have the correct sign, and significantly contribute to explaining real GDP growth.

6 Conclusions

We have analyzed the measure of economic vulnerability adopted by the United Nations, EVI, and proposed to extend it by considering additional indicators to take into account the ability of a country to recover from shocks. We have further proposed a multivariate approach, based on PLS-SEM, for estimating economic vulnerability indices. We show that extended measures of vulnerability exhibit a stronger correlation to real GDP growth, thus validating the usefulness of the approach. The PLS-SEM approach, which computes the latent variable "vulnerability" as a linear combination of the manifest variables, has also shown that some of the manifest variables used in computing the EVI enter the PLS-SEM with negative weights, casting doubts to the appropriateness of a weighted average for measuring a composite vulnerability index.

Dealing with a three-way data table we set our analysis in the frame of repeated PLS-SEM. We defined an empirical strategy to evaluate our results, which could provide a useful starting point for the adoption of the same methodology over different datasets.

While our results show that an extended measure of vulnerability is indeed appropriate, the adoption of PLS-SEM as an estimation method deserves further research. We have shown that the method provides useful insights on the appropriateness of the chosen determinants of vulnerability, but its implementation is obviously more expensive, with respect to computing a simple weighted average, and the gains obtained should further be evaluated against the additional costs.

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Appendix 1 – Data sources and definitions

Our data and results can be viewed at http://gennaro.zezza.it/files/abz

Code	Variable	Definition	Avail.	Source
POP	Population, total. Log transformation	Total population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship--except for refugees not permanently settled in the country of asylum, who are generally considered part of the population of their country of origin. The values are midyear estimates.	1975-2013	UN-PD
REMOTE	Distance from main world markets – adjusted for landlockedness	Remoteness is measured as a weighted average of the distance to the main world markets. Weights are given by the minimum average distance to a significant fraction of the world market and choose the threshold of one third. The *minimum distance* is the minimum average distance to reach a given size of the world markets. It fits requirements, because it is an exogenous measure and weights differ for each country. Guillaumont (2007b)	1975-2013	CEPII; UNSD-NA
EXPCON	Concentration and diversification indices of merchandise exports and imports by country	Export concentration measures the degree of market concentration. We use the standardized Herfindahl-Hirschmann index published by UNCTAD. Values vary between 0 and 1, with 0 corresponding to absence of concentration (maximum diversification), 1 corresponding to maximum concentration.	1975-2013	UNCTAD Stat
AGRSH	Share of Agriculture, Forestry and Fishing in GDP	Calculated dividing the value added of agriculture, hunting, forestry and fishing by the total gross value added of all sectors in the economy	1975-2013	UNSD-NA
COAST	Share of population in low elevated coastal zones	Calculated by dividing the number of people living in areas contiguous to the coast with an elevation of less than five meters by the total population of the country	1990-2013	CIESIN
VICTIMS	Population affected by natural disasters	Total affected are people that have been injured, affected and left homeless after a disaster are included in this category.	1979-2013	EM-DAT
AGRINST	Instability of	Calculated by estimating the trend of agricultural production by a mixed-trend linear regression and	1980-2013	FAOSTAT

Code	Variable	Definition	Avail.	Source
	agricultural productions	using the standard deviation of the difference between trend and actual values as a measure of instability		
EXPINST	Instability of total exports	Instability of total exports measures the volatility of total exports of goods and services. It is a proxy for the risk of shocks in the exports revenues. Calculated by estimating the trend of export earnings by a mixed-trend linear regression and using the standard deviation of the difference between trend and actual values as a measure of instability	1990-2013	UNSD-NA
SURFACE	Surface area (sq. km). Logs	Surface area is a country's total area, including areas under inland bodies of water and some coastal waterways. Following the procedure in Feindouno-Goujon (2015) we chose a lower bound for surface at 1000sq.km, and an upper bound at 2.5 million sq.km. The final index is obtained from SURFACE = 100*(max(X)-X)/(max(X)-min(X)) where X is the log of the bounded surface, so that largest countries have a value of zero, and smallest countries a value of 100	1960-2016	WB-WDI
IMPCONC	Concentration index for imports	Import concentration measures the degree of market concentration. We use the standardized Herfindahl-Hirschmann index published by UNCTAD. Values vary between 0 and 1, with 0 corresponding to absence of concentration (maximum diversification), 1 corresponding to maximum concentration.	1995-2016	UNCTAD Stat
FDI	Foreign direct investment, net inflows (% of GDP)	Incoming FDI may help finance investment and growth, but reliance on FDI may increase the probability of being hit by an adverse financial shock. When net incoming FDI were negative, they have been set to zero. We assume that FDI affect both exposure and resilience	1970-2016	WB-WDI
AID	Official Development Assistance and Official Aid (% of GDP)	Net official development assistance (ODA) consists of disbursements of loans made on concessional terms (net of repayments of principal) and grants by official agencies of the members of the Development Assistance Committee (DAC), by multilateral institutions, and by non-DAC countries to promote economic development and welfare in countries and territories in the DAC list of ODA recipients. It includes loans with a grant element of at least 25 percent (calculated at a rate of discount of 10 percent). Net official aid refers to aid flows (net of	1960-2015	WB-WDI

Code	Variable	Definition	Avail.	Source
		repayments) from official donors to countries and territories in part II of the DAC list of recipients: more advanced countries of Central and Eastern Europe, the countries of the former Soviet Union, and certain advanced developing countries and territories. Official aid is provided under terms and conditions similar to those for ODA. We assume that AID affect both exposure and resilience		
FDEBT	Net flows on external debt, public and publicly guaranteed (%of GDP)	Public and publicly guaranteed long-term debt are aggregated. Public debt is an external obligation of a public debtor, including the national government, a political subdivision (or an agency of either), and autonomous public bodies. Publicly guaranteed debt is an external obligation of a private debtor that is guaranteed for repayment by a public entity. Net flows (or net lending or net disbursements) received by the borrower during the year are disbursements minus principal repayments. Long-term external debt is defined as debt that has an original or extended maturity of more than one year and that is owed to nonresidents by residents of an economy and repayable in currency, goods, or services. Data are in current U.S. dollars, scaled by GDP in current U.S. dollars. We set to zero negative values, before computing the index.	1970-2016	WB-WDI
DEBTS	Debt service on external debt, public and publicly guaranteed	Public and publicly guaranteed debt service is the sum of principal repayments and interest actually paid in currency, goods, or services on long-term obligations of public debtors and long-term private obligations guaranteed by a public entity. Data are in current U.S. dollars, scaled by GDP in current U.S. dollars. We chose to apply an upper bound to 200 percent of GDP	1970-2016	WB-WDI
GFCF	Gross fixed capital formation	Gross fixed capital formation includes land improvements (fences, ditches, drains, and so on); plant, machinery, and equipment purchases; and the construction of roads, railways, and the like, including schools, offices, hospitals, private residential dwellings, and commercial and industrial buildings. According to the 1993 SNA, net acquisitions of valuables are also considered capital formation. Data are in current U.S. dollars, scaled by GDP in current U.S. dollars.	1960-2016	WB-WDI
CC	Control of Corruption	Control of Corruption captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites	1996-2016	WB-WGI

Code	Variable	Definition	Avail.	Source
		and private interests. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5.		
GE	Government effectiveness	Government Effectiveness captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5.	1996-2016	WB-WGI
PS	Political Stability and Absence of Violence/ Terrorism	Political Stability and Absence of Violence/Terrorism captures perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including politically-motivated violence and terrorism. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5.	1996-2016	WB-WGI
RL	Rule of Law	Rule of Law captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5.	1996-2016	WB-WGI
RQ	Regulatory Quality	Regulatory Quality captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5.	1996-2016	WB-WGI
VA	Voice and Accountability	Voice and Accountability captures perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately	1996-2016	WB-WGI

Code	Variable	Definition	Avail.	Source
		-2.5 to 2.5.		
GDPPC	GDP per capita	GDP per capita, PPP adjusted, in constant 2011 international dollars	1990-2016	WB-WDI

Legenda:

CEPII: Centre d'Etudes Prospectives et d'Information Internationales

CIESIN: Center for International Earth Science Information Network at Columbia University

EM-DAT: Emergency Disaster Database

FAOSTAT: Faostat Database

UNPD: United Nations – Population Division

UNSD-NA: United Nations Statistics Division – National Accounts Main Aggregate Database

Note: all EVI indicators can be downloaded from http://byind.ferdi.fr/en/evi

WB governance indicators are available from http://info.worldbank.org/governance/wgi/

Figures

Figure 1. Correlation between the EVI and the EVI-E indices

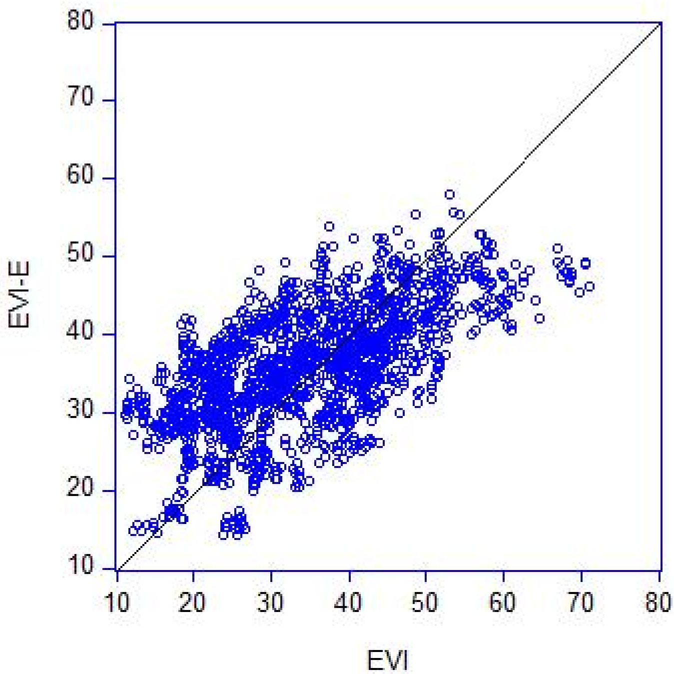

Figure 2. Frequency distribution of EVI and EVI-E

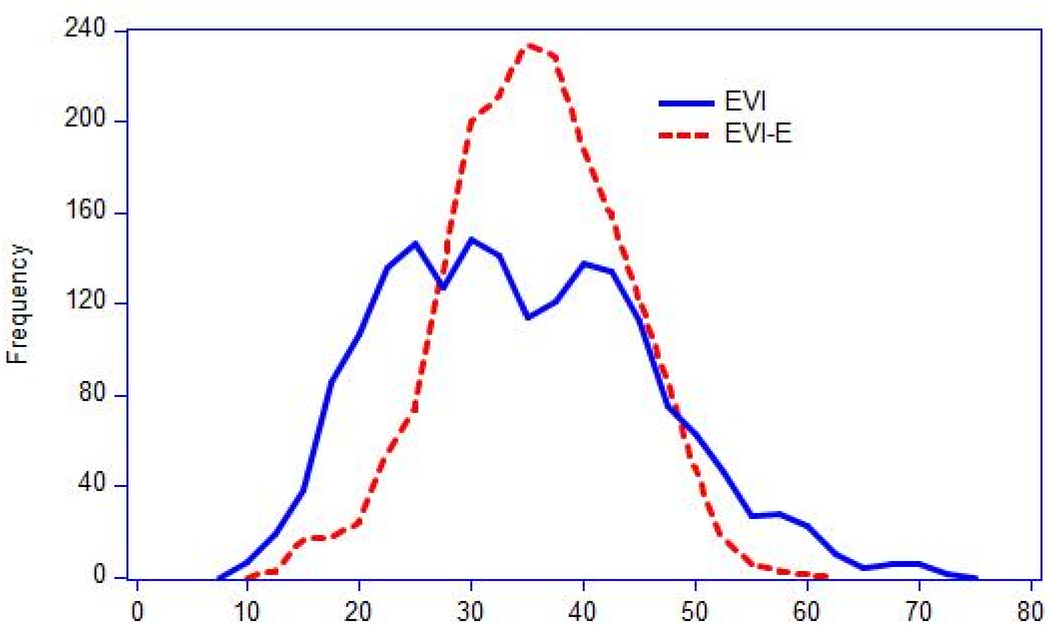

Figure 3. EVI and EVI-E over time for all countries.

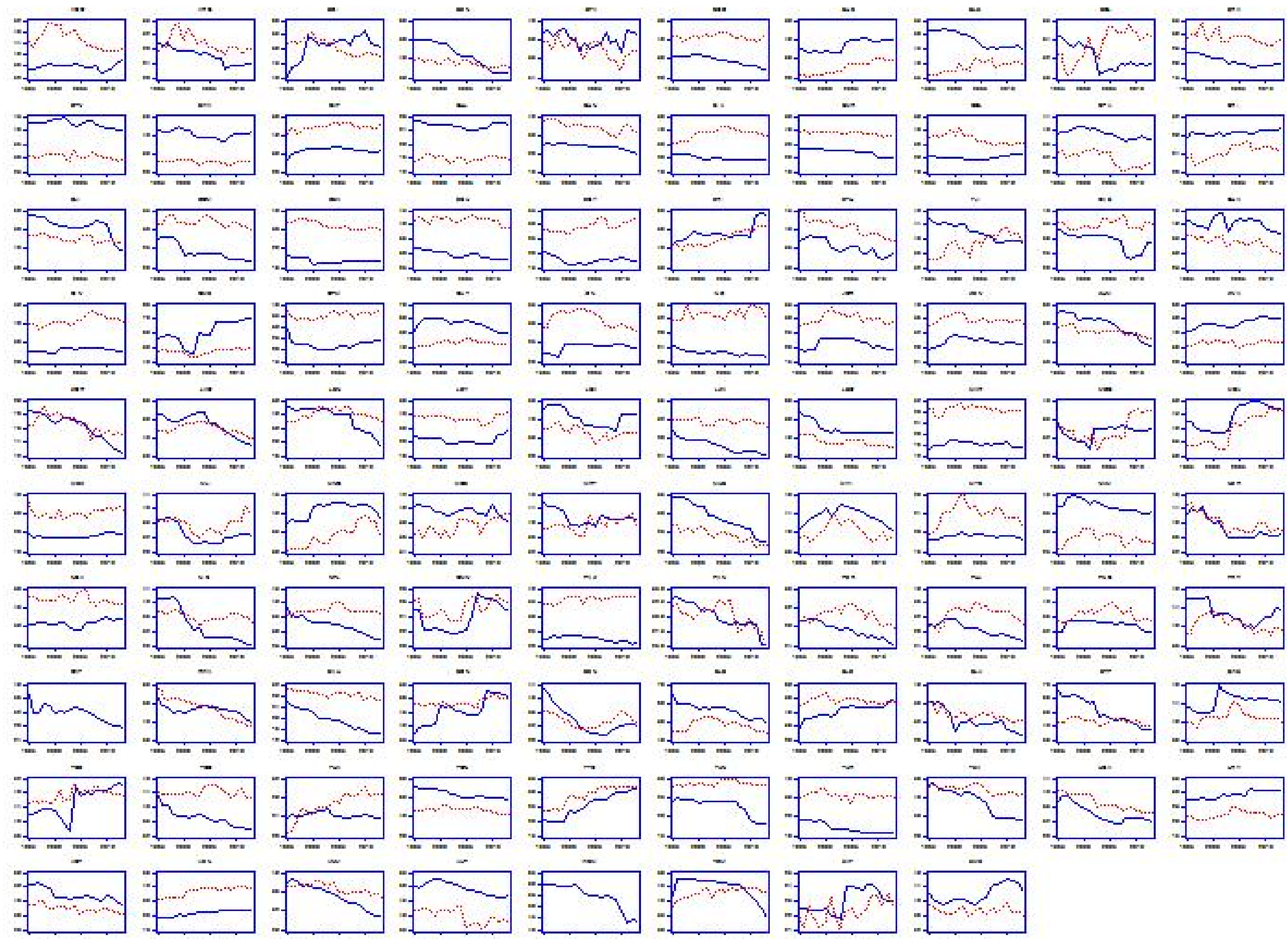

Figure 4. Change over time of the Remoteness sub-index

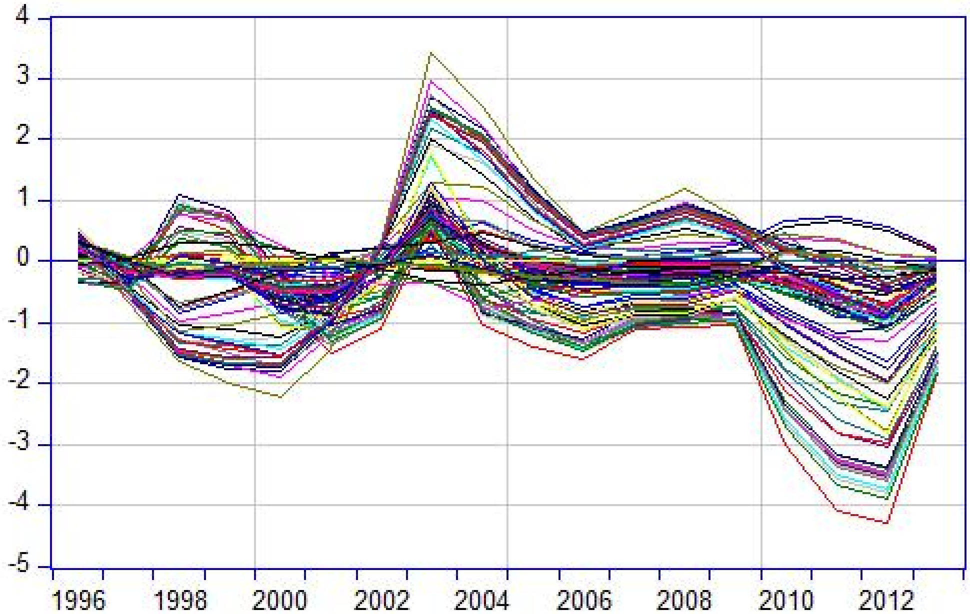

Figure 5. Causal model representation or *path diagram*

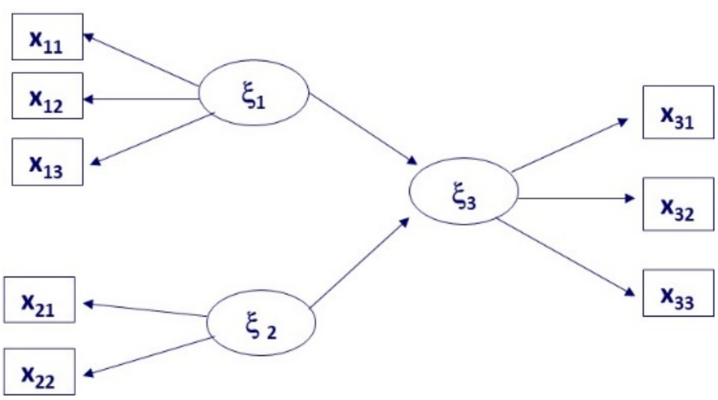

Figure 6. The EVI Path Model

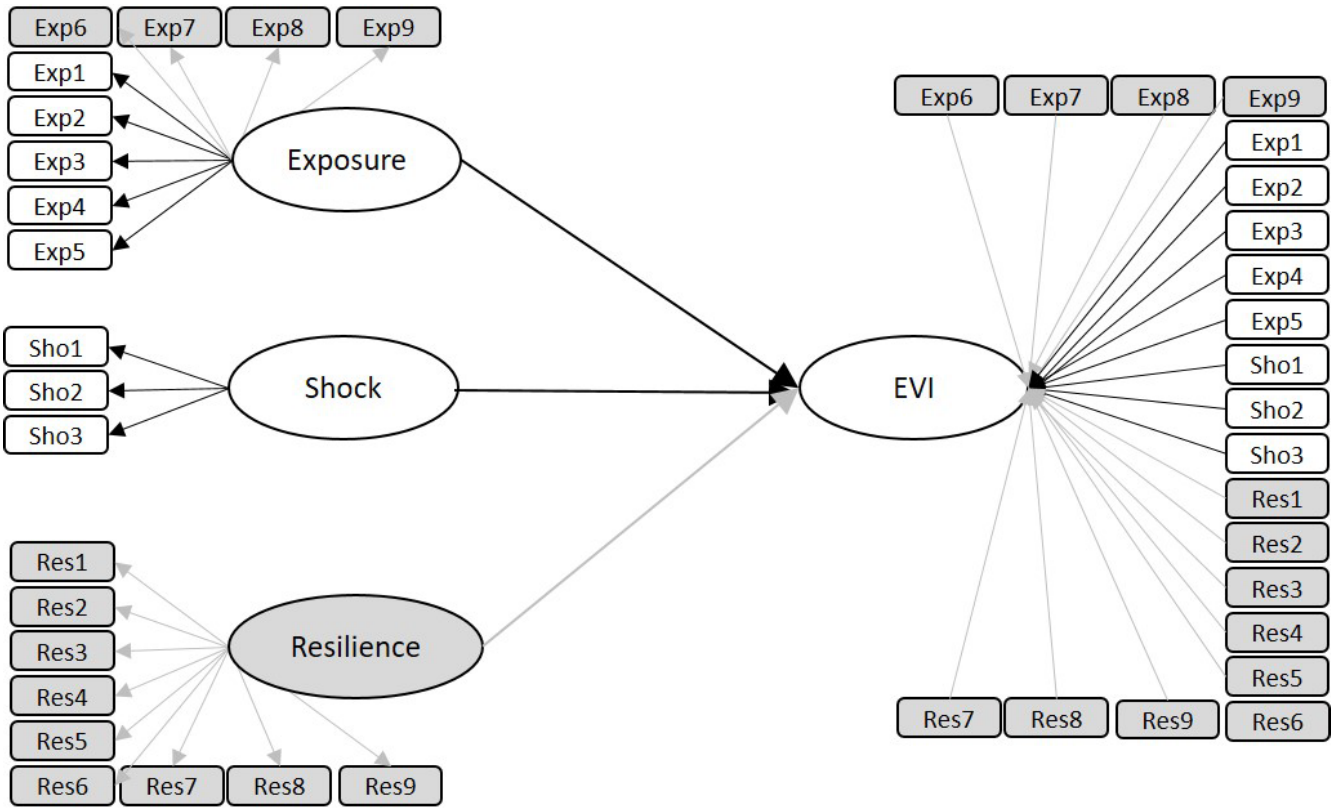

Figure 7. Outer weight of manifest variables