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STRUCTURAL VULNERABILITY AND FRAGILITY: AN ASSESSMENT BASED ON COMPOSITE INDICATORS

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RESUME

Les concepts de vulnérabilité et de fragilité sont au cœur du débat sur la définition et la mise en œuvre des objectifs de développement durable. Cette thèse propose des outils pour évaluer la vulnérabilité structurelle et la fragilité sous divers aspects: économique, social et environnemental. L'approche proposée pour appréhender ces concepts repose sur la construction et le raffinement d'indicateurs composites. Elle est composée de quatre chapitres.

Dans le Chapitre 1, nous construisons des séries rétrospectives de l'indice de vulnérabilité économique (EVI) proposé par le Comité des politiques de développement (CDP) des Nations Unies pour l'identification des Pays les Moins Avancés (PMA). Il ressort de nos analyses que la vulnérabilité économique structurelle des PMA reste supérieure à celle des non-PMA. De plus, en se focalisant sur le cadre africain, nous montrons que les Etats fragiles sont économiquement plus vulnérables que les Etats non fragiles et que, la différence entre les deux groupes de pays est essentiellement due à l'ampleur des chocs. Enfin, en utilisant une approche basée sur la stochastique dominance et un horizon temporelle de cinq ans pour évaluer dans le temps l'évolution de l'EVI et de ses principales composantes, nous observons qu'il n'y a pas de baisse significative de l'EVI et de ses principales composantes au premier ordre. En revanche, une diminution généralisée peut être conclue au second ordre.

Le Chapitre 2 est consacré à la question de la résilience structurelle à travers un indice de capital humain (HAI). Nous commençons par présenter les séries rétrospectives du HAI et de

ses composantes, pour lesquelles des outils économétriques ont été utilisés pour imputer de manière consistante les données manquantes. En second lieu, nous analysons la dynamique du HAI en évaluant la contribution de chacune de ses composantes. Enfin, nous débattons de la problématique cruciale de la pondération. En prouvant que la structure de corrélation entre les indicateurs est étroitement liée à la question de la pondération, nous proposons un nouveau système de poids basé sur le rapport de corrélation et la linéarité (ou non linéarité) entre les composantes.

Le Chapitre 3 a trait à la vulnérabilité au changement climatique. Après avoir mis en lumière le flou existant autour de la définition et de la mesure de la vulnérabilité au changement climatique, nous construisons un indice composite appelé « Physical Vulnerability to Climate Change Index (PVCCI) ». Cet indice repose uniquement sur les caractéristiques physiques du changement climatique et est indépendant des politiques présentes et futures des pays. Il a donc vocation à être utilisé pour l'allocation internationale des ressources. Nous expliquons la méthodologie spécifique utilisée pour la construction du PVCCI et présentons les résultats pour les pays en développement. Pour finir, le Chapitre traite de la relation entre conflits civils et vulnérabilité au changement climatique, mesurée ici par le PVCCI. Nous montrons que le PVCCI a un effet positif et significatif sur les conflits. Cet effet est particulièrement plus significatif lorsque nous prenons en compte l'incidence des conflits. Mais une fois que le conflit est mesuré par son déclenchement (« onset »), la relation entre le PVCCI et les conflits civils se trouve affaiblie.

Le Chapitre 4 part du constat que les pays africains accusent encore un retard dans l'attraction des investissements directs étrangers (FDI). Nous soupçonnons les facteurs de vulnérabilité économique structurelle, mesurée par l'EVI, d'être en partie responsables du manque d'intérêt relatif des investisseurs étrangers à l'égard de l'Afrique. Nous estimons un modèle spatial à correction d'erreur sur la période 1980-2010 pour évaluer les relations dynamiques entre les IDE et ses déterminants, y compris l'EVI en Afrique. Notre analyse révèle qu'à long terme, il existe une relation négative et significative entre les IDE et l'EVI. Les résultats suggèrent également qu'un EVI élevé dans les pays voisins a un impact négatif sur les IDE du pays hôte. Pour finir, nous montrons que la vulnérabilité économique structurelle joue un rôle important dans l'explication de l'écart en termes d'IDE entre les pays africains à faible revenu et les pays africains à revenu intermédiaire. La part de

l'agriculture, de la foresterie et de la pêche dans le Produit Intérieur Brut (PIB) apparait comme le principal facteur contribuant à cet écart.

Mots clés : Vulnérabilité ; Fragilité ; Capital humain ; Développement durable ; Séries chronologiques; Imputations ; Composite ; Vérification des hypothèses ; Etudes comparatives de pays ; Changement climatique; Conflits civils; Investissement direct étranger; Modèle spatial à correction d'erreur ; Cointégration.

Codes JEL : C21; C43; C82; F21; I15; I25; O15; O15; O57; Q01; Q34; Q54.

SUMMARY

Vulnerability and fragility are at the heart of the global debate arising from the definition and implementation of the sustainable development goals. This PhD dissertation offers enhanced tools to assess structural vulnerability and fragility from various aspects: economic, social, and environmental. The proposed approach for apprehending these concepts is based on the construction and refinement of composite indicators. It is divided into four chapters.

In Chapter 1, we build the retrospective series of the economic vulnerability index (EVI), proposed by the United Nations' Committee for Development Policy (CDP). Some choices and measures are discussed, such as the methodology used to calculate the instabilities of exports and agricultural production. From our analyses, it appears that the structural economic vulnerability of LDCs is still higher compared to non-LDCs. As well, focusing on the African context, we show that fragile African states are economically more vulnerable than non-fragile African states, and the difference between the two groups of countries seems to come from the difference in the magnitude of shocks. Finally, employing a stochastic dominance approach and using a five-year testing horizon to assess the evolution of the EVI and its main components over time, we observe that there is no real decline of the EVI and its main components at the first order sense. But, an overall decrease can be concluded at the second order sense of dominance.

The second chapter focuses on the issue of structural resilience through the Human Assets Index (HAI), another index designed by the UN-CDP for identification of LDCs. We start with a presentation of retrospective series of the HAI and its components, for which, to a limited extend, we have used econometric tools to consistently impute missing data. Secondly, we analyze the HAI's dynamics by assessing the contributions of each component to this. Finally, we debate about the choice of equal weighting for the four components in the HAI. Taking into account the fact that the correlation between indicators is closely linked to the issue, we propose a new scheme pattern based on the correlation ratio and linearity (or nonlinearity) dependence between components.

The third chapter is devoted to the climate change vulnerability. We design a composite indicator called "Physical Vulnerability to Climate Change (PVCCI)". This indicator based only on the physical characteristics of climate change is independent of present and future country policy, and aims to be used for international allocation of resources. After explaining the specific methodology used to build the PVCCI and presenting the results for developing countries, we investigate the relationship between civil conflict and vulnerability to climate change measured here by the PVCCI. We show that, the PVCCI has a positive and significant effect on civil conflict. This effect is particularly relevant when the conflict is proxied by incidence. But once the conflict is measured by onset, we notice a weakness in the relationship between the PVCCI and civil conflict.

The starting point of the fourth chapter is that African countries are still lagging behind when it comes to attracting Foreign Direct Investments (FDI). We suspect the structural economic vulnerability, measured by the Economic Vulnerability Index (EVI), in part, responsible for the relative lack of interest of foreign investors towards Africa. We estimate a spatial error correction model during the time period from 1980 to 2010 to assess the dynamic relationships between FDI and its determinants including EVI in Africa. Our finding reveals that in the long run, there is a significant negative relationship between FDI and EVI. The results also suggest that a high EVI in neighboring countries negatively affects the amount of FDI into a host country. Later on, we also observe that structural economic vulnerability plays an important role in explaining the FDI gap between African Low-Income Countries and African Middle-Income Countries. The share of agriculture, forestry and fishery in Gross domestic products (GDP) appears as the strongest contributing factor to this difference.

Keywords: Vulnerability; Fragility; Human capital; Sustainable development; Historical series; Imputation; Composite; Hypothesis testing; Comparative studies of countries; Climate change; Civil conflict; Foreign direct investment; Spatial Error Correction Model; Cointegration.

JEL codes: C21; C43; C82; F21; I15; I25; O15; O15; O57; Q01; Q34; Q54.

INTRODUCTION

Over the last few decades, vulnerability assessment has become a buzzword in international development policy. Vulnerability to shocks is increasingly perceived as a serious threat to the objective of sustainably eradicating poverty because it is shown to matter for growth and poverty reduction. Large shocks may result in a destruction of country income and wealth and an increase in poverty. Since each country has its own vulnerability, anti-poverty objectives and linkages must be rooted in a solid national strategy, where objectives should be set within a clear hierarchy. The achievement of certain goals contributes automatically to the achievement of the others. Addressing vulnerability requires identification of the sources and determinants of vulnerability, including a conceptual clarification with respect to its broadening scope. Therefore, particular attention should be paid to economic, social and environmental dimensions of vulnerability. These dimensions of vulnerability are at the heart of the 2030 sustainable development agenda.

Assessing vulnerability is a powerful analytical tool for examining a number of development issues raised by the developing countries' harmful external environment. The concept of vulnerability is however often confusing because of the divergent meanings attached to it by different researchers. The development and research communities have proposed a myriad of definitions of vulnerability that further blur the definitional consensus. In the most general sense, vulnerability can be defined as the likelihood of a system being negatively affected by some sort of perturbation or sudden shock going beyond the normal range of variability[1]. At first glance, it seems reasonable to identify vulnerability as a condition that takes into account both sides of risks: an external side of risks to which countries are subject (exposure to shocks and their magnitude); and the internal side linked to the ability of countries to mitigate shocks (resilience). But the risk to be durably affected by exogenous shocks depends on the size of the shocks and on the exposure to the shocks. This approach of vulnerability is close to Guillaumont's[2] dynamic definition of vulnerability as "the risk that economic growth of a country is markedly and extensively reduced by shocks".

As the world moves quickly, it is fundamental to know as soon as possible when things go wrong. Against this background, researchers, practitioners and policy need more effective instruments to identify and monitor situations of vulnerability, and consequently to make context-specific responses possible. In this regard, the last few decades have witnessed a proliferation of indicators across various dimensions of vulnerability that should not be tackled in binary terms but rather as a continuum. Since vulnerability is a complex and multifaceted concept, the assessment of vulnerability requires holistic measures using composite indicators.

The concept of composite indicator was introduced in 1990s to capture the complexity and multidimensionality of a range of development issues. Since then, international organizations like United Nations and the World Bank have developed composite indicators including the Human Development Index (HDI), the Gender Empowerment Measure (GEM), the Doing Business (DB) indicators, and the Worldwide Governance Indicators (WGI). The contributions of think-tanks and consultancies are also significant. Freedom House, the Economist Intelligence Unit, and Transparency International have produced indices such as the Political Rights and Civil Liberties, the Quality of Life Index, and the Corruption Perception Index[3].

Within the framework of assessing vulnerability, composite indicators offer several advantages. Producers tend to present a range of possible uses for vulnerability indices, mainly articulating around:

- Policy guidance

[1] Gallopin (2006), *Linkages between vulnerability, resilience, and adaptive capacity*.
[2] Guillaumont (2009), *Caught in a trap. Identifying the least developed countries.*
[3] Foa and Tanner (2015), *Methodology of the Indices of Social Development.*

- Public awareness
- Assessment of vulnerability and evaluation of national policy framework
- Research
- Risk analysis

Composite indicators are based on sub-indicators that may have no common meaningful of measurement. Technically, composite indicators are mathematical combinations of a set of individual indicators that represent dimensions of a concept whose description is the objective of the analysis[4]. A typical composite indicator CI is built as follows:

$$CI = \sum_{i=1}^{n} w_i x_i \qquad (1)$$

Where x_i is a normalized variable, w_i is the weight attached to x_i. $\sum_{i=1}^{n} w_i = 1$ *and* $0 \le w_i \le 1$, $i = 1,2,...,n.$

Constructing a composite indicator is a complex task that involves several alternatives and every step increases the probability of uncertainty and measurement error. The debate within the scientific community seems to indicate that there is not a composite indicator universally valid for all areas of application. Its validity depends on the strategic objectives of the research and the choice of a reliable theoretical framework, the selection of the more representative indicators and their treatment in order to compare and aggregate them.

Specifically, from the formula of composite indicator presented above, it is clear that normalization and weighted summation (aggregation) of the normalized variables are the two main steps in the process of building composite indicators. The purpose of normalization is to reduce the measurements to a standard scale, which helps to avoid the dominance of extreme values in a data and partially corrects data quality problems. Various normalization methods[5] exist in the literature, among which stand out z-score or Gaussian normalization, min-max normalization, distance to reference normalization or Denominator-Based Weight (DBW) normalization, indicators above or below the mean, proportionate

[4] See Saisana and Tarantola(2002), *State-of-the-art report on current methodologies and practices for composite indicator development.*

[5] See OECD (2008), *Handbook on Constructing Composite Indicators: Methodology and user guide.*

normalization and so on. In this illustration, the two most used approaches are min-max normalization and z-score with the advantages and disadvantages of both.

The min-max technique is by far the most widely used method, especially in the standardization of internationally oriented indicators such as the HDI. It rescales data into different intervals based on minimum and maximum values. The advantage of this method is that boundaries can be set and all indicators have an identical range $[0,1]$. However, the normalized values do not maintain proportionality, and the difference in variance is not fully eliminated. This type of normalization does not imply any standardization of different variables, which hence have different means and variances in general.

A popular alternative to the min-max normalization is given by the z-score normalization. Z-score normalization is used, for example, to establish the Knowledge Economic Index from the World Bank Institute and the Child Growth Standards Index from the World Health Organization. It consists of subtracting the mean from an indicator value and then dividing by its standard deviation. Thus, standardized variables have the same mean and variance, removing one source of heterogeneity among variables. The main advantage of this technique is that it provides no distortion from the mean, adjusting for different scales and variance. It should be preferred when extreme values exist in the dataset since such values are taken into account in a manner that does not distort their impacts on a composite indicator. However, z-score normalization does not enhance comparison across the same aggregate indicator over the years if the mean and variances change over time. Additionally, practitioners have observed that the technique of z-score does not fully adjust for outliers and may be expected not to work well, particularly when the distribution is much skewed or long tailed.

Once the variables are normalized, they need to be combined in a meaningful way. This crucial phase of the construction of the composite indicators gives rise to two interrelated aspects: the assignment of weights to the components when combining them and the choice of the synthetic function. Both aggregation and weighting methods need to be founded in theory. The two aspects have a significant impact on the outcome of the composite index and can dramatically change the ranking of a particular unit[6].

The trade-off between components of a composite index is not always desirable. The weighting system which is applied needs to be transparent, and may be applied to reflect the underlying data quality of the indicators by assigning less weight to those variables where data problems exist. A number of weighting techniques exist. Some are derived using statistical methods, such as factor analysis (e.g., Principal Components Analysis); others from participatory methods, like analytical hierarchy process. Most of the time though, the choice of weights appears to be ad hoc and arbitrary, depending on expert opinion to better reflect policy priorities or theoretical factors. Also for simplicity sake, researchers apply neutral approach based on equal weights to all underlying components, suggesting that there is no hierarchy between them.

How are the scores of the components combined into an overall score? The choice of aggregation method depends on the aim of the work and on the type of “users” (researchers or the general public). Most indices use linear aggregation methods based on the simple addition of equally weighted components. This type of aggregation is considered to be simple because it uses an easily understandable mathematical function. Moreover, it assumes perfect substitutability between all components: poor score in one component can be compensated by sufficiently high scores of others components. But this assumption may suffer from its weak theoretical justification particularly when some components are fundamental. As a result, an increasing number of composite indices are made using geometric aggregation, which assumes a multiplicative relationship of the variables rather than an additive, as stated in the underlying assumption of linear aggregation. Geometric aggregation is partially compensable, because it rewards more countries with higher scores[7] or penalize low values. By way of illustration, the couples $\{50,50\}$ and $\{70,30\}$ have the same score (50) using linear aggregation while the scores become 50 and 46, respectively with the

[6] The rules for combining indicators are well documented in the Handbook on Composite Indices from OECD (2008).

[7] The non-compensatory approach is represented by the Multi-Criteria Analysis (MCA). But the main drawback of it is the difficulty in computing when the number of countries is high.

Geometric aggregation is possible for strictly positive data. But due to the chosen normalization method, it may not be feasible. One of the best ways of dealing with this situation is the use of quadratic aggregation that combines geometric and linear aggregation properties.

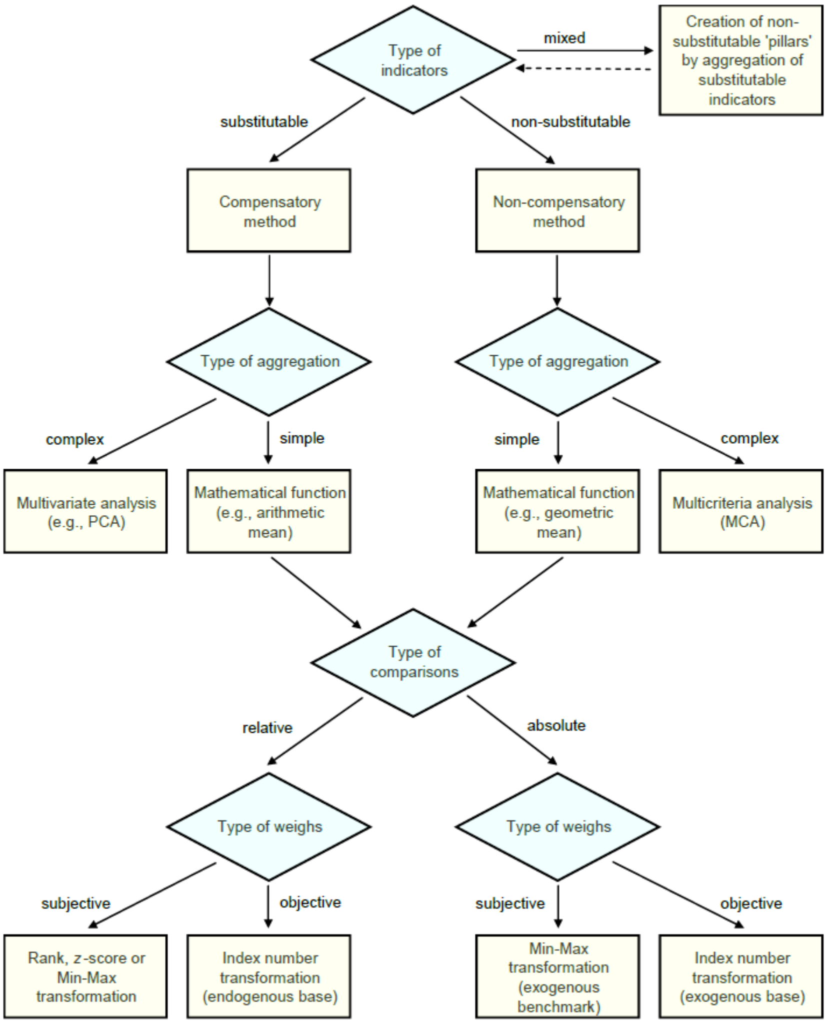
use of geometric aggregation. This means that the latter couple is penalized for the imbalance in its score. Hence countries with low scores should prefer a linear rather than a geometric aggregation.

In light of the above, what decision rules should be applied for composite indices construction? It appears that no universal method exists. The construction of composite indices is much determined by both formal and heurist elements, and incorporates some expert knowledge on the phenomenon. In order to obtain reliable results, one can use objective and right methodology by choosing the scheme proposed by Mazziota and Pareto[8]. Figure 1 outlines these general guidelines to be followed in the construction of composite indicators. But it is difficult in practice to strictly follow this step-by-step approach.

That being so, measuring vulnerability across countries may at first sight seems a purely academic exercise, which is a prerequisite for adequately dealing with fragile and vulnerable countries. Indeed, if they are reliable, vulnerability indices could be of use for development policy as a tool particularly for determining which countries need more assistance from the international community. To this end, vulnerability indices should be primarily conceived as a criterion of aid allocation, and live up to the donors' expectations. This implies that vulnerability indices can have direct repercussions on people through resource allocation.

[8] Mazziota and Pareto (2013), *Method for Constructing Composite Indices: One for All or All for One.*

Figure 1: Decision chart for the construction of a composite indicator



Source: Mazziota and Pareto (2013)

This thesis offers enhanced tools to assess vulnerability from various aspects: economic, social, and environmental. The proposed approach for apprehending the concept is based on the construction and refinement of composite indicators. It is organized in four chapters. The two first chapters are intended to present and propose a further analysis of two of the three indicators used by the United Nations' Committee for Development Policy (UN-CDP) for identification of the Least Developed Countries (LDCs).

In the first chapter, we have constructed the retrospective series of the Economic Vulnerability Index (EVI) over the 1990—2013 period. Diversification of the economy is at the heart of the EVI, and a deliberate and effective policy of diversification sources of income determined on a national basis is a good way to cope with the risk of both commodity price fluctuations and poor harvests. The EVI is used for identification of LDCs, and as an allocation criterion for smoothing their graduation. It focuses on the structural characteristics of economic vulnerability. Overall, we show that the structural economic vulnerability of LDCs is still higher compared to non-LDCs. But employing a stochastic dominance approach to study the evolution of the EVI and its main components over time using a five-year testing horizon, we observe that there is no real decline of the EVI and its main components at the first order sense. On the other hand, an overall decrease can be concluded at the second order sense of dominance.

The second chapter focuses on the issue of structural resilience through the Human Assets Index (HAI), another index designed by the UN-CDP for identification of LDCs. We start with a presentation of retrospective series of HAI and its components, for which, to a limited extend, we have used econometric tools to consistently impute missing data. Secondly, we analyze the HAI dynamics by assessing the contributions of each component to this. Finally, we debate about the choice of equal weighting for the four components in the HAI. Taking into account the fact that the correlation between indicators is closely linked to the issue, we propose a new scheme pattern based on the correlation ratio and linearity (or nonlinearity) dependence between components.

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CHAPTER 1: STRUCTURAL ECONOMIC VULNERABILITY

I - Introduction

There is growing recognition and understanding that vulnerability should be a significant concern of public policies. At the same time, in response to this increased interest amongst development actors, researchers and policy makers, there has also been a sharp increase in the production of various indices which provide an overview of the vulnerability. Generally, when applied to both macro and micro level, vulnerability is the risk of being hampered by exogenous shocks, either natural (e.g., droughts) or external (e.g., fall in terms of trade) as a result of exposure to such shocks.

Economic vulnerability of developing countries has been an important issue in the development literature for around 50 years but its interest has been growing since the 1990s. The concept is well-documented in the literature and most of indices are not tackled in binary terms but rather as a continuum. Since the indices' objectives influence their contents, some dimensions included in the indices are unquestionably more critical than others, and the outcomes may be different from each other. Some economic vulnerability indices are based on a minimalist concept while others are more comprehensive. In general the indices capture structural conditions that expose countries to economic or financial shocks. But most of the indices also include the resilience of economies to these shocks which is more linked to current policy and less to structural factors.

In the early version of economic vulnerability index, applied to small islands, Briguglio (1992) associated vulnerability with three components i) exposure to external economic conditions measured by the ratio of imports and exports to GDP, ii) remoteness and insularity measured by the ratio of transport and freight costs to exports proceeds and iii) disaster proneness measured by disaster damage to GDP. In 1997, the author adjusted the index by adding three new variables (exports concentration, dependence on strategic imports and dependence on foreign sources of finance) but excluded the variable measuring proneness to natural disasters[9]. Briguglio and Galea (2003) presented another index of economic vulnerability for 117 countries, of which 23 are small states. Their index contains four components: economic openness (exports and imports as a ratio of GDP), dependence on a narrow range of export of goods and services, dependence on strategic imports (average imports of commercial energy as a percentage of domestic energy production) and peripherality (ratio of transport and freight costs to trade). Atkins et al. (1998; 2000) considered the GDP volatility as a manifestation of economic vulnerability. To construct their index, they regressed GDP volatility on three explanatory variables: economic openness measured by exports of goods and non-factor services as a percentage of GDP, lack of exports diversification and impact of natural disasters (measured as proportion of the population affected by such events over a long period of time). The final index is an average of the three explanatory variables weighted by their respective coefficients obtained from the estimated equation. The index covers 111 countries.

Liou and Ding (2004) used factor analysis to construct a vulnerability index from a set of six indicators: domestic economic scale, international trade capacity, development level, degree of output volatility, inflows of external resources, and institutional capacity. According to the authors, a region's income volatility reflects an area's income "riskiness"; they argued that larger economies are prone to being less vulnerable. The Commonwealth Vulnerability Index (CVI) is based on three indicators: export dependency, export diversification and susceptibility to natural disasters (Easter, 1998). Turvey (2007) assessed the economic vulnerability through the country's exposition to human and physical pressures, risks and hazards in temporal and spatial contexts. Four indicators were used by the author: i) a

[9] Prior to that, in 1995, Briguglio expanded his 1992's index to five structural factors: economic openness, export concentration, peripherality, dependence on strategic imports, and dependence on foreign sources of finance.

"peripherality" index as a proxy to measure remoteness and insularity, ii) a "coastal" indicator as a proxy for risk of flooding, iii) an "urbanization" indicator expressed as the proportion of population living in urban areas and iv) an indicator capturing the vulnerability to natural disasters expressed as a percentage of the population affected by natural disasters. The index was established for 100 countries and the author reached the conclusion that SIDS tend to be more vulnerable than larger countries: eight small island countries were among the nine most vulnerable countries[10]. In the same vein, examining the linkages between macroeconomic performance and natural disasters, Baritto (2008) proposed the Geographical Vulnerability Index (GVI). The author argued that nations that are highly impacted by natural disasters are also highly susceptible to economic and financial shocks[11]. He used the index proposed by Briguglio and Galea (2003) to which he included additional components such as poverty rate and the share of primary production in GDP. As a result, an economy that is more dependent on primary sectors such as agriculture is at a higher risk of being hampered by external shocks, given commodity price volatility. Adrianto and Matsuda (2004) also incorporated environmental variables into economic vulnerability indicators.

To construct a vulnerability index, a few studies used the approach based on the probit model, in the spirit of the literature on early warning system models (EWS). Dabla-Norris and Bal Gündüz (2014) developed an index which measures a country's vulnerability to sudden growth declines in the event of large exogenous shocks in low-income countries. A range of indicators[12] is examined to identify variables and thresholds to separate crisis from non-crisis cases. The same methodology was subsequently used by Easterly and Kraay (2000) and IMF (2011). Easterly and Kraay (2000) estimated a panel probit regression relating growth

[10] Many studies have highlighted the high vulnerability of small island economies (Briguglio, 2004; Adrianto and Matsuda, 2004; Méheux et al., 2006; Van der Velde et al., 2007; Logossah, 2007; Guillaumont 2008, 2010; Barnett and Campbell, 2010). There are a number of underlying causes: geographic features (small size, remoteness, exposure to major hazards, fragility of ecosystems,…), historical context (high dependence on the outside world, privileged and ongoing relationships with old political guardianships,…), the social situation (insecurity, difficult labour market conditions,…), the economic structure (tight local markets, low level of economic diversification,…).

[11] In Baritto (2008), the economic impact of natural disasters is measured by the ratio of economic losses to net capital formation.

[12] Various kinds of explanatory variables have been used in Dabla-Norris and Bal Gündünz (2014): the size and exposure of the shocks, majority of policy variables such as the rate of exchange (mis)alignment, the stock of external reserves, debt-to-GDP ratios, and the previous growth or the previous occurrence of crises.

downturns (negative growth rates) to a large set of structural variables in developing and advanced economies.

It results from the above that the key features of economic vulnerability indices are more structural and less related to current and future policies that tend to change more rapidly. It is in this sense that Guillaumont (2009), for his part, emphasized that the aim of measuring structural vulnerability is to capture the extent to which a country is intrinsically vulnerable, regardless of its current policies. He suggested that a clear distinction should be made between structural vulnerability and general vulnerability. While structural vulnerability includes those factors that are independent of a country's current political choices (such as population size and remoteness), general vulnerability also depends on the resilience of the country to the shocks, which is more associated to current policies. Being structural, vulnerability index does not change much from one year to the next. Therefore, an index is most useful to classify countries according to their frequency of shocks or exposure. If vulnerability is driven by country's structural characteristics, resilience can be seen as those appropriate policies that enable a country to cope with the effects of shocks. To some significant degree, the vulnerability of poor nations is structural: the structure of their economies is often dependent on physical and geographical characteristics, which increase the exposure from environmental hazards. Exogenous shocks explain to a large extent the agricultural and exports instabilities that these countries face. These aspects of vulnerability are at the heart of the Economic Vulnerability Index (EVI) designed by the United Nations' Committee for Development Policy (CDP). The index used for identification of the Least Developed Countries (LDCs), and as and aid-allocation criterion for smoothing their graduation, focuses on the structural characteristics of vulnerability.

Economic vulnerability indices refer to particular features of multivariate distributions, and statistical tests for differences in these distributions would be useful to establish whether trends in the indices reflect significant changes over time. To that end, making inference regarding various forms of stochastic dominance ordering plays an important role in the analysis. The concepts of first, second, and third order stochastic dominance (SD1, SD2, and SD3, respectively) are discussed by Mc Fadden (1989), Anderson (1996), Davidson and Duclos (2000), Barret and Donald (2003), Linton et al. (2005). Several tests for various forms of stochastic dominance (SD) are proposed. For example, Anderson (1996) constructed tests based on Wald statistics calculated from two independent samples and Davidson and Duclos (2000) proposed tests based on Wolak's (1989) test for inequality constraints. However their tests may not be consistent because the comparisons are made at a fixed number of arbitrarily chosen points. On the other hand, McFadden (1989) and Barrett and Donald (2003) considered Kolmogorov-Smirnov type tests that compare the objects at all points and showed the consistency of their tests. But their tests are conservative in the sense that the significance can be strictly less than the pre-specified significance level if the underlying data generating process is not on the least favorable points. Linton et al. (2005) instead used a subsampling method to construct the critical values and showed that their tests have asymptotically exact size on the boundary points in the null hypotheses. Linton et al. (2010) proposed a bootstrap testing procedure that is asymptotically similar over a large set of distributions in the boundary of the null hypothesis. Although their test is a significant advance in the inference literature on stochastic dominance orderings, simulation-based evidence suggests that it is conservative in finite samples on configurations in the boundary of the null hypothesis outside of the least favorable case.

We conduct pairwise SD comparisons over time for the retrospective series of the EVI and its main components. This exercise provides insight into whether there has been an overall decrease in the EVI and its main components. Similar works were conducted by Makdissi and Wodon (2004) to compare CO_2 emissions between 1985 and 1998, and found that there has been a first order dominance up to a level, but not for all levels of CO_2 emissions. They also found that there has been an overall increase in emissions and water pollution over a 13-year period. Recently, Pinar et al. (2013) considered a stochastic dominance approach for measured human development such as the official equally-weighted HDI and they assessed the evolution of the official equally-weighted HDI and its main components over time.

The plan of this chapter is as follows. Section 2 describes the United Nations CDP's economic vulnerability index (EVI), presents several insights emerging from analysis and shows the important implications for some categories of countries. Section 3 presents the construction methodology of the retrospective EVI and its components. Section 4 discusses the SD, the pairwise SD methodology from Barrett and Donald (2003), and presents the empirical results of over time comparisons of the EVI and its main components. Section 5 contains concluding remarks.

II - The CDP's economic vulnerability index (EVI)

II - 1) A brief history and description

Economic vulnerability has three main determinants: the size and likelihood of shocks, the exposure to these shocks, and the resilience or the capacity for reacting to them. The persistent vulnerability should be measured by an indicator that reflects the structural handicaps faced by a country. In this respect, only the first two determinants of the economic vulnerability depend on country structural features; by contrast, resilience relies on country current economic policy.

One of the indices designed for this purpose is the Economic Vulnerability Index (EVI) established by the United Nations Committee for Development Policy (UNCDP). The EVI is designed to reflect the risk associated with exogenous shocks. The index is already used for the identification of the least developed countries (LDCs) both for inclusion into and the graduation from the list of these countries[13]; it can also be used as criteria for the international allocation of concessional resources dedicated to economic development.

The EVI was originally established in 2000, and was revised in 2005 for the CDP's 2006 triennial review of the list of LDCs (see Appendix 1). Unchanged in the 2009 review, the index was slightly revised in 2011 for the 2012 review, and remains unchanged since then[14]. Since 2005 to present, the EVI has two main components, namely exposure to shocks and size of shocks. For the triennial reviews of the list of LDCs in 2006 and 2009, the index was made up of seven sub-components (the structure is shown in Figure 1):

- 4 sub-components reflecting exposure to shocks: population size, remoteness from world markets, merchandise exports concentration and share of agriculture, forestry and fisheries in GDP.

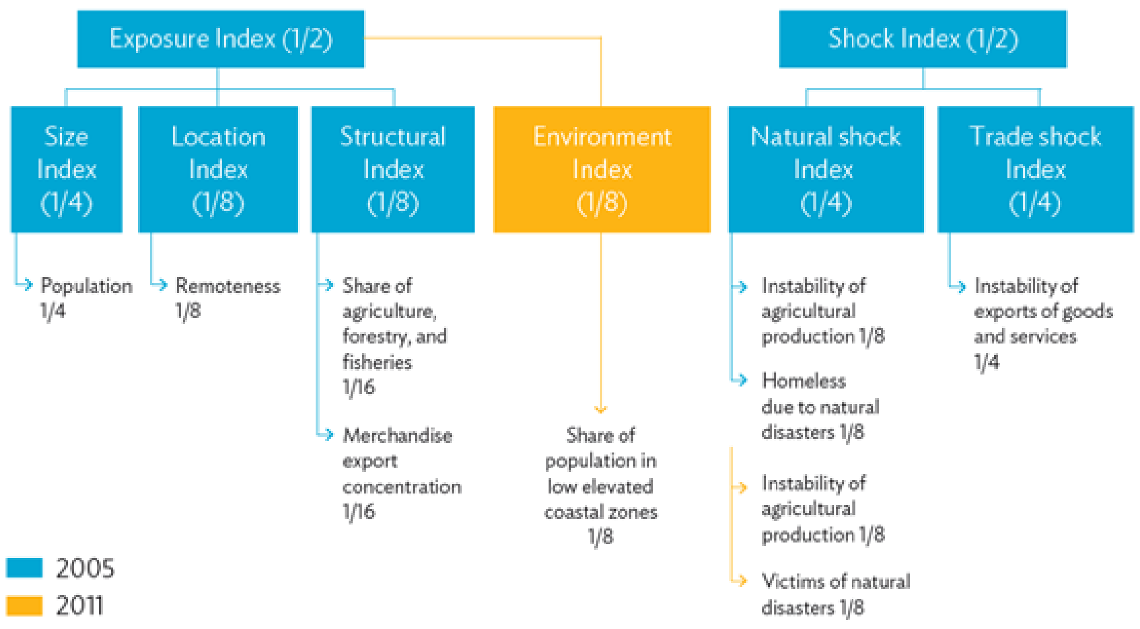
[13] The two other indices used to this end are GNI per capita and Human Assets Index (HAI). A country will qualify to be added to the list if it meets the admission thresholds on all three criteria and does not have a population greater than 75 million. GNI per capita's thresholds are $1,035 for inclusion and $1,242 for graduation. The HAI's thresholds are 60 for inclusion and 66 for graduation. The EVI's thresholds are 36 for inclusion and 32 for graduation.
[14] See history and details in UNDESA 2011 or Guillaumont 2009a, 2009b.

- 3 sub-components reflecting the intensity of recurrent shocks: the victims of natural disasters, the instability in the agricultural production and the instability of exports of goods and services.

The rationale for each sub-component is presented in Appendix 2.

As can be seen from Figure 1, the change made in 2011 is twofold. The first one was to modify the definition of one of the sub-components relating to natural hazards by replacing the homelessness due to natural disasters by the victims of natural disasters[15]. Althought this change may seem minor, it turns out that there is a low correlation of rank (23 %) between the two indices, whereas both come from the same data source (Cariolle et al., 2015). The second change was more important from a conceptual point of view: the component of exposure to shocks included a new environmental variable which is the share of population living in low elevated coastal zones (LECZ). The addition of this new sub-component is detrimental to the importance ascribed to the size of the population.

Figure 1: Structure of the Economic Vulnerability Index, 2005—2009 and since 2011



Source: united Nations Committee for Development Policy (UN-CDP).

[15] Victims of natural disasters are defined as people killed or affected (i.e. people requiring immediate food, water, shelter, sanitation or medical assistance).

II - 2) Rescaling or normalization of components

The components of vulnerability have not the same unit of measurement; the standardization of primary data is required. Thus, the EVI is a relative indicator in the sense that the score of each country for each component is positioned on a standardized scale whose extreme points reflect the minimum and the maximum recorded in the data. In other words, the primary data are transformed into indices and scaled between 0 and 100 through the min-max normalization procedure. The lower and upper bounds are provided in the Table 1. The scores of the EVI are ranked from the least vulnerable country (0) to the most vulnerable country (100). With the exception of the component of the size of population, primary variables are positively related to economic vulnerability. The formula to obtain the index is: $I = 100 * [(Value - Min)/(Max - Min)]$. As for the size of population that is negatively related to economic vulnerability, it is normalized as follows: $I' = 100 * [(Max - Value)/(Max - Min)]$ or $I' = 100 - I$.

II - 3) Aggregation and weighting of components

As shown in Figure 1, the principle of the EVI is to combine with equal weights a group of three sub-components which reflects the intensity of recurrent shocks, natural and external, and a group of four (or five sub-components) reflecting exposure to those shocks. The formula can be written as:

$$EVI = 0.5 * Exposure\ Index + 0.5 * Shock\ Index$$

Since the change made in 2011, the exposure index is the weighted average of five sub-components: $Exposure\ Index = 0.25 * Population\ Size + 0.25 * Remoteness + 0.25 * Share\ of\ population\ in\ low\ elevated\ coastal\ zones + 0.125 * Merchandise\ export\ concentration + 0.125 * Share\ of\ agriculure, forestry, and\ fisheries\ in\ GDP$

The latter two sub-components capture the structure of the economy, which can therefore be measured through an index as follows: $Structural\ Index = 0.5 * Merchandise\ export\ concentration + 0.5 * Share\ of\ agriculture, forestry, and\ fisheries\ in\ GDP$.

The shock index is the weighted average of three sub-components: $Shock\ index = 0.25 * Instability\ of\ agricultural\ production + 0.25 * Victims\ of\ natural\ disasters + 0.5 * Instability\ of\ exports\ of\ goods\ and\ services$.

The first two sub-components of the shock index make it possible to calculate an index of natural shocks as follows: $Natural\ shocks\ index = 0.5 * Victims\ of\ natural\ disasters + 0.5 * Instability\ of\ agricultural\ production$. The sub-component of the instability of exports of goods and services reflects trade shocks.

Table 1: Bounds and weights of sub-components in the overall index

Components	Sub-components	Minimum	Maximum	Weight in the EVI (in %)
Exposure Index	Population size	150000	100000000	12.5
	Remoteness from world markets	10	90	12.5
	Merchandise export concentration	0.1	0.95	6.25
	Share of population in LECZ	0	35	12.5
	Share of primary sector in GDP	1	60	6.25
Shock Index	Instability of agricultural production	1.5	20	12.5
	Instability of exports of goods & services	5	35	25
	Victims of natural disasters	0.005	10	12.5

Source: united Nations Committee for Development Policy (UN-CDP).

II - 4) Bias induced by the addition of the environmental element (LECZ)

To measure the risk associated with sea level rise, the UNCDP introduced a new environmental component in the EVI, which is the share of population living in low elevated coastal zone. While this variable is relevant for some groups of countries, such as small islands, it is less relevant for arid countries such as Sahelian countries in Africa. In fact, the idea behind the addition of this climate component is to take into account the vulnerability of small islands which, in light of the high proportion of their population living in low elevated coastal zones, are likely to be harmed by climate change more than other groups of countries, as a result of sea-level rise. However, the vast majority of African countries, for example, are more concerned with another type of climate phenomenon, namely aridity and the risk associated with desertification. In arid areas, projections point to droughts and longer dry periods, while coastal areas are often faced with sea level rise, leading to coastal erosion, flooding, and an increase in groundwater salinity and ecological degradation.

The addition of the part of the population living in LECZ unbalances the EVI by the increase of the vulnerability of the small islands and the decrease of the vulnerability of countries exposed to aridity and some small mountainous island states (see Guillaumont, 2014). Overall, beyond the bias caused by the population living in LECZ, the interest of adding a component of vulnerability to climate change in the EVI is highly questionable, especially if the index is used in a formula for the allocation of concessional resources. Indeed, the EVI captures a risk or handicap to economic growth while an indicator of vulnerability to climate change captures a very long-term risk.

II - 5) Towards a simpler, more consistent and more balanced EVI? *

Taking into account certain limits such as those mentioned above would make it possible to build a more relevant EVI. Thus, the bias caused by the addition of the climatic variable could be corrected in different ways.

A first possibility would be to ignore the climate component for obtaining an EVI close to that of the 2006-2009 triennial reviews[16]. The second option would be to replace the proportion of the population living in LECZ by the proportion of the population living in dry land zone (DLZ). This would take much more into account the specificity of some countries, especially most African countries. One could consider a third option that would consist to average two indicators: the share of the population living in LECZ and the share of the population living in DLZ. And finally, an even more balanced way would take the maximum of the two indicators.

In the exposure components, the presence of the size of the country (measured by the population) increases the vulnerability of small states that are characterized by the small population size. Moreover, the exposure related to export concentration only accounts for merchandise exports and excludes services trade. Indeed, a high concentration of services, in particular tourism, may be a source of vulnerability for SIDS that tend to be heavily dependent. However, it should be noted that, even without a conceivable synthetic index of

*This subsection is resulting from a far-reaching reflection to which I have contributed to Professor Guillaumont's side. It is discussed briefly in the Working Paper entitled "Vulnerability and Resilience: A conceptual Framework Applied to Three Asian Countries – Bhutan, Maldives and Nepal" and published on the Asian Development Bank's website.

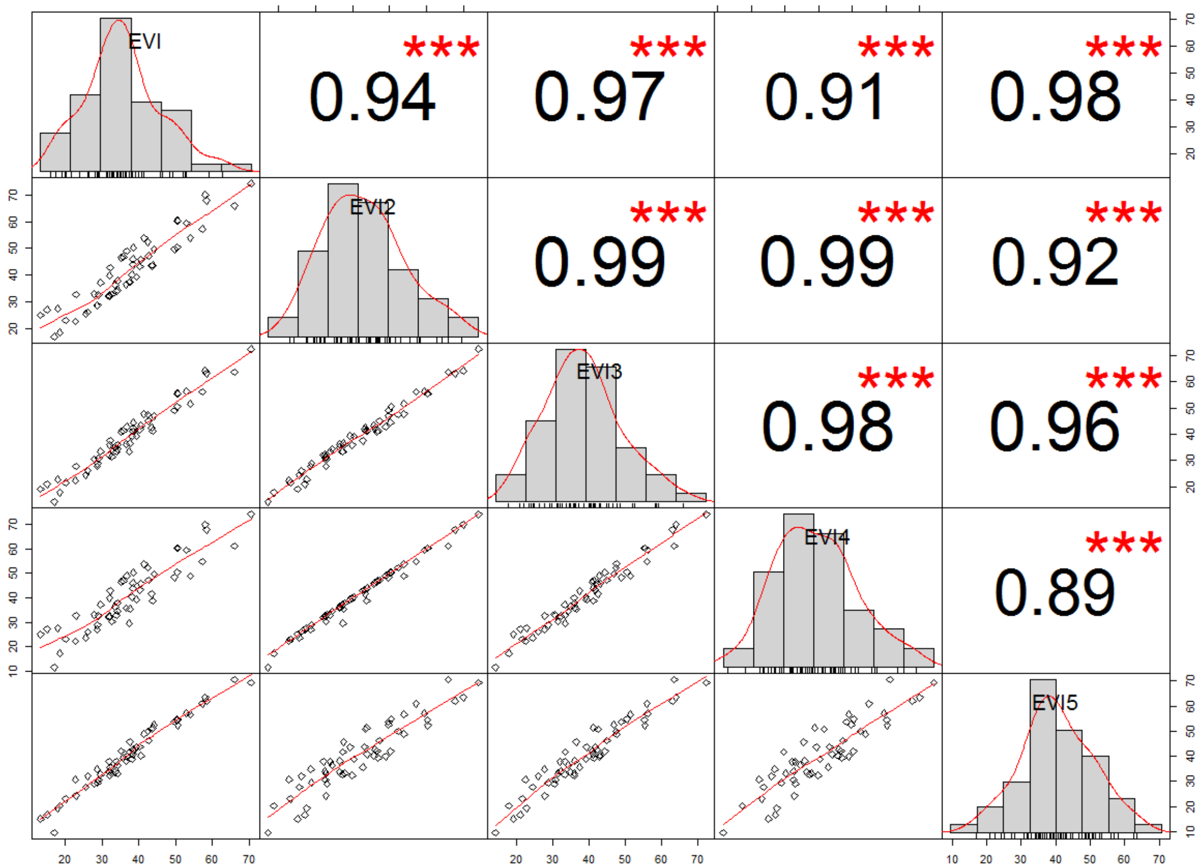
[16] By maintaining however the variable "Victims of natural disasters" introduced since the 2012 triennial review.

concentration of goods and services the vulnerability associated to services is captured in the EVI through the instability of exports of goods and services as a shocks index rather than as an exposure index (with a weight of 25 % of the EVI).

II - 6) Application of different options with the climatic variable of the EVI: sensitivity analysis for African countries

With the different options defined from the climatic variable (other variables remain unchanged), one could in addition to the official version of the EVI, define four other EVIs. Figure 2 shows the Spearman's rank between the various EVIs constructed with different options considered for the climate component. The different EVIs are highly correlated, indicating that the results remain close and do not move away from each other. This apparent low sensitivity can be attributed to two factors. The first factor is linked to the weight of the climate component (25% of the exposure sub-index and 12.5% of the global index), which does not allow the change made in the climatic component to have a significant impact on the overall EVI. The second factor concerns the "additivity" of the EVI's sub-components through the use of a weight arithmetic average as aggregation method. Indeed, the additive method allows the sub-indices to fully compensate each other. A zero score of the exposure index would still allow a country to reach 50 % of the EVI if the shock index is at its peak, i.e. 100. Therefore, a change in one of the exposure variables may have an impact on the exposure index but this effect is dampened or annihilated in the overall EVI due the aggregation method.

Figure 2: Correlations between different considered options of the EVI



Notes: EVI corresponds to the official EVI as established by the CDP since its 2012 version; EVI2 corresponds to the EVI whose climatic component is measured by the maximum between the part of the population living in low elevated coastal zones (LECZ) and the part of the population living in dry land zones (DLZ); EVI3 corresponds to the EVI whose climatic component is measured by the simple average of the part of the population living in LECZ and the part of the population living in DLZ; EVI4 corresponds to the EVI calculated using the share of the population living in DLZ as a climatic component in place of the population living in LECZ; EVI5 is the EVI calculated without the climate component as in 2006 and 2009 reviews.

Nevertheless, some countries are sensitive to the different options considered for the climatic component. For example, the use of the average of the part of the population living in LECZ and the part of the population living in DLZ has a strong impact on the vulnerability of certain categories of countries, making them relatively less vulnerable compared to others: Madagascar (-20 ranks), Comoros (-44 ranks), Burundi (-44 ranks). In contrast, Algeria (+44 ranks), Côte d'Ivoire (+30 ranks) become relatively more vulnerable. Rankings and changes are in the same order but with even greater impact when replacing the part of the population living in LECZ by the part of the population living in DLZ.

Another imbalance could come from the merchandise export concentration index, whose relevance is indeed debatable. Here we recall that the EVI is also proposed as an aid allocation criterion. In doing so, for an aid allocation formula that focuses on structural economic vulnerability, most of oil and mineral exporting countries will be favored; thus altering the consistency and equity objectives that aid allocation should satisfy. In fact, resources derived from oil and mineral enable these countries to raise the level of their per capita income, a component also used in the allocation formula. The presence of this variable in the EVI increases the vulnerability of countries exporting hydrocarbon fuels (especially oil) and minerals. As well, for consistency issues, export concentration must concern both goods and services. However, the index established by UNCTAD and used for the calculation of the EVI covers only exports of goods. No classification of services corresponding to the Standard International Trade Classification (SITC) has yet been developed. Thus, the export concentration index used in the EVI excludes tourism and financial services, which remain important for some countries, especially SIDS.

Furthermore, one of the major limitations of the merchandise export concentration index is already taken into account through one of the shock variables, namely the instability of exports of goods and services. The latter variable has the advantage of covering exports of both goods and services. An analysis carried out on all African countries shows a significant correlation between the merchandise export concentration and the instability of exports of goods and services (see Table 2).

It can be seen that the index of the share of the population living in LECZ is significantly correlated with the remoteness index (-0.6), with population size (0.37), with victims of natural disasters (-0.33). Also, the correlation seems to be significant between victims of natural disasters index and the remoteness index. Standard deviations appear to be important across all sub-components, highlighting a strong disparity among African countries in terms of vulnerability. Compared to other sub-components, the remoteness index, and the share of the primary sector in GDP as well as the victims of natural disasters seem high for African countries.

Table 2: Mean, standard deviation of the EVI's sub-components and Spearman rank correlation

Indicateur	Mean	Standard deviation	Spearman rank correlation 1.	2.	3.	4.	5.	6.	7.
1.Population size	37.31	23.93							
2.Remoteness from world markets	51.55	22.54	0.06						
3.Merchandise export concentration	41.14	26.27	0.24	-0.04					
4.Share of population in LECZ	12.78	18.34	0.37**	-0.6***	-0.04				
5.Share of primary sector in GDP	52.52	26.4	-0.29*	-0.01	-0.07	-0.15			
6.Instability of agricultural production	25.2	18.08	0.04	0.05	-0.15	-0.1	0		
7.Instability of exports of goods & services	33.58	33.75	0.06	0.07	0.37**	-0.13	0.22	-0.06	
8.Victims of natural disasters	61.98	28.73	0.03	0.38**	-0.07	-0.33*	0.21	0.14	0.12

No matter what options are chosen, this exercise highlights that African countries are structurally vulnerable from economic point of view. Even if EVI relies on structural characteristics of the economy, one can suspect a link between the structural economic vulnerability and the fragility of African countries. Fragile states are essentially characterized by the lack of core state functions, further aggravated when the legitimacy, authority, and capacity of state institutions are weak. It is therefore reasonably safe to evaluate the link between structural economic vulnerability and fragility, notably in the context of Africa.

II - 7) Is there a link between structural economic vulnerability and fragility in Africa?

The concept of fragility initially introduced by political scientists is very popular in recent years in the economic literature as evidenced by a large number of research and publications on the subject. Fragile states are generally defined as states that lack the capacity and /or willingness to perform the basic functions of the state (maintaining security, enabling economic development, ensuring the essential needs of the population) (OECD, 2008). Fragility is associated with weak and unstable institutions, persistence of extreme poverty, authority failure, service entitlement failure and legitimacy failure. Because of its multidimensional aspect, the term “fragile state” coexists with several synonyms: “weak state”, “failing state”, “failed state” or “collapsed state”. The notion of fragility should reflect the risk for a country to fail rather than the fact it has already failed.

State fragility is often presented as close to structural vulnerability, although it is conceptually quite different. While state fragility is a measure of a lack of resilience, structural economic vulnerability significantly influences state fragility through the structural determinants of resilience (Guillaumont and Guillaumont Jeanneney, 2009). This being so, state fragility is a sociopolitical dimension of vulnerability. It depends on structural vulnerability, which can be considered as a partial and indirect measure of fragility. Exogenous shocks and other sources of instability are factors of economic and social deterioration. For instance, states' structural capabilities influence the probability that various exogenous shocks will translate into conflict, because they determine the degree to which countries are able to successfully address insecurity. In addition to their detrimental effect on economic growth, shocks are factors that cause poverty, social unrest, violence and civil wars. More generally, they make the stability, efficiency, sound management and governance more difficult.

Structural economic vulnerability also impacts the duration of state fragility. Indeed, countries that fall into fragility situations often remain there for a long time and it becomes very difficult for them to get out of this status. 35 countries considered as "fragile" in 1979 by the World Bank are still fragile in 2009. The vast majority of fragile states are located in Africa. Their fragility persists due to several factors including conflicts, problems of governance, weak institutions and lack of social cohesion. An illustration of the link between structural economic vulnerability and fragility can be found in the relationship between the EVI and the 2014's harmonized list of fragile states prepared by the OECD[17].

Fragile African states are economically more vulnerable than non-fragile African states (see Figure 3). The difference between the two groups of countries within the meaning of the EVI seems to come from the difference observed at the level of the shock's component. No clear difference is observed in the exposure component. This is confirmed by a t-test of the difference of means for the EVI and its components (and sub-components) between the two groups of countries (see Table 3). It appears that African fragile states are no more exposed to shocks than African non-fragile states. By way of example, population size and remoteness from world markets (accounting for cumulatively 50 % of the exposure index) are not significantly different in the two groups. In contrast, the indices of merchandise

[17] Fragile situations have: either a) a harmonized average CPIA country rating of 3.2 or less, or b) the presence of a UN and/or regional peace-keeping or peace-building mission during the past three years. This includes only IDA eligible countries and non-member or inactive territories/countries without CPIA data. It excludes IBRD only countries for which the CPIA scores are not currently disclosed.
This harmonized list drawn up by the OECD includes 22 African countries. It must be pointed out that since 2015, the OECD does not provide the list of fragile states; it builds a holistic view of state fragility that goes beyond fragile and conflicting states alone. This brings news elements to the finalization of the Sustainable Development Goals (SDGs)

export concentration and the share of primary sector in GDP are significantly lower in African non-fragile states than in African fragile states. This result highlights the role played by the lack of economic diversification in the fragile situations of most African economies. Interestingly, to a lesser extent, structural economic vulnerability linked to the share of the population living in LECZ seems to be lower in African non-fragile states than in African fragile states. The difference is statistically significant at the 10 % threshold.

Box 1: **Evolution of the OECD's methodology for drawing up the list of fragile states**

Since 2005, the OECD has been compiling the list of fragile states with the aim of distinguishing fragile states from other developing countries. The methodology used has evolved over time. In the 2005 and 2006 reports, the OECD used the World Bank's list of fragile states by defining fragile states by those whose the CPIA is in the bottom two quintiles. The 2007 list was also established from the same approach but included some unclassified countries such as democratic People's Republic of Korea and many other countries clustered just above the fourth quintile cutoff. In order to make the list much more robust, with the inclusion of, for example, the security dimension, the 2008, 2009 and 2010 lists combined three indices of fragility: the CPIA from World Bank, the ISW index from the Brookings institution and the CIFP index from Carleton University. The two additional indices added 10 countries to the 38 others identified using the CPIA alone. Since 2011, the fragile states list has been produced by combining the harmonized list of fragile states established by multilateral development banks including the World Bank, the African Development Bank and the Asian Development Bank, with countries scoring 90 or above on the FSI produced by the Fund for Peace. Thus the list presented 45 fragile states in 2011, 47 in 2013, 51 in 2014. Note that no list was published in 2012. The 2015 list established a list of 50 fragile states taking into account three dimensions of the fragility inspired by SDG 16 (violence, access to justice, institutions) and two dimensions of the global SDG (resilience, economic foundations). All countries (not only those traditionally considered as fragile) were assessed in terms of their progress or achievement in the five dimensions of SDG 16. It appears that the list of the 50 most vulnerable countries in these 5 dimensions does not differ substantially from the list obtained through the 2014's harmonized list of World Bank, the African Development Bank, the Asian Development Bank, and the FSI (for scores above or equal to 90).

Source: OECD (2015)

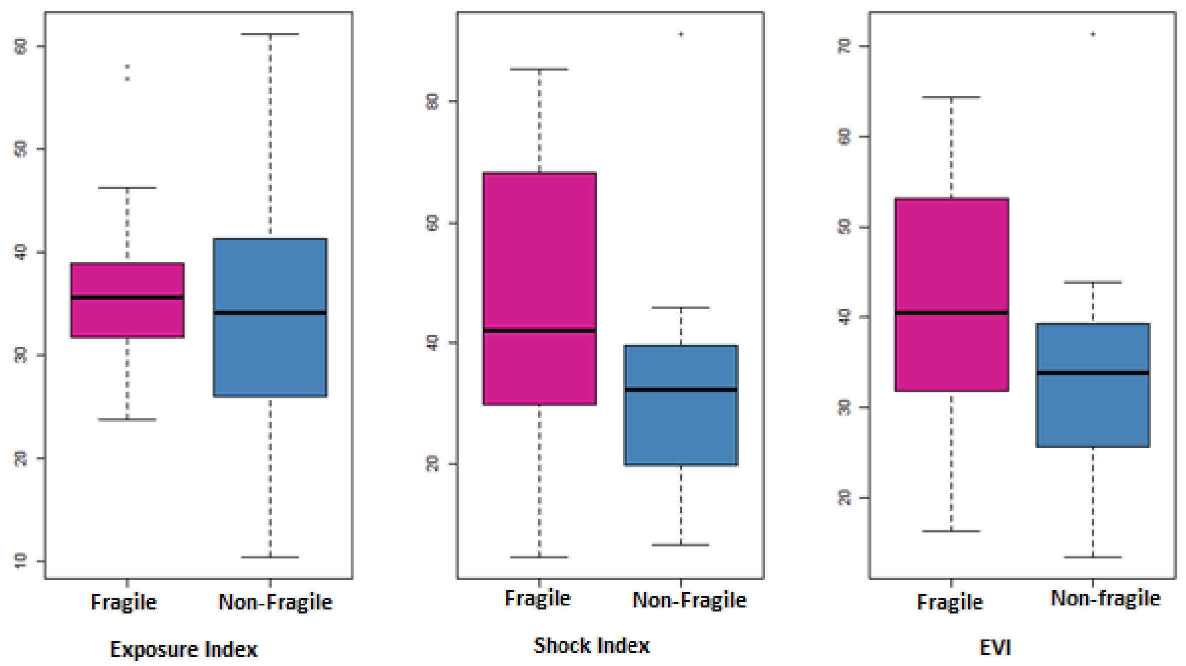
Note: OECD: Organisation for Economic Co-operation and Development; CPIA: Country Policy and Institutional Assessment; ISW: Index of State Weakness; FSI: Fragile State Index.

Table 3: Comparison of the averages of the EVI, its components and sub-components between African fragile states and African non-fragile states

Indicators	Fragile states	Non-fragile states	Difference	Student T-test
EVI	**42.4**	**32.92**	**9.48**	**2.737***
Exposure Index	**36.73**	**33.92**	**2.81**	**0.969**
Population size	**35.83**	**38.15**	**-2.32**	**-0.385**
Remoteness from world markets	**52.66**	**51.82**	**0.84**	**0.137**
Merchandise export concentration	**53.27**	**32.24**	**21.03**	**2.936***
Share of population in LECZ	**7.95**	**15.86**	**-7.91**	**-1.728***
Share of primary sector in GDP	**47.65**	**27.46**	**20.19**	**2.710***
Shock Index	**48.06**	**31.91**	**16.15**	**2.812***
Instability of agricultural production	**23.56**	**27.07**	**-3.51**	**-0.721**
Instability of exports of goods & services	**53.76**	**19.03**	**34.73**	**3.785***
Victims of natural disasters	**61.18**	**62.51**	**-1.33**	**-0.163**

Notes: *, *** indicate the significance level of 10 % and 1% respectively.
Le calculation is performed on all 54 African countries, 22 of which are considered fragile according to the 2014 Harmonized list of fragile states

Figure 3: Box plot of the EVI and its components: African fragile states vs African non-fragile states



The lessons drawn from this section highlight that the EVI, despite its few limitations, appears as a relevant indicator capturing structural economic vulnerability of countries. It is also inextricably associated with the fragility in Africa. Nonetheless, it is fundamental to be able to assess this kind of vulnerability over time by opting for a dynamic approach. This leads us to the construction of retrospective series of the EVI and its components.

III - Building annual retrospective series of the EVI*

The 2006, 2009, 2012 and 2015 Triennial Reviews of the EVI are available on the United Nations Committee for Development Policy (UN-CDP) website. However these official EVI values, as well as the former from the 2000 and 2003 Reviews, are dedicated to cross-country comparison purposes at the year of the respective Reviews. Due to the revisions in methodology occurring over time, and primary data updating, these official EVI values do not allow intertemporal comparisons, for instance to assess the changes in vulnerability (see Cariolle et al., 2015 for a discussion on the consequences of these changes in the methodology and of data updating). This problem can be solved by calculating retrospective EVI's series based on constant definitions.

This section presents an updated version of the retrospective EVI previously calculated by the Ferdi that followed the previous UN-CDP Reviews' calculation principles (Cariolle, 2011 and Cariolle and Goujon, 2013). These retrospective series were at that time made available to the public through the Ferdi website. Since January 2015, the "byind.ferdi.fr" website (Build your Index) also allows the users to compute their own retrospective EVI, by applying another composition of the index, different from the one retained by the UNCDP. More recently, the UNCDP has opened *StatPlanet Graphical Interface*, a visual and retrieval tool for 2006, 2009, 2012 and 2015 data[18]. After the release of 2015 data, the UN-CDP had envisaged to construct its own retrospective series, but this is not so for the moment.

We then use here the definition of the 2015 UN-CDP's review and update data for the period from 1990 until 2013 (and since 1970 for some sub-components)[19]. We present the

*This section is partially taken from Feindouno and Goujon (2016): "The Retrospective Economic Vulnerability Index, 2015 update" Working Paper Ferdi.

[18] http://esango.un.org/sp/ldc_data/web/StatPlanet.html.

[19] While this section is being written, it is possible for us to compute an EVI covering the period 1990—2014 (and 1970—2014 for some sub-components). But to be able to compare the retrospective series of EVI with the UNCDP's EVI, we restrict our calculations to the period 1990—2013.

retrospective EVI calculation method in the form of a technical sheet for each component and sub-component of the EVI.

The retrospective calculation follows some general rules:

- Calculations of retrospective EVI closely follow the UN-CDP's methodology. Some marginal adjustments are however necessary. We describe them as "special treatment" within concerned components.

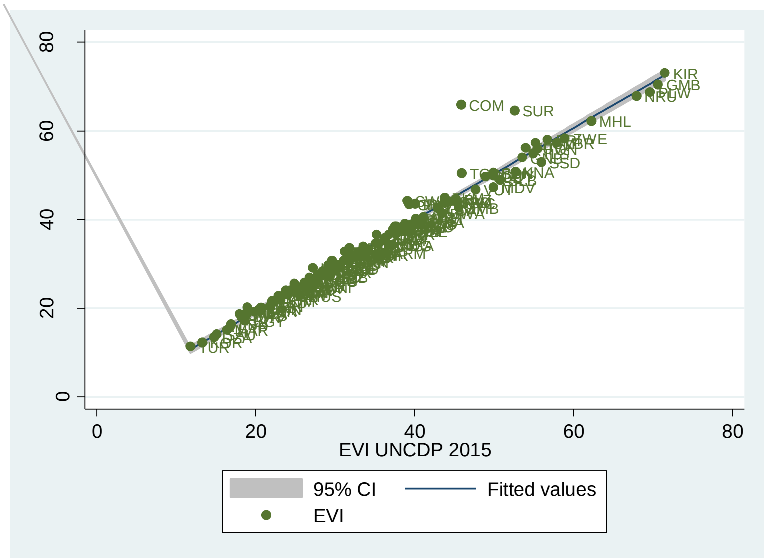
- Annual EVI is calculated for the longest period for which data is available (back to 1975 for some components, but back to 1990 for the EVI).

- Sources of primary data are identical to those used by the UN-CDP 2015's review.
- Our calculations have been done at the end of 2015, some months after the UN-CDP's ones, and then can make use of primary data further updated.
- Comparisons are made to ensure there are no significant or unexplained differences between UN-CDP's official figures and our results for the last covered year.

III - 1) UN-CDP 2015 EVI official values versus retrospective 2015 EVI values

Figure 4 displays the high correlation (Spearman's rank correlation coefficient = 99.3%) between the EVI official values from the UN-CDP 2015 Review and those of our retrospective EVI 2015 (values correspond to the year 2013). The gaps in ranking observed for countries such as Comoros and Suriname arise mainly from the recent updating of the primary data on exports of goods and services that occurs between UN-CDP's and our calculations (see further below).

Figure 4: Correlation between EVI scores of the UN-CDP 2015 Review and of the retrospective 2015 database, year 2013



For the year 2013, the retrospective 2015 EVI average is 41.6 for LDCs against 31.6 for non-LDCs. We report the distribution of the retrospective 2015 EVI and its components for the year 2013, for both LDC versus non-LDC groups (see Appendix 3.a), and for both African fragile states and African non-fragile states (see Appendix 3.b).

Figure 5: EVI scores of the retrospective 2015 database on the map, year 2013

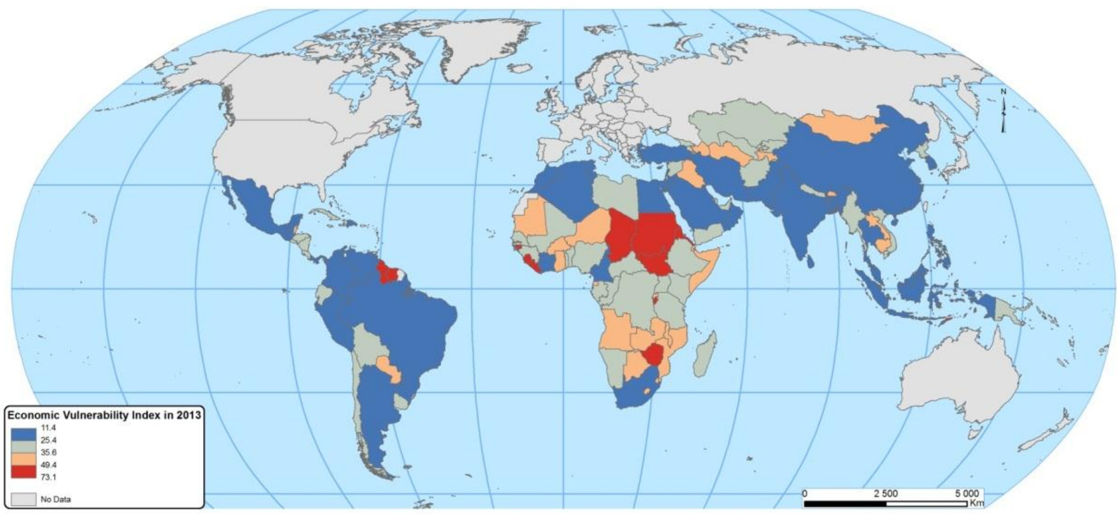
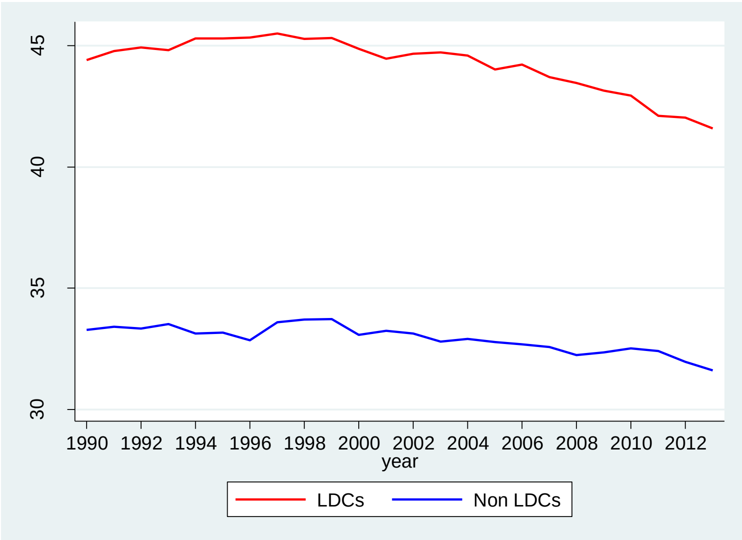


Figure 6 plots the average evolution of the retrospective 2015 EVI in LDCs and non LDCs, from 1990 to 2013. Data cover a complete set of 145 countries (48 LDCs and 97 non LDCs). Structural economic vulnerability measured by the EVI is significantly higher in LDCs than in non-LDCs in average over 1990—2013. Although average EVI has decreased in both categories of countries, it decreases faster in LDCs than in non-LDCs in recent years, specifically since 2003—2004. Retrospective 2015 EVI values for the years 1990, 2000, 2010 and 2013 in the 48 LDCs are reported in Appendix 5.

Figure 6: Evolution of the average retrospective 2015 EVI, LDCs versus non-LDCs



What follows is the presentation of the method for the calculations of the retrospective series of the 8 sub-components of the EVI.

III - 2) Population size

Figure 7.a shows a high correlation (Spearman's rank correlation coefficient=99.3%) between the population index of the UN-CDP 2015 review and of the retrospective 2015 database.

As previously noted, the smaller the population, the higher is the value of population index indicating a greater vulnerability. According to Figure 7.b, the average population index is higher in non-LDCs than in LDCs. The difference between the two categories of countries in terms of population is tending to grow as the years go by. For instance, in 1990 the population index LDCs was 49.7 in LDCs versus 50.2 in non-LDCs while in 2013 the score is 41.3 in LDCs versus 45.1 in non-LDCs. These trends reflect a higher average rate of population growth in LDCs, which has been almost twice the average rate of non-LDCs.

Figure 7.a: Correlation between the Population size index of the UN-CDP 2015 review and of the retrospective 2015 database, 2013

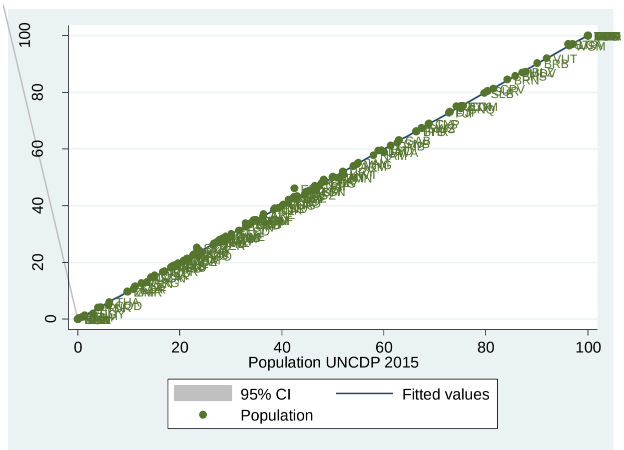


Figure 7.b: Evolution of the retrospective 2015 Population size index, LDCs versus non-LDCs averages

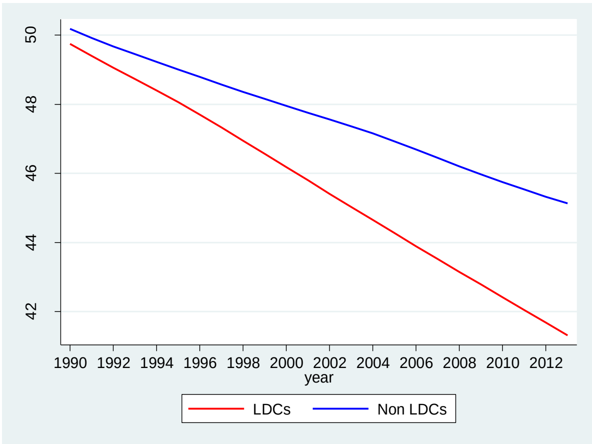


Figure 7: Population size index: Correlation and Evolution

III - 3) Remoteness from world markets

For a country, the remoteness component is the trade-weighted minimum average distance to reach 50% of the world markets. We use the same methodology as the UN-CDP in its 2012 and 2015 reviews. The following calculation is done for each year.[20]

For each country i, partner countries j are ranked according to their distance from country i. The group of the closest countries is hence progressively selected until 50% of the World market is reached for country i (by the simple sum of partners' market shares). The trade-weighted average distance is then computed vis-à-vis this group of selected partners, using the distances between country i and selected partners j, and selected partners' market shares:

$$Min \sum_{j \in J} Dij * \frac{X_j}{X} \ \ with \ J = \left\{ j \ such \ that \sum_{j \in J} Xj \ \geq X/2 \right\}.$$

[20] CDP Secretariat. Note on measuring remoteness for the identification of LDCs. August 2015.

Where $\frac{X_j}{X}$ is the market share of partner j and D_{ij} is the distance between country i and partner j.

Market share is calculated using 3 year $(t-2,t)$ average trade (import + export) for each country:

- X is the 3-year Average Trading Volume = 0.5 * (3-year Avg. Imports + 3-year avg. Exports)
- Market share of country j = $\frac{X_j}{X}$ = Avg. 3-year trading volume of country j / Avg. 3-year World volume

The trade-weighted average distance is normalized at this stage (using a log-transformation) to get a Distance index that lies between 0 and 100. *Distance index* is then adjusted for the additional handicap of being a landlocked country:

Remoteness = [0.85*Distance + 0.15*L]

With *L* a variable indicating whether the country is landlocked (L=100) or not (L=0).

Remoteness is then normalized using a second min-max procedure such that the Remoteness index now lies between 0 (lowest remoteness) and 100 (strongest remoteness).

Following the unchanged UN-CDP definition, there is no difference in the calculation principle between the 2015 and the 2012 retrospective series. The definitions of the 2012 and 2015 series significantly differ from the ones of the 2009 series (on the way in which market shares are computed and trade partners are selected, see Cariolle, 2011, and Cariolle and Goujon, 2013).

Figure 8.a displays an almost perfect correlation between the official EVI and the retrospective EVI for the year 2013, with a Spearman's rank correlation coefficient of 99.8%.

The remoter the country is, the higher the index is, signaling a higher vulnerability. Figure 8.b shows that LDCs are remoter from world markets than non-LDCs and that the gap between LDCs and non-LDCs remained stable over time. Remoteness decreases over time for both categories of countries with a substantial acceleration since the year 2009, signaling the rebalancing of market shares in favor of the south.

Figure 8: Remoteness index: Correlation and Evolution

Figure 8.a: Correlation between the remoteness index of the UN-CDP 2015 review and of the retrospective 2015 database, 2013

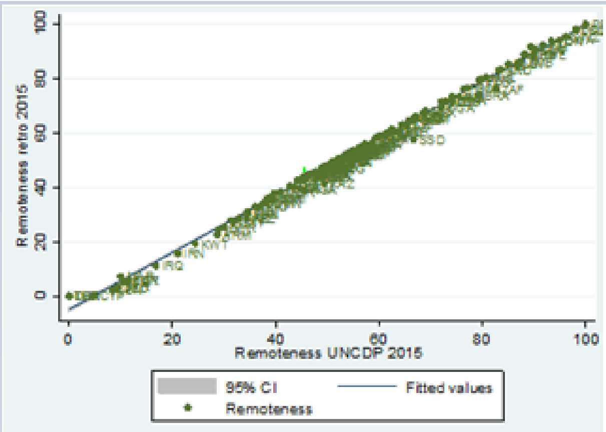
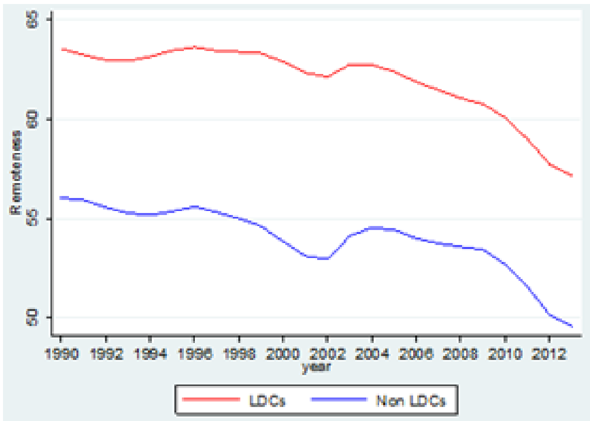


Figure 8.b: Evolution of the retrospective 2015 remoteness index, LDCs versus non-LDCs averages



III - 4) Merchandise export concentration

The export concentration index is derived from a Herfindahl-Hirschmann index applied to exports of merchandises (excluding services) as categorized by the three-digit level of the Standard International Trade Classification (SITC). This index is primarily lying between 0 and 1, a high level of concentration being associated with a score close to 1 (a country exporting only one product out a large number of products would score 1). The Herfindahl-Hirschmann Index formula is :

$$H_j = \frac{\sqrt{\sum_{i=1}^{n}\left(\frac{x_i}{X_j}\right)^2} - \sqrt{1/n}}{1-\sqrt{1/n}}$$

Where X_j is total exports of country j, x_i is the value of exports of product i, and n the number of products at the three-digit SITC level.

The concentration index used in the EVI is based on a 3-year (the current and the 2 previous years) moving average of H_j. The index is then normalized using the min-max procedure with the bounds specified below. Following the revision in the UN-CDP practices, the 2009 retrospective concentration index was based on annual data while the 2012 and 2015 versions are based on a 3-year rolling average of the data. Various attempts to fill pre-1995 missing data that were applied for the retrospective EVI 2009 have been ruled out in the 2012 and 2015 versions, implying that this component is now less documented than in the 2009 database. However, country and time coverage improved in the UNCTAD database, and so between the 2012 and 2015 retrospective EVI versions.

Figure 9.a below displays an almost perfect correlation between both indexes, with a Spearman's rank correlation coefficient of 99.0% (signaling that there has been no significant update in the raw database of H_j from UNCTAD). Figure 9.b below displays the evolution of LDCs and non-LDCs averages. The more concentrated the merchandise exports are, the higher the index is. The figure clearly shows that export concentration in LDCs is higher than in non-LDCs and that the gap remains over time. Concentration has decreased in the 1990s, but more rapidly for non-LDCs on average, and is more or less stable since then for both groups.

Figure 9: Merchandise export concentration index: Correlation and Evolution

Figure 9.a: Correlation between the export concentration index of the UN-CDP 2015 review and of the retrospective 2015 database, 2013

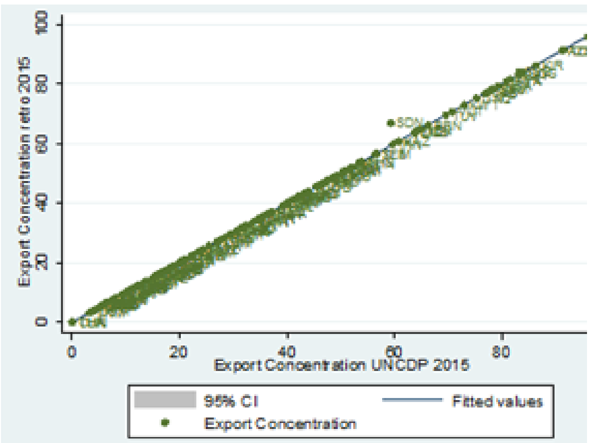
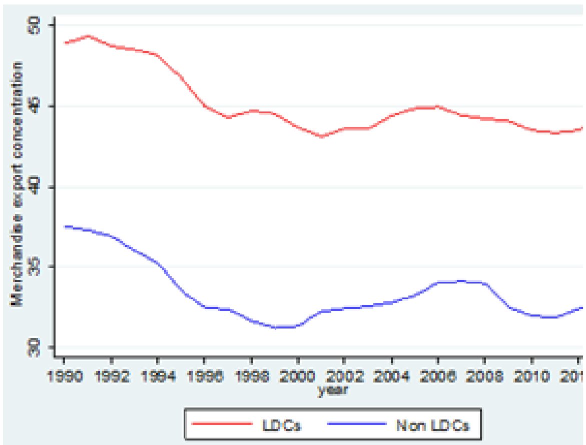


Figure 9.b: Evolution of the retrospective 2015 export concentration index, LDCs versus non-LDCs averages



III - 5) Share of agriculture, forestry and fisheries in GDP

The CDP uses a 3-year average of the share of agriculture to GDP, on 2011—2013 for the 2015 Review. The corresponding retrospective index in year t is accordingly based on a 3-year rolling average over $\left[t, t-2\right]$.

As in 2012, the 2015 UN-CDP values and retrospective series are based on a 3-year rolling average. It differs from the 2009 retrospective series that were based on annual data, following the UN-CDP definition. Some countries require more specific treatment.

- For Yemen, over the period 1970—1987, values of the share of agriculture to GDP are the averages of the two Yemen's values.
- For Sudan from 1970 to 2007, we used data of former Sudan.
- For Ethiopia and Eritrea from 1970 to 1989, we use data of former Ethiopia.

Figure 10: Share of agriculture, forestry and fisheries in GDP: Correlation and Evolution

Figure 10.a: Correlation between the share of AFF in GDP index of the UN-CDP 2015 review and of the retrospective 2015 database, 2013

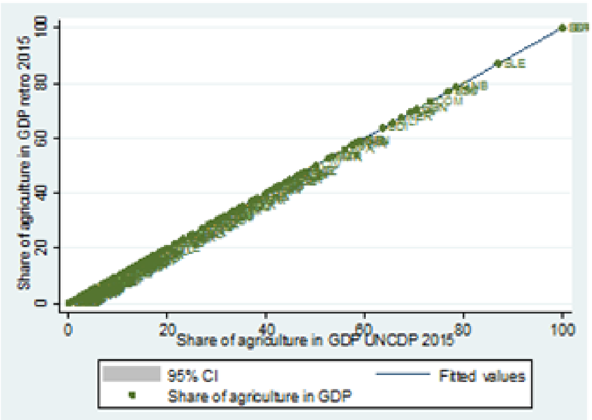
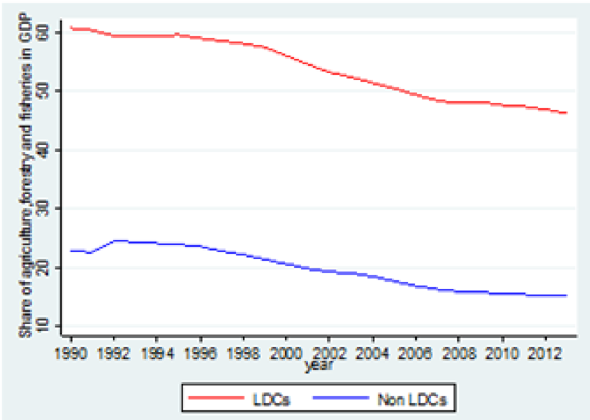


Figure 10.b: Evolution of the retrospective 2015 share of AFF in GDP index, LDCs versus non-LDCs averages



Note: AFF refers to agriculture, forestry and fisheries

Figure 10.a shows a perfect correlation between both indexes with a Spearman's rank correlation coefficient that equals 100%, suggesting no change in the primary data used over 2015. As shown in Figure 10.b, LDCs have a much higher share of agriculture, forestry and fisheries in GDP than non-LDCs, on average. The average index has decreased over time for both groups but faster in LDCs, resulting in a slight reduction of the gap between the two groups.

III - 6) Share of population living in low elevated coastal zone

It measures the share of the population in a country that lives in low elevated coastal zones, defined as areas contiguous to the coast below a certain elevation threshold. The elevation threshold used by the UN-CDP decreased from 10 meters in the 2012 review to 5 meters in the 2015 review. This is the only significant change in the UN-CDP's EVI methodology between 2012 and 2015. In the 2015 review, the UN-CDP uses data from CIESIN-LECZ Version 2 (2013)[21]. Data are available for the years 1990, 2000 and 2010 (and 2100)[22]. The UN-CDP uses data for the year 2010 unless otherwise indicated.

To generate annual data, we simply assume linear trends in the series:

- for years between 1990 and 2000, we interpolate data using the annual average change between 1990 and 2000: *Annual average change*$_{1990\text{-}2000}$ = $(LECZ_{2000} - LECZ_{1990})/11$
- for years between 2000 and 2013, we interpolate and extrapolate data using the annual average change between 2000 and 2010: *Annual average change* $_{2000\text{-}2010}$ = $(LECZ_{2010} - LECZ_{2000})/11$

In the retrospective EVI 2012, we constructed data for years prior to 1990, by extrapolating data using the trend between 1990 and 2010. We do not reproduce this here.

As we have already pointed out, this sub-component of the EVI did not appear in the 2006-2009 reviews since it has been introduced in the methodology of the UN-CDP 2012 review. Except revisions on the threshold and on the upper bound, and change in the primary databases, the calculation principle is the same in the 2015 and 2012 reviews.

In the 2012 review, UN-CDP used data on population in LECZ for the year 2000 from the CIESIN-LECZ Version 1 (2007)[23]. In the retrospective EVI 2012, we used updated data of CIESIN-PLACE III (2012) that then provided estimates for years 1990, 2000, and 2010 (at this

[21] Center for International Earth Science Information Network - CIESIN - Columbia University. 2013. Low Elevation Coastal Zone (LECZ) Urban-Rural Population and Land Area Estimates, Version 2. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC). http://dx.doi.org/10.7927/H4MW2F2J.

[22] for 202 countries with contiguous coastal elevations in the following categories: less than or equal to 1m, 3m, 5m, 7m, 9m, 10m, 12m, or 20m.

[23] McGranahan, G., D. Balk, and B. Anderson. 2007. Low Elevation Coastal Zone (LECZ) Urban-Rural Population Estimates, Global Rural-Urban Mapping Project (GRUMP), Alpha Version. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC). http://dx.doi.org/10.7927/H4TM782G.

time, we however detected some erroneous data that we replaced by estimates from the CIESIN-PLACE II (2007).

In the 2015 retrospective series, we use the same database than the UN-CDP, CIESIN-LECZ Version 2 (2013), which is the latest available from CIESIN. Moreover, we follow the special treatments applied by UN-CDP for some territories (detailed in the database that can be retrieved from UN-CDP website,[24] see below). This induces a very higher correlation between the UN-CDP 2015 and retrospective 2015 series than between the UN-CDP 2012 and retrospective 2012 series. Dominica, Equatorial Guinea, Saint Kitts and Nevis, Saint Vincent and the Grenadines, Samoa, Sao Tome and Principe, the Solomon Islands, Tonga, have inappropriate values in CIESIN-LECZ version 2 (2013). For these countries, we use data from CIESIN-PLACE III (2012). However, in the CIESIN-PLACE III, values for the year 2010 are not correct for the Marshall Islands, Micronesia, Nauru, Palau, Seychelles, and Tuvalu. Therefore, we apply the value of the year 2000 for the 2010 data. Given their insular condition and the relative low value of the upper bound, these treatments do not induce major changes. Similarly, the erroneous values of the Maldives and Kiribati for the year 2010 in the CIESIN-LECZ version 2 lead us to replace them by their values in the year 2000.

Figure 11: Share of population living in low elevated coastal zone: Correlation and Evolution

Figure 11.a: Correlation between the UN-CDP 2015 review's index of the share of population in LECZ and of the retrospective 2015 database, 2013

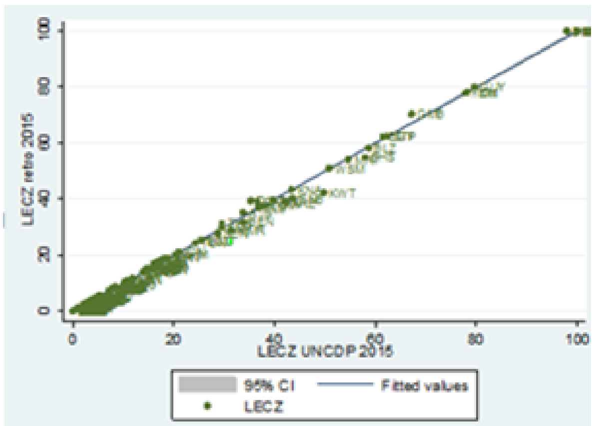


Figure 11.b: Evolution of the retrospective 2015's index of the share of population in LECZ, LDCs versus non-LDCs averages

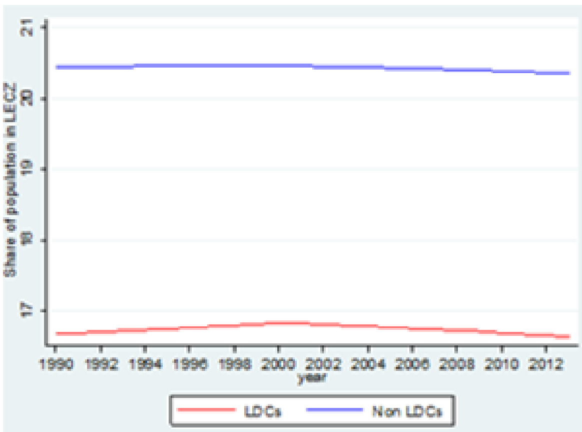


Figure 11.a displays a 99.9% correlation between LECZ scores of the UN-CDP 2015 review and 2013 scores of our retrospective database. This high correlation is explained by the fact

[24] http://www.un.org/en/development/desa/policy/cdp/ldc/ldc_data.shtml

that we use the same primary database version (the latest available) and apply the same treatment of special cases than UN-CDP. Figure 11.b shows a higher share of population in LECZ in non-LDCs than in LDCs, on average, the former group including more landlocked countries. The index has remained almost stable over time for both groups.

III - 7) Instability of exports of goods and services

In the 2015 review, UN-CDP assumes the reference value around which export deviations are computed as a mixed trend (with both deterministic and stochastic components) estimated over 1993—2013 (21 years), using data transformed in logarithm, following the equation:

$$Log\, Y_t = \alpha + \beta \cdot \log Y_{t-1} + \gamma \cdot T + u_t \qquad (1)$$

with Y_t being the export variable, and T a time trend. Estimated Y_t from the equation are then rescaled using an exponential transformation. The deviations between observed exports values Y_t and the estimated Y_t from the above equation (ε_t), are used to compute the instability index, according to the following formula:

$$Instability_t = 100 \times \sqrt{\frac{\sum_{t-k}^{t} \varepsilon_t^2 / Y_t}{(k+1)}}$$

We follow UN-CDP that computes this indicator over 21 years (1993—2013). Our retrospective series is computed for each year t over a rolling window $[t, t-k]$ with $k = 20$, starting in 1990, as we get raw data starting in 1970.

A few important differences can be noted compared to database coming from the previous reviews. In the 2015 version, raw data are exports of goods and services in constant USD. In the 2012 version, following the UN-CDP practice, raw data were exports of goods and services in current USD, deflated by the import unit value index for developing and emerging countries retrieved from the IMF International Financial Statistics. This causes discrepancies between the two versions 2012 and 2015, in either UN-CDP's data or our retrospective series. Moreover, instability index is computed on a 21 years period in 2015, against 20 in 2012. In the 2012 retrospective series, we used exports data prior to 1970 from an older version of the IMF database to compute instability index for the 1980s (for less than half of the countries). We don't replicate this in 2015. Compared to the 2009 series, the period used to compute instability index is also different (see Cariolle, 2009, and Cariolle and Goujon, 2013).

Following the UN-CDP practice, we generate historical annual data on exports for Sudan and South Sudan by splitting exports of former Sudan prior to 2008. We first compute the relative weight of exports of both countries over 2008—2013. Second, we apply this relative weight to the series of annual exports data of former Sudan over 1970—2007. We similarly generate annual data for Ethiopia and Eritrea over 1970—1989 from former Ethiopia data, by using relative weight of both countries over 1990—2013.

Figure 12: Instability of exports of goods and services: Correlation and Evolution

Figure 12.a: Correlation between export instability index of the UN-CDP 2015 review and of the retrospective 2015 database, 2013

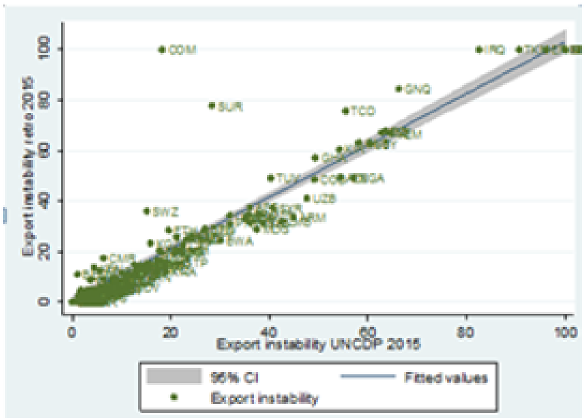


Figure 12.b: Evolution of the retrospective 2015 export instability index, LDCs versus non-LDCs averages

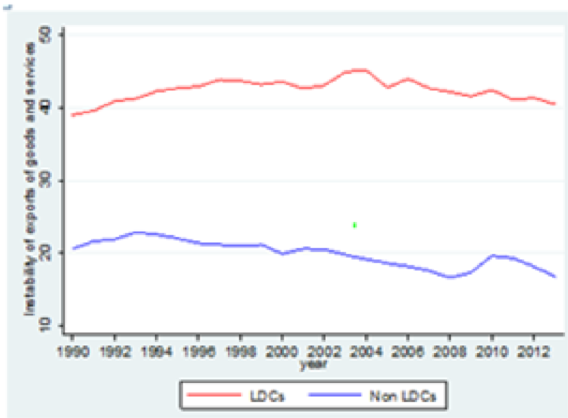


Figure 12.a displays a 96.4% correlation between export instability scores of the UN-CDP 2015 review and 2013 scores of our retrospective database. One can observe discrepancies in some export instability scores between UN-CDP and our estimates (e.g. Suriname, Comoros). Given that we use the same methods, they are explained by primary data updating in UN-stats between the UN-CDP 2015 review and our calculations (for instance, for Comoros, before the min-max transformation, the UN-CDP reports an instability score of 10.5% against 37.8% for our estimates). According Figure 12.b, LDCs experienced greater export instability than non-LDCs, on average, and the gap has slightly widened over time. Indeed, export instability index has slowly decreased since the 1990s in non-LDCs, but only since the 2000s in LDCs.

Box 2: **A small revision is required for the calculation's methodology of the Instability of exports in the Economic Vulnerability Index**

The instabilities, as calculated for some indices such as Economic Vulnerability Index (EVI), suffer from a problem of estimating the trend value with respect to which they are measured (see a discussion of these issues in Cariolle and Goujon (2015). The results may significantly change depending on the equation chosen for the trend estimation. The usual log-linear method is to regress flows (exports of goods and services, remittances, etc.) on a time variable and the lagged (1) dependent variable (a so-called mixed trend, both determinist and stochastic). Moreover, the length of the period covered by the estimation is likely to vary, as it has been the case for EVI (here taken at 21 years, differing from the last practice for EVI where a 15-year period was used). The squared value of the time variable should capture a possible nonlinearity of the determinist trend over the 21-year period. This is supported by the tests carried out on several countries. For example, referring to the exports of goods and services series for Bhutan, Maldives, and Nepal, we conclude that the best model is that which adds the squared value of the time variable to the usual model.

Source: Author

III - 8) Instability of agricultural production

The instability of agricultural production index follows the same calculation principles as for the export instability index. The UN-CDP computes the reference value as a mixed trend (with both deterministic and stochastic components) estimated over 1993—2013 (21 years), using data transformed in logarithm, following the equation:

$$Log\, Y_t = \alpha + \beta \cdot \log Y_{t-1} + \gamma \cdot T + u_t$$

With Y_t the volume index of agricultural production and T a time trend. Estimated Y_t from the equation are then rescaled using an exponential transformation. Because UN-CDP estimates this trend over 21 years (1993—2013), we estimate it each year over $[t, t-k]$ with $k = 20$.

The difference between observed agricultural production values Y_t and the estimated Y_t from the above equation (ε_t) are used to compute the instability index, according to the following formula:

$$Instability_t = 100 \times \sqrt{\frac{\sum_{t-k}^{t} \varepsilon_t^2 / Y_t}{(k+1)}}$$

We follow UN-CDP that computes this indicator over 21 years (1993—2013). Our retrospective series is computed for each year t over a rolling window [t; t-k] with k = 21, starting in 1980, as we get raw data starting in 1960. The UN-CDP 2012 review at that time used a 20-year period. Other period lengths were used in the 2009 version (see Cariolle, 2009). Continuous data updating in FAO database can be a major cause of discrepancies between UN-CDP versions, as well as between our retrospective series. Prior to 1995, the average value of the Federated States of Micronesia is used for Palau and Micronesia. Likewise, as done by UN-CDP, we apply the values of former Sudan to Sudan and South Sudan.

Figure 13: Instability of agricultural production: Correlation and Evolution

Figure 13.a: Correlation between the agricultural production instability index of the UN-CDP 2015 review and of the retrospective 2015 database, 2013

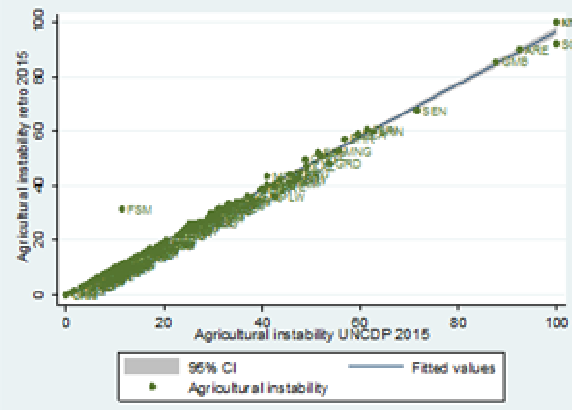


Figure 13.b: Evolution of the retrospective agricultural production instability index, LDCs versus non-LDCs averages

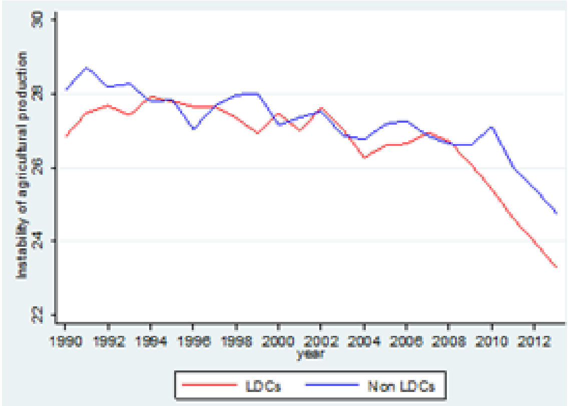


Figure 13.a displays a 99.3% correlation between agricultural instability scores of the UN-CDP 2015 review and 2013 scores of our retrospective database. The difference in instability scores between the two databases are explained by updates of FAO-stats since the UN-CDP 2015 review. Additionally, for Micronesia, the difference can be explained by the specific treatments used by UN-CDP for generating values and the period used for the calculation of the instability (period of 19 years while the period of 21 years has been used for the other countries). According to Figure 13.b, until recently, the average index of agricultural production instability is similar and shows a very slow decreasing trend for both groups. The average index falls more rapidly since 2008 for non-LDCs and later since 2011 for LDCs.

III - 9) Victims of natural disasters

We follow the UN-CDP's methodology to compute the disaster index as an average on a period of 20 years. The UN-CDP in its 2015 review uses data on victims of natural disasters from OFDA/CRED international Disaster Database (EMDAT)[25]. We first calculate the annual number of people killed or affected by natural disaster from EMDAT (which we report to total population) for each year covering the period 1960—2013. Second, we calculate an annual average of the share of victims to total population on a rolling period of 20 years.

$$Victims_t = \frac{\sum_{s=t-19}^{t}\left(\frac{victims_s}{population_s}\times 100\right)}{20}$$

Since the 2012 UN-CDP review, the index of "victims of natural disaster" has replaced the index of "homeless due to natural disaster" previously used in the 2006 and 2009 reviews. For the retrospective EVI 2009, the calculation method was also different (see Cariolle, 2009). Special treatments primarily concern pre-2012 data generation for Sudan and South Sudan. For this, we calculate for each year the share of their population in total population of former Sudan, and then multiply it by the total victims of natural disasters recorded by former Sudan.

Figure 14: Victims of Natural disasters: Correlation and Evolution

Figure 14.a: Correlation between the victims of natural disasters index of the UN-CDP 2015 review and of the retrospective 2015 database, 2013

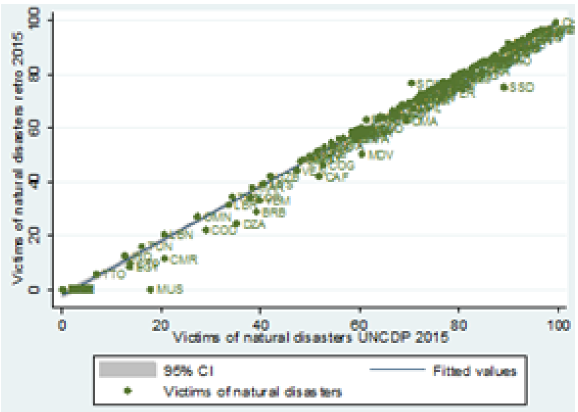
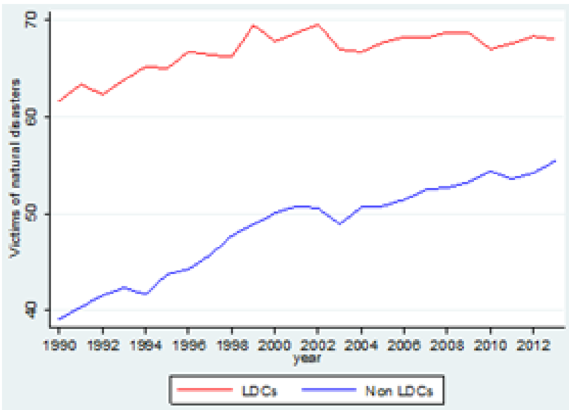


Figure 14.b: Evolution of the retrospective victims of natural disasters index, LDCs versus non-LDCs averages



The victims of natural disasters index obtained by UN-CDP is highly correlated with our retrospective series (see Figure 14.a). Differences in estimates for some countries are explained by an update in EMDAT database between UN-CDP's release and the time of our

[25] Their calculations are carried out over the period 1995—2013. According to EMDAT, the updates may imply major modifications in the historical data. Regarding the historical series, the further we go on the past, the lesser is the quality of disaster recording.

calculations. Figure 14.b shows that, on average, LDCs have been more affected by natural disaster than non-LDCs. The index increases for both groups. This may be partly due to a wider recording coverage of disasters and victims over time. However, this can also capture a real increase in disaster frequency or intensity due to climate change and/or an increase in population density in disaster-prone areas. The increasing trend is more acute for non-LDCs average, reducing the gap between LDCs and non-LDCs.

We conclude this section by saying that the construction of retrospective series of EVI is an important exercise aiming to regularly assess the evolution of the structural economic vulnerability over time. It is a crucial tool for the research purpose, but also, and particularly, for policy makers that need to measure progress towards reducing vulnerability goal and could help in identifying factors that continue to adversely affect this goal. We have seen that EVI has decreased over time in LDCs and non-LDCs (particularly faster in recent years in LDCs), but is there a general decrease? For the purpose of disentangling whether this observed change have to be attributed to individual countries or there has been an overall change concerning all countries, we adopt stochastic dominance (SD) pairwise comparisons of EVI and its two main components over two points in time (a five-year testing horizon).

IV - Analysis of the global evolution of the EVI and its components: a stochastic dominance approach

SD provides an effective and viable tool for examining the statistical significance of the substantial differences between the cumulative distribution functions (CDFs) with tests for stochastic orderings expressing the common preferences of rational decision-makers. The study of SD is very relevant in the sense that the approach is nonparametric: the criteria do not impose explicit functional forms of probability distributions and require minimal assumptions about returns distribution and preferences. This allows practitioners, including decision-makers to draw strong conclusions when SD conditions are met. If SD holds, one can make robust inferences over all indices that share a common set of properties.

In our case, various applications of SD can be done within the framework of the indices. One may be interested in simultaneous comparisons between different indicators of economic vulnerability. For example, one might want to test whether one country stochastically dominates another with respect to several variables. Or, one might want to test whether one country dominates in some dimensions while another dominates in others. The aim of this section is to investigate whether the decrease in EVI and its main components is due to a few countries or a widespread decrease observed in all countries. For that purpose, we use first order and second order SD.

IV - 1) First, second and nth degree SD criteria

SD is closely related to comparisons of different distributions to each other, particularly in the context of comparing social welfare, inequality, and poverty. Given U_i for $i=1,2$ the utility function class, where $u \in U_1$ if $u' > 0$; $u \in U_2$ if $u' > 0$ and $u'' \leq 0$ where u' and u'' are the first and second derivatives. Also define U_n as the set of all functions where the even derivatives are negatives and all odd derivatives are positive, when the n derivatives are assumed to be known. SD1 and SD2 denote the first and the second degree stochastic dominance rules, respectively. Let F_1 and F_2 be the cumulative distributions of two distinct uncertain options X and Y. SD of F_2 with respect to F_1 by SD1 and SD2[26] is equivalent to and requires tests of the following:

SD1: $F_2(X) \leq F_1(X)$ for all X

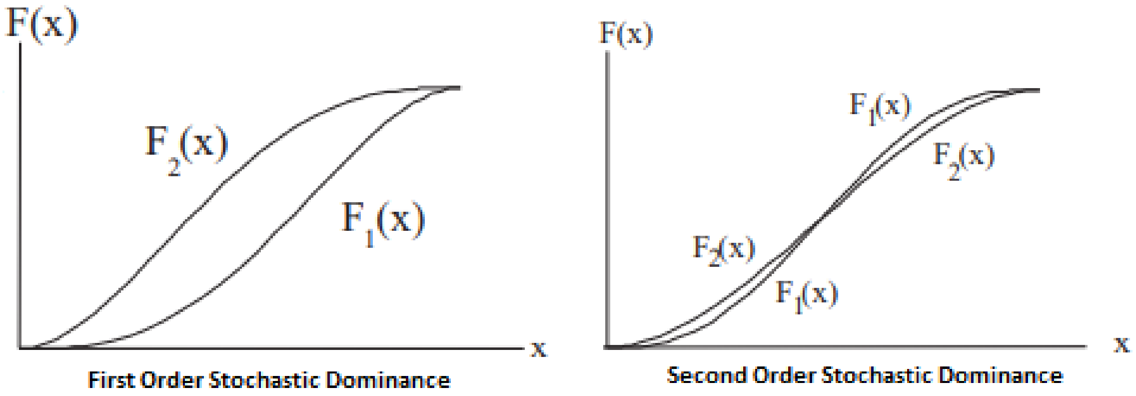
SD2: $\int_{-\infty}^{x} [F_1(t) - F_2(t)] dt \geq 0$ for all X

The least one strict inequality must hold.

For proof of SD1 and SD2, see Hadar and Russel (1969), Hanoch and Levy (1969) and Rothschild and Stiglitz (1971). The three papers produced by the authors paved the way for a new paradigm called stochastic dominance, with hundreds of studies following them. While the two first papers developed SD1 and SD2, Rothschild and Stiglitz (1971) focused mainly on the definition of risk and how to quantify it. By searching for the appropriate risk measure, they developed SD2 rule for prospects with equal means.

[26] If we are interested in SD of F_2 with respect to F_1 by SD3, the requirement should be:
SD3: $\int_{-\infty}^{x} \int_{-\infty}^{v} [F_1(t) - F_2(t)] dtdv \geq 0$ for all X, and $E_{F_2}(X) \geq E_{F_1}(X)$.

Figure 15: Illustration of First and Second order Stochastic Dominance



IV - 2) Tests for SD of a composite index over time

In view of the illustration proposed in Figure 15, first order SD would reveal information whether there has been a pointwise decrease (or increase) in the indicator over time, and this is valid throughout the sample size for all countries. This is reflected by the fact that the distribution of $F_2(X)$ is everywhere above that of distribution $F_1(X)$, the curves do not intersect. As for second order SD, it would suggest that there is no decrease (or increase) for all countries, but an overall decrease (or increase) in the indicator. The CDFs curves intersect.

We examine the stochastic dominance of the retrospective EVI and its evolution over the period 1990—2013. It is well known that there is a one way relationship between the different forms of SD as suggested not only by the functions that are being compared but also by their implications for social welfare. For the ease of analysis, since the EVI is an indicator of vulnerability (a high score of the EVI means that country is vulnerable), we consider $EVI*$ computed as follows: $EVI* = 100 - EVI$. $EVI*$ may therefore be considered as an indicator of low vulnerability moving in the same direction with the social welfare.

We make a pairwise comparison of the retrospective $EVI*$ over two points in time. Let's consider two points in time with the cumulative distributions functions of the $EVI*$ given by G and F ; and $\pi_j(z;G)$ and $\pi_j(z;F)$ the integral operators that integrate the functions G and F at point z and to order $j-1$ so that:

$$\pi_1(z;G) = G(z),$$
$$\pi_2(z,G) = \int_0^z G(t)dt = \int_0^z \pi_1(t;G)dt),$$
$$\pi_3(z,G) = \int_0^z \int_0^t G(s)dsdt = \int_0^z \pi_2(t;G)dt$$

SD1 of G over F corresponds to $\pi_1(z;G) \leq \pi_1(z,F)$. If the CDF of the $EVI*$ in 1990, $F(z)$ is always at least as large as that of the CDF in 2000, $G(z)$ at any point, then the proportion of countries below a particular level of the $EVI*$ for the year 1990 is higher than that of 2000. Therefore, the 2000 $EVI*$ stochastically dominates its 1990 counterpart in the first order. When the two CDFs curves intersect, then the ranking is ambiguous. In this situation we cannot state whether one distribution first order dominates the other. This leads to an ambiguous situation which makes it necessary to use higher order SD analysis.

SD2 of G over F corresponds to $\pi_2(z;G) \leq \pi_2(z,F)$ for all z and the social welfare in the population summarized by G is at least as large as that in the F population, for any utility function U that is monotonically increasing and concave, that is $U'(z) > 0$, $U''(z) \leq 0$. SD2 is verified, not by comparing the CDFs themselves, but comparing the integrals below them. Given lower and upper boundary levels, it consists in determining the area beneath the curves and, if the area beneath the $F(z)$ distribution is larger than the one of $G(z)$, then in this case $G(z)$ stochastically dominates $F(z)$ in the second order degree. SD2 implies an overall improvement and not a pointwise dominance over all the points of the support of one distribution over another[27].

[27] There is no guarantee that SD2 will hold, so one may want to look for third order dominance. SD3 of G over F corresponds to $\pi_3(z;G) \leq \pi_3(z,F)$ for all z and the social welfare in the population summarized by G is at least as large as that in the F population for any utility function U that satisfies $U'(z) > 0$, $U''(z) \leq 0$ and $U'''(z) \geq 0$. The general hypotheses for testing SD of the index over time of order j can be written compactly as:

$H_0^j : \pi_j(z;G) \leq \pi_j(z;F)$ for all $z \in [0, \bar{z}]$,

$H_1^j : \pi_j(z;G) > \pi_j(z;F)$ for some $z \in [0, \bar{z}]$.

Stochastic dominance of any order G over F implies that G is no larger than F at any point. In this case there is an improvement of the index over time. Thus, if the EVI^* in 2000 dominates the EVI^* in 1990, then there is an improvement in the country welfare by the reduction in its vulnerability over time. The alternative hypothesis is the converse of the null and implies that there is at least some index value at which G (or its integral) is strictly larger than F (or its integral). In other words SD fails at some point for G over F. One can in principle distinguish between the case where F and G coincide and the case where G dominates F by reversing the roles they play in the hypotheses and redoing the tests. In this case, we can say that there can be improvements in the reduction of vulnerability levels for some countries and no improvement or even deterioration over time can be concluded for some other countries.

Tests statistics and asymptotic properties

Let's consider two time-dependent samples from two distributions (e.g., for EVI^* in 1990 and 2000). To allow for different sample sizes we need to make assumptions on the sampling process about the way in which sample sizes grow.

Assumption 1:

(i) $\{X_i\}_{i=1}^{N}$ and $\{Y_i\}_{i=1}^{M}$ are independent random variables from distributions with CDF's F and G respectively;

(ii) the sampling scheme is such that as N and $M \to \infty$, $N/(N+M) \to \lambda$ where $0 < \lambda < 1$.

Assumption 1 (i) deals with the sampling scheme and would be satisfied if one has samples of indices (for example EVI^*) from different segments of a population or separate samples across time. Assumption (ii) implies that the ratio of the sample sizes is finite and bounded away from zero.

The empirical distributions used to construct the tests are respectively,

$$\widehat{F}_N(z) = \frac{1}{N}\sum_{i=1}^{N} 1(X_i \le z),\ \widehat{G}_M(z) = \frac{1}{M}\sum_{i=1}^{M} 1(Y_i \le z).$$

The test statistics for testing the hypotheses can be written compactly as follows: $\widehat{S}_j = \left(\frac{NM}{N+M} \right)^{1/2} \sup_z (\pi_j(z;\widehat{G}_M) - \pi_j(z;\widehat{F}_N))$.

π_j is a linear operator, then

$$\pi_j(z;\widehat{F}_N) = \frac{1}{N}\sum_{i=1}^{N} \pi_j(z;1_{X_i}) = \frac{1}{N}\sum_{i=1}^{N} \frac{1}{(j-1)!} 1(X_i \le z)(z - X_i)^{j-1}$$

where 1_{X_i} denotes the indicator function $1(X_i \le x)$ (Davidson and Duclos, 2000).

We consider tests based on a decision rule of the form

"reject H_0^j if $\widehat{S}_j > c_j$"

Where c_j are critical values obtained by simulation methods.

In order to make the result operational c_j should satisfy $P(\overline{S}_j^F > c_j) \equiv \alpha$ or $P(\overline{S}_j^{G,F} > c_j) \equiv \alpha$ (some desired probability level such as 0.05 or 0.01). For testing orders of dominance beyond the first, the distribution of the test statistics will depend on the underlying CDFs. In particular $\overline{S}_j^F$ will depend on F while $\overline{S}_j^{G,F}$ will depend on both G and F. A wide variety of existing tests from the statistics and econometrics literature could also be used[28].

IV - 3) Results

To compare the distribution themselves, we apply a Kolmogorov-Smirnov test based on bootstrap methods from Barrett and Donald (2003). This test requires that the observations in each sample are independent[29]. In Table 4, the vertical column represents the years from 1995 to 2013 that are tested for stochastic dominance against years from 1990 to 2010.

[28] McFadden (1989), Anderson (1996), Davidson and Duclos (2000), Barrett and Donald (2003), Linton et al.(2005).

[29] Roughly, in our case, we can consider that this condition is fulfilled given the structure of the EVI. From the point of view of shocks in developing world, it is rare for countries' shocks to be interlinked, they can be affected by price shocks on world markets, but because they are price-takers, no one influences the other. Natural disasters can be linked in the context of a neighborhood but this does not affect all countries at the same time. Similarly for the exposure components, neither the population nor the economic structure of the different countries depends upon each other.

Percentage levels in the table represent the significance level of stochastic dominance. The results suggest that in general, there is no decrease in EVI using a 5 year testing horizon. In most cases, the Kolmogorov-Smirnov test indicates that neither distribution dominates the other in a first order sense. The only exceptions are the EVI* in 1990 and 1995 which are dominated by the 2000 and 2013 years in the first order sense at the 10 percent level. Moreover no distribution dominates the 2000 year in both first and second order senses. Except this, there is agreement that the following years dominates the EVI* of the previous years in the second order sense. With regard to exposure sub-index, we find that no distribution dominates the 2000, 2005 and 2010 years at both first and second order senses. We note only one SD in the first order sense (the 2000 year Exposure* dominates the 1995 year at the 5 percent level) but a SD in general in the second order sense at 1 percent level. For Shock sub-index, there is unanimously a SD in second order sense, while only two cases of first order dominance are observed: the distribution in 2013 dominates the ones of 2000 and 2005 at 10 and 5 percent levels respectively. This indicates a general reduction of shocks for all countries in 2013 compared to the years 2000 and 2005 and can be seen as an improvement of the ability of countries to better withstand external shocks through the implementation of adaptation measures. Moreover, this result is consistent with a comment made in section 3 stating that EVI decreases faster in LDCs than in non-LDCs, specifically since 2003—2004, even though, we do not distinguish LDCs from non-LDCs. But its remains clear that the latter group of countries is less affected by shocks than the first one.

To supplement our analysis, we also apply the Linton et al. (2005) subsampling approach to EVI and its main components to compare the findings with Barrett and Donald (2003) bootstrapping approach. Linton et al. (2005) relax the independence assumption and their test for stochastic dominance can deal with both dependent samples and dependent observations within samples. The null hypothesis is that the EVI* (Exposure* and shock*) in the following years dominates the EVI* (Exposure* and shock*) of the previous years. The p-values for SD1 and SD2 are reported in Table 5. In most cases, the null hypothesis is not rejected, suggesting the presence of an overall decrease in vulnerability over time. The only exceptions are that: i) we reject the null hypothesis that the EVI* in 2013 dominates the EVI* in 1995, 2005 and 2010 at any order; ii) we reject the null hypothesis that the EVI* in 1995 dominates the EVI* in 1990 at the first order sense. Regarding Exposure*, we observe the rejection of the null hypothesis that the year 2000 dominates the previous years at any order. Similarly, we cannot conclude that the year 2005 dominates the year 1995 at any order. The Exposure* in 2013 dominates the years 1990 and 1995 at the first order but one cannot reject SD2. The same is true by comparing the year 2005 with the year 1990. It seems that the decrease in the EVI over time is driven by the decrease in shocks components. In fact, there is agreement that the Shock* in following years dominates the Shock* of the previous years. The only exception is that we reject the null hypothesis that the Shock* in 2013 dominates the Shock* for the period 1995 to 2010 at any order.

Some discrepancies remain between the results obtained from Barrett and Donald (2003) method and those obtained from Linton et al. (2005). For the first, in most cases, dominance exists only at the second order while the latter shows the dominance at any order in general. Also, the most striking difference concerns that EVI* and Exposure* in 2000 is dominated at any order by the years 2005, 2010 and 2013 when we use the Linton et al. (2005) approach as opposed to the Barret and Donald (2003) approach. These glaring differences should deserve closer investigation. The main reason responsible for this discrepancy is that the null hypothesis in the Barrett and Donald (2003) approach excludes equality from dominance, whereas it is included in the null hypothesis of Linton et al. (2005).Thus, under-rejection of dominance over time could be occurred as there could be many equal outcomes that would favour dominance. At the same time, the sampling theory tests are likely to suggest dominance if there is a large range of population segments where the probability of dominance is 1, even if there are some limited ranges where the probability is close to 0. To this, we can add that the Linton et al (2005) approach requires a balanced dataset and, in doing so, a more homogeneous panel. However, despite our efforts to build comprehensive data, some countries lack data for some years (e.g. Eritrea, Ethiopia, South Sudan, Timor-Leste, etc.). Even if such cases are very rare, they could still influence the results of the tests. For these reasons, we would be inclined to support the research findings from the Barret and Donald (2003) approach.

Table 4: Stochastic dominance based on Barrett and Donald (2003) bootstrapping approach

Stochastic dominance results for EVI*						
		1990	1995	2000	2005	2010
1995	SD1	ND				
	SD2	1%				
2000	SD1	10%	5%			
	SD2	1%	1%			
2005	SD1	ND	ND	ND		
	SD2	1%	1%	ND		
2010	SD1	ND	ND	ND	ND	
	SD2	1%	1%	ND	1%	
2013	SD1	10%	10%	ND	ND	ND
	SD2	1%	1%	ND	1%	1%
Stochastic dominance results for Exposure*						
		1990	1995	2000	2005	2010
1995	SD1	ND				
	SD2	1%				
2000	SD1	ND	5%			
	SD2	1%	1%			
2005	SD1	ND	ND	ND		
	SD2	1%	1%	ND		
2010	SD1	ND	ND	ND	ND	
	SD2	1%	1%	ND	ND	
2013	SD1	ND	ND	ND	ND	ND
	SD2	1%	1%	ND	ND	ND
Stochastic dominance results for Shock*						
		1990	1995	2000	2005	2010
1995	SD1	ND				
	SD2	1%				
2000	SD1	ND	ND			
	SD2	1%	1%			
2005	SD1	ND	ND	ND		
	SD2	1%	1%	1%		
2010	SD1	ND	ND	ND	ND	
	SD2	1%	1%	1%	1%	
2013	SD1	ND	ND	10%	5%	ND
	SD2	1%	1%	1%	1%	1%

Notes: EVI*=100-EVI; Exposure=100-Exposure index; Shock*=100-Shock index. ND means that there is no stochastic dominance at that order.

Table 5: Stochastic dominance based on Linton et al. (2005) subsampling approach

Stochastic dominance results for EVI*						
		1990	1995	2000	2005	2010
1995	SD1	0.094				
	SD2	0.433				
2000	SD1	0.999	0.999			
	SD2	0.999	0.999			
2005	SD1	0.812	0.715	0.999		
	SD2	0.509	0.438	0.999		
2010	SD1	0.609	0.221	0.999	0.706	
	SD2	0.472	0.340	0.999	0.260	
2013	SD1	0.307	0.066	0.997	0.076	0.009
	SD2	0.190	0.003	0.999	0.007	0.001
Stochastic dominance results for exposure*						
		1990	1995	2000	2005	2010
1995	SD1	0.226				
	SD2	0.804				
2000	SD1	0.009	0.077			
	SD2	0.043	0.004			
2005	SD1	0.003	0.018	0.247		
	SD2	0.970	0.065	0.111		
2010	SD1	0.000	0.018	0.911	0.995	
	SD2	0.971	0.526	0.609	0.525	
2013	SD1	0.000	0.040	0.949	0.963	0.609
	SD2	0.486	0.371	0.516	0.426	0.666
Stochastic dominance results for Shock*						
		1990	1995	2000	2005	2010
1995	SD1	0.961				
	SD2	0.523				
2000	SD1	0.828	0.695			
	SD2	0.813	0.158			
2005	SD1	0.722	0.280	0.758		
	SD2	0.749	0.120	0.168		
2010	SD1	0.621	0.254	0.391	0.211	
	SD2	0.925	0.238	0.289	0.341	
2013	SD1	0.407	0.001	0.008	0.000	0.009
	SD2	0.905	0.020	0.018	0.068	0.043

Notes: EVI*=100-EVI; Exposure=100-Exposure index; Shock*=100-Shock index. P-values for the null hypothesis that the given index in the following years dominates the index of the previous years are reported.

V - Concluding remarks

Despite the challenges associated with the development of indicators relating to economic vulnerability, many indicators have been developed. The literature review explored the current state of research on economic vulnerability indicators. As a result, most of organizations and researchers combined policy-induced factors under the heading of resilience and structural factors. Despite all being related to vulnerability, the background concepts differ, meaning that their underlying rationale differs. While some aim to depicting a general vulnerability including resilience, others aim at focusing on structural features of vulnerability. But the differences with regard to their comprehensiveness are even more crucial. For purposes of measuring the economic vulnerability of developing countries, we focus on structural factors that capture the extent to which each country is intrinsically vulnerable, regardless of its current policies. This thinking is inspired by equity and fairness reasons and by requests from policy makers to take into account structural factors of vulnerability as a criterion for aid allocation. In fact, the formula proposed by multilateral institutions is essentially based on performance in order to reward the best performing countries by a larger amount of aid. But some countries face structural handicaps that prevent them from performing well.

In this work, we propose an index of structural economic vulnerability devised by the United Nations for identifying LDCs. The EVI captures only the factors that make a country structurally vulnerable. These factors reflect the risk for a country seeing its economy growth, and more generally its development rate, durably slowed down by exogenous shocks, independently of its policy choices. The EVI has undergone some changes since its inception, and these changes are not inconsequential. One striking example is the inclusion of an environmental variable in the index since the 2012 triennial review. Through an application on African countries, we have shown how this change creates an unbalance in the EVI. Also, we point to the limits of another exposure variable that is the merchandise export concentration.

Then, we assess the link between structural economic vulnerability and fragility in Africa. We show how structural economic vulnerability constitutes a trap for fragile states by the increase in the duration of fragile situation. Fragile African states are economically more vulnerable than non-fragile African states, and the difference between the two groups of countries seems to come from the difference observed at the level of the shock's component.

Another purpose of this chapter is to detail the methods used to build retrospective series of the EVI and each of its components, which cover 145 countries over the 1990—2013 period. Overall, the analysis of the series shows that the vulnerability of LDCs, although decreasing faster than that of non-LDCs, is still higher compared to the level of non-LDCs. With the exception of the variables of the population size and the share of population living in LECZ, LDCs display a high level of vulnerability at any year. The two series do not intersect anywhere. But that is not the case with the instability of agricultural production for which the two series intersect at nine points, even if the level of this variable falls more rapidly since 2008 for non-LDCs and later since 2011 for LDCs.

Lastly, we apply consistent SD tests to examine whether there has been an overall decrease in the EVI and its main components. Using a five-year testing horizon, our results do not show a real decline of the EVI and its main components at the first order sense but an overall decrease can be concluded at the second order sense of dominance. This suggests that the CDF of the following years and the one of the previous cross, meaning that the dominance is not general because the conditions are not met for some countries. However, the integrate CDF of the following years dominates that of the previous years over the period of time in most of cases. That is particularly true for shock index, suggesting a form of "learning" against external shocks.

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Appendices

Appendix 1: EVI and its components over time

2011

Economic Vulnerability Index (EVI)

- Population
- Remoteness
- Merchandise export concentration
- Share of agriculture, forestry and fisheries in GDP
- **Share of population in low elevated costal zones**

- **Victims of natural disasters**
- Instability of agriculture production
- Instability of exports of goods and services

2005

Economic Vulnerability Index (EVI)

- Population
- **Remoteness**
- Merchandise export concentration
- **Share of agriculture, forestry and fisheries in GDP**

- **Homelessness due to natural disasters**
- Instability of agriculture production
- Instability of exports of goods and services

2002

Economic Vulnerability Index (EVI)

- Population size
- Export concentration
- Share of manufacturing and modern services in GDP

- Instability of agricultural production
- Instability of export of goods and services

1999

Economic Vulnerability Index (EVI)

- **Population size**
- Export concentration
- **Share of manufacturing and modern services in GDP**

- **Instability of agricultural production**
- **Instability of export of goods and services**

1991

Economic Diversification Index (EDI)

- **Export concentration ratio**
- Share of manufacturing in GDP
- **Share of employment in industry**
- **Per capita electricity consumption**

Notes: New components in bold. Prior to 1991, the idea behind contained a single variable which was the share of manufacturing in GDP. The first attempt to design a composite index has been done in 1991 under the name of "Economic Diversity Index (EDI)". The name Economic Vulnerability Index (EVI) was given at the first time in 1999 in preparation of the 2000 triennial review.

Source: CDP secretariat

Appendix 2: The variables used in the EVI: the rationale, temporal coverage, data source, update frequency

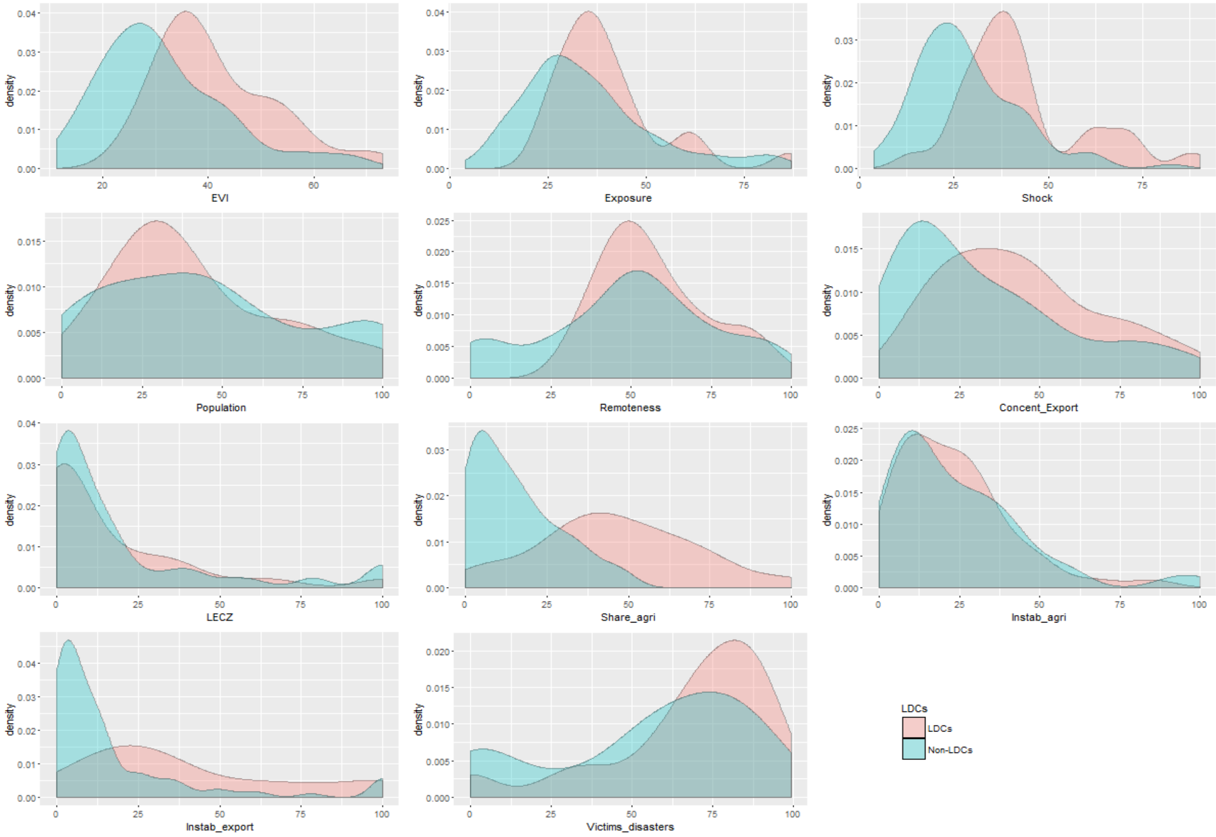
Variables	Why? What measure?	Temporal coverage(*)	Data source	Update frequency
Population size (in logarithm)	▪ Smaller countries are more exposed to economic, trade and environmental shocks. ▪ The population in a country as of 1 July of the year.	1950-2015	Population Division of the UNDESA in its World Population Prospects database, available from http://esa.un.org/unpd/wpp/index.htm and http://data.un.org	Annually
Remoteness from world markets	▪ The remoteness inhibits growth and opportunities to trade by increasing transport costs and the difficulty of diversifying the economy. ▪ For each country i, partners countries j are ranked according to their distance from country i. The group of the closest countries is hence progressively selected until 50% of the world market is reached for country i.	1970-2015	▪ The data on bilateral physical distance between the exporting country and its trading partners (importers) is from Centre d'Etudes Prospectives et d'Informations Internationales (CEPII). ▪ The data on the market share of each trading partner in world markets is from the UN Statistics National Accounts Main Aggregates Database (http://unstats.un.org/unsd/snaama/).	Annually
Merchandise export concentration	▪ The indicator reflects the exposure to trade shocks resulting from a concentrated export structure. The more concentrated, the less resilient, the more exposure to shocks. ▪ It is derived from a Herfindahl-Hirschmann index applied to exports of merchandises.	1995-2014 (UNCTAD database), completed over the period 1970-1994 by the Cerdi-Ferdi database.	UNCTAD	Annually
Share of agriculture, forestry, and fisheries in GDP	▪ The indicator reflects the exposure of countries caused by their economic structure because agriculture, forestry and fisheries are particularly subject to natural and economic shocks; the higher, the less resilient, the more exposure to shocks. ▪ Percentage share of agriculture, fisheries and forestry (ISIC A-B) in GDP.	1970-2015	United Nations Statistics Division in its National Account Main Aggregate Database http://unstats.un.org/unsd/snaama .	Annually (December of each year)
Share of population living in low elevated coastal zones	▪ Climate change increases the vulnerability of coastal areas in some countries and territories, especially the sea level rise combined with extreme climatic events such as storms. ▪ The share of the population in a country that lives in low elevated coastal zones, defined as areas contiguous to the coast below a certain elevation threshold (5 meters).	1990, 2000, 2010. The annual change for each of the decades is used to generate the annual data by interpolation over the period 1990-2015.	Columbia University, Center for International Earth Science Information Network (CIESIN) http://sedac.ciesin.columbia.edu/data/sets/browse	Unspecified

Variables	Why? What measure?	Temporal coverage(*)	Data source	Update frequency
Victims of natural disasters	▪ The indicator reflects the vulnerability to natural shocks, in particular the human impact of natural disasters associated with these shocks. (The larger, the bigger the shock). ▪ The share of the population victim of natural disasters. Victims are defined as people killed or affected (i.e., people requiring immediate food, water, shelter, sanitation or medical assistance). It covers weather and climate-related disasters (such as floods, landslides, storms, droughts and extreme temperatures) as well as geo-physical disasters (such as earthquakes or volcanoes).	1900-2015 (with less precision for the most distant years)	▪ UNDESA Population Prospects Database, http://esa.un.org/unpd/wpp/index.htm. ▪ Emergency Disasters Database (EM-DAT) - WHO collaborating Centre for Research on the Epidemiology of Disasters (CRED) http://www.emdat.be/	Annually
Instability of agricultural production	▪ The indicator reflects the vulnerability of countries to natural shocks, in particular impacts of droughts and disturbances in rainfall patterns. (The higher, the larger the shock) ▪ Standard error of the regression of " total agricultural production in real terms" on its past values (21 years) as well as on a trend variable.	1961-2014	Food and Agriculture organization of the United Nations available from http://faostat3.fao.org/home/E.	Annually
Instability of exports of goods and services	▪ The indicator reflects the instability of export earnings, or the capacity of a country to import goods and services from current export earnings. ▪ Standard error of the regression of exports of goods and services in constant USD on their past values (21 years) as well as on a trend variable.	1970-2014	United Nations Statistics Division's National Account Main Aggregates Database (http://unstats.un.org/unsd/snaama).	Annually

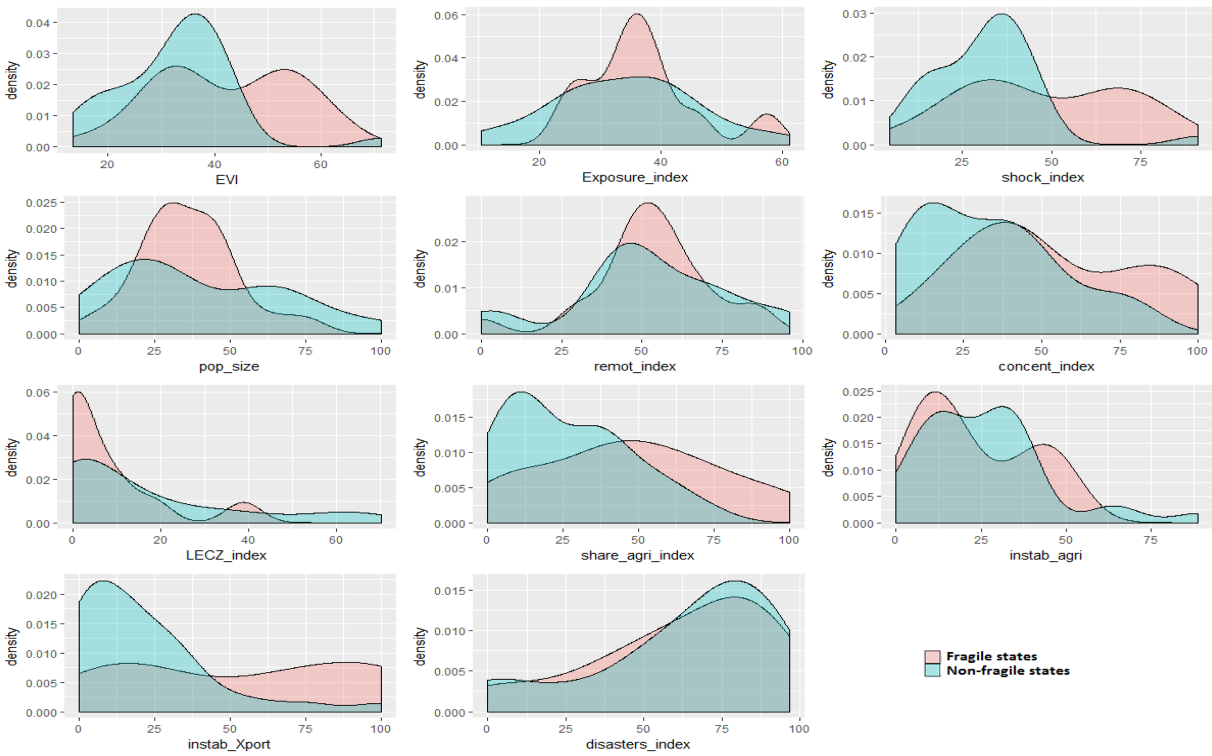
(*) temporal coverage available as of May 10, 2017.

Appendix 3: Distributions

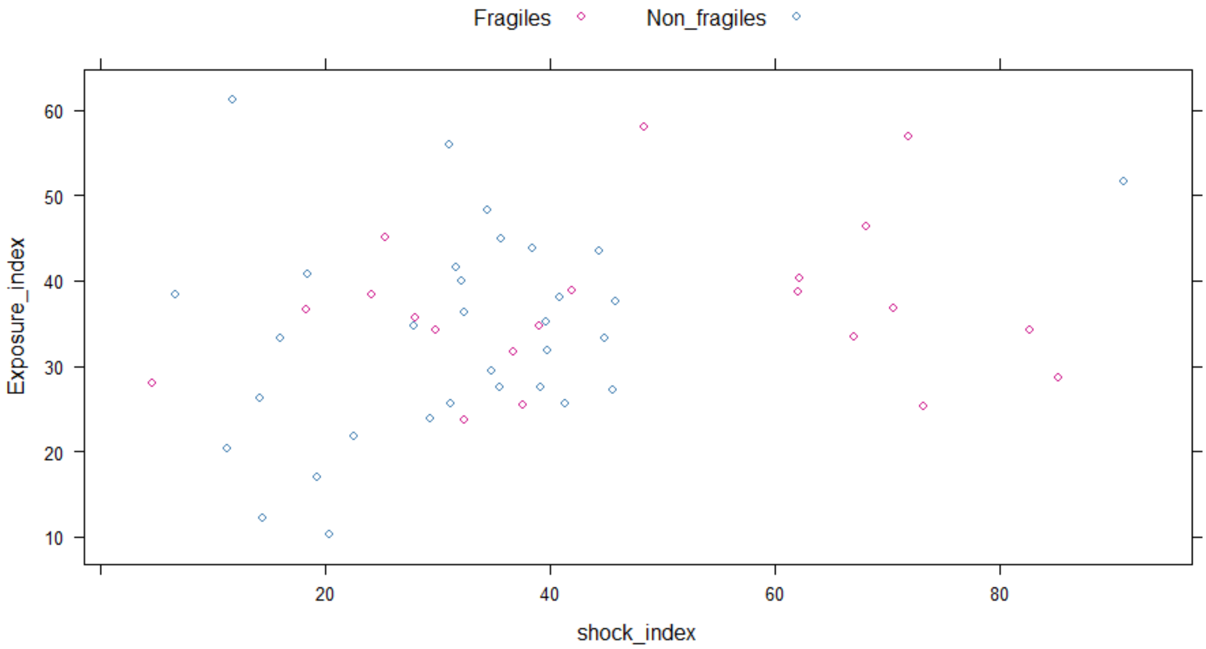
Appendix 3.a: Distribution of the retrospective 2015 EVI and its components, LDCs versus non-LDCs, 2013



Appendix3.b: Distribution of the retrospective 2015 EVI and its components, African fragile states versus African non-fragile states, 2013



Appendix 4: Shock index (x) and Exposure index (y) for African fragile states and African non-fragile states



Appendix 5: Evolution of the retrospective 2015 EVI in LDCs

Country	ISO_3	EVI 1990	EVI 2000	EVI 2010	EVI 2013
Afghanistan	AFG	31,02	36,25	36,30	34,65
Angola	AGO	33,76	36,40	34,42	38,43
Burundi	BDI	40,24	53,48	56,64	50,47
Benin	BEN	49,40	48,14	32,19	32,77
Burkina Faso	BFA	38,56	38,20	36,64	38,51
Bangladesh	BGD	35,37	31,69	26,64	24,33
Bhutan	BTN	34,91	43,97	40,70	40,13
Central African Republic	CAF	30,61	33,00	31,15	31,96
Democratic Republic of the Congo	COD	29,74	35,64	29,08	28,83
Comoros	COM	53,11	56,00	66,16	65,92
Djibouti	DJI	52,54	53,02	52,50	38,47
Eritrea	ERI				58,02
Ethiopia	ETH				33,55
Guinea	GIN	24,03	24,73	26,41	25,61
Gambia	GMB	54,72	48,49	68,34	70,49
Guinea-Bissau	GNB	50,45	57,07	56,62	53,98
Equatorial Guinea	GNQ	57,45	52,15	48,02	43,49
Haiti	HTI	32,68	36,83	35,70	33,27
Cambodia	KHM	43,95	52,46	43,65	37,57
Kiribati	KIR	81,47	84,71	80,40	73,06
Lao People's Democratic Republic	LAO	56,09	50,91	39,86	35,70
Liberia	LBR	46,99	65,83	59,43	57,25
Lesotho	LSO		43,15	42,58	42,51
Madagascar	MDG	36,48	30,81	33,40	34,21
Mali	MLI	38,19	32,55	32,55	32,25
Myanmar	MMR	34,93	33,21	33,55	32,05
Mozambique	MOZ	34,66	39,66	40,52	38,15
Mauritania	MRT	51,94	39,52	41,21	40,64
Malawi	MWI	40,30	44,98	42,86	40,28
Niger	NER	46,94	39,90	37,04	36,73
Nepal	NPL	38,80	33,05	29,05	26,95
Rwanda	RWA	47,17	44,47	45,14	39,37
Sudan	SDN	36,53	47,44	52,06	50,59
Senegal	SEN	45,91	34,94	31,98	32,10
Solomon Islands	SLB	65,75	56,37	50,28	48,89
Sierra Leone	SLE	29,30	37,56	43,33	49,69
Somalia	SOM	44,32	50,30	38,79	35,85
South Sudan	SSD			44,36	52,96
Sao Tome and Principe	STP	67,19	58,33	41,38	37,39
Chad	TCD	41,92	43,13	48,85	50,44
Togo	TGO	41,12	37,63	34,42	33,95
Timor-Leste	TLS			54,46	54,89
Tuvalu	TUV	73,72	71,10	59,47	56,15
United Republic of Tanzania	TZA	47,50	42,28	29,67	27,97
Uganda	UGA	37,62	35,71	32,76	32,00
Vanuatu	VUT	53,95	52,42	47,14	46,82
Yemen	YEM	40,20	46,86	42,12	34,50
Zambia	ZMB	38,08	40,40	46,17	42,68

CHAPTER 2: HUMAN ASSETS INDEX: INSIGHTS FROM A RETROSPECTIVE SERIES ANALYSIS*

I - Introduction

Human development relies on the creation of an environment in which people can develop their full potential and lead productive and creative lives, in accordance with their needs and interests. It is therefore, beyond economic growth, to broaden the choices available to the population. An important part of this broadening of choices is based on human capital, namely, the range of human capabilities that determines what people can do or be in life. The international agenda of sustainable development has identified human capital as a key determinant of long-run growth. The availability of education and health services to people is one of the major ways of improving the quality of human resources required for economic growth and development. The importance of human capital goes back at least to Adam Smith (1776)[30] who held that the wealth of nations depends in part on the health, nutrition, skills and knowledge of their people. He argued that poor health and nutrition and lack of education contribute to lower economic productivity. A major turning point in the concept of human capital, however, occurred in the late 1950s with the emergence of a micro-

*This chapter is an enhanced version of the article co-authored with Michaël Goujon and published in the Social Indicators Research.

[30] Sir William Petty (1690) was perhaps the first to try to define and measure human capital. His thesis was that factors other than land and population were important in determining the wealth of a nation. Cantillon (1755) also discussed the concept of human capital but he was faintly interested in the value created by human capital. Irving Fisher (1897) used the earliest the term “human capital” in economics with a formal meaning.

founded model of rational choice in human capital investment associated to Schultz (1959, 1961), Becker (1962, 1964) and Mincer (1958, 1974) at the University of Chicago.

Human capital refers to the stock of competencies, skills, knowledge and personalities attribute embodied in individuals which facilitate their ability for the creation of personal, economic and social value (OECD, 2001). It appears as one of production elements which can generate added-values through inputting it. Individual learning is then seen as an investment process of increasing the productivity of the workforce by training more. The use of the term "human capital" is also explained by the fact that it is a form of capital incorporated into individuals. Unlike other types of capital, especially physical (machinery and capital goods) and financial, human capital exists and physically disappears with its owner. The benefits of human capital are economic and social. On the economic side, the benefits associated with investing in human capital are in the form of increased income and its earning power for the individual making the investment. Social benefits include an increase in life expectancy for the most educated, a decline in unwanted fertility in less developed countries, and greater participation in life civic and social.

Measuring human capital can serve a number of purposes, especially when assessing the long-term sustainability of a country's development path, and to measure the output and productivity of education and health sectors. The diversity of the approaches to measuring human capital calls for efforts to develop consistent measures based on theoretically sound and practically feasible methodologies. Since human capital is not a one-dimensional concept, researchers and institutions resort to composite indicators. One of the main challenges concerns the choice of the different variables to be included in the measurement of human capital. The pillars of human capital can contain indicators relating to quantitative and qualitative aspects of education and health, including both input and output indicators. The input indicators refer to access to education and healthcare, education funding and healthcare expenditure. The output indicators refer to completion, progress and transition indicators for education and morbidity and mortality indicators for health.

Social factors of a structural nature include variables such as the level of human capital and its distribution throughout the economy as well as the level of income. For this purpose, the index should reflect an overview of the state of a country's human capital over the long-term. This approach does not fit political cycles or business investment horizons; but lack of such long-term planning can perpetuate continued wasted potential in a country's population and losses for a nation's growth and productivity. Because of their low human capital and low income levels, some countries often lack the resources to effectively cope with shocks. They are locked in a vicious cycle because they are underdeveloped and the shocks to which they are exposed keep them in a situation that lowers their human capital and income levels in the long run. That is why the low level of human capital became one of the three criteria used by the United Nations Committee for Development Policy (UN-CDP) for identifying Least Developed Countries (LDCs)[31].

Since 1991, the UN-CDP has used a composite index to measure human capital at the country level. In 2003 this index was reshaped and was renamed "Human Assets Index" (HAI). The HAI is a composite indicator which combines four indicators, two indicators of health and nutrition outcomes (Percentage of the population undernourished, Mortality rate for children aged five years or under) and two indicators of education (Gross secondary school enrolment ratio, Adult literacy rate). The primary data for each variable of the HAI are rescaled and converted into index values using a min-man procedure. The HAI is then calculated as the simple average of the four components indices. Each component carries an equal weight of 25 % in the HAI and the normalized scores vary between 0 and 100.

Every three years, the UN-CDP computes and publishes the HAI for the triennial reviews of the LDCs. Since the 2006 review, the overall methodology and the four components of the index have remained unchanged[32]. While the bounds used in the min-man procedure were readjusted in 2009 and 2012 by the UN-CDP following changes in the extreme values observed, they remained unchanged for the 2015 review. Then, even if these methodological changes remain marginal, the analysis of trends in human capital requires the calculation of retrospective series with a constant definition over time and time series that are updated and comparable over time. The construction of retrospective series faces

[31] The two other criteria are the GNI per capita and the Economic Vulnerability Index. See Guillaumont (2009) and UN-DESA-DPAD-CDP webpage on LDCs: http://www.un.org/en/development/desa/policy/cdp/index.shtml.

[32] Since the 1990s, changes in the methodology concerned the definitions of the components: in 1999, Per capita calorie supply is replaced by average calorie intake per capita as a percentage of the requirement, and life expectancy at birth is replaced by under-five mortality rate. In 2002, combined primary and secondary school enrolment ratio is replaced by the gross secondary school enrolment ratio. In 2005, average calorie intake per capita as a percentage of the requirement is replaced by percentage of population undernourished.

various challenges. The main one is historical data availability, which is especially weak for social statistics in developing countries.

In the section 2 of this chapter, we present a set of retrospective series of HAI using the 2015 review definition and update time series of its components, for which, to a limited extend, we have used econometric tools to consistently impute missing data. The detailed method of imputations is presented in the Appendix 1. In section 3, retrospective series of HAI allows us to give insight into the HAI dynamics by closely examining the contributions of components to the change of the overall index. As well, we explore the change in standard deviations within each component of the HAI and distribution analyses.

Another important question that is often debated for the composite indicators is component's weights. The choice of equal weighting for the four components in the HAI made by the UN-CDP aims at building a simple composite index, where all components are assumed to be equally important. However, the genuine importance of components also depends on the characteristics of the statistical distribution of the components and their correlation structure (Paruolo et al., 2013). In the section 4, we apply a sensitivity analysis to reveal the importance of each component in the composite index. We also propose a new weighting pattern that is optimized based on the correlation ratio and linearity (nonlinearity) dependence between components.

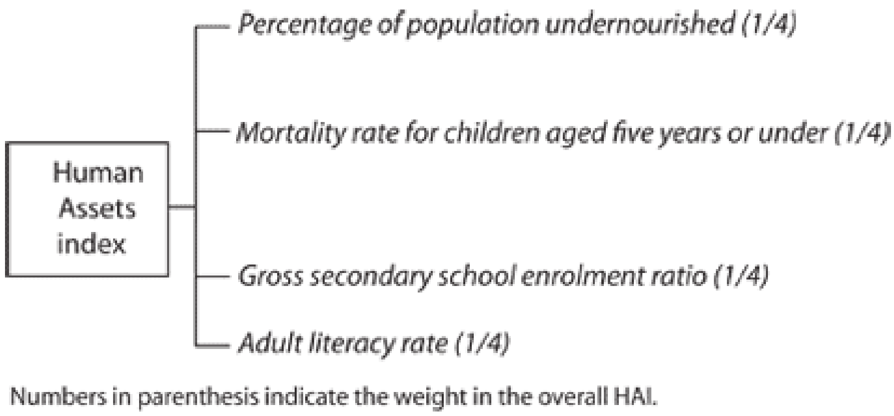
II - The Human Asset Index retrospective series[33]

II - 1) The rationale for Human Asset Index retrospective series

As shown in Figure 1, the HAI is a composite indicator which combines four indicators, two indicators of health and nutrition outcomes (Percentage of the population undernourished, Mortality rate for children aged five years or under) and two indicators of education (Gross secondary school enrolment ratio, Adult literacy rate).

[33] This section is a modified version of the working paper "Human Assets Index retrospective series: 2016 update" co-authored with Michaël Goujon (Ferdi Working Paper N°179, 2016).

Figure 1: The Human Assets Index and its four components



Source: Source: united Nations Committee for Development Policy (UN-CDP).

The primary data for each variable are rescaled and converted into index values using a min-max procedure. The normalized index values then vary between 0 and 100, a higher value signaling a high human capital (i.e.: a low undernourishment and mortality, and a high school enrolment and literacy). The HAI is then calculated as the simple average of the four components indices, each component carrying an equal weight of 25 % in the HAI.

Every three years, the UN-CDP computes and publishes the HAI for the triennial reviews of the LDCs. Since the 2006 review, the overall methodology and the four components of the index have remained unchanged. While the bounds used in the min-max procedure were readjusted in 2009 and 2012 by the UN-CDP following changes in the extreme values observed, they remained unchanged for the 2015 review. Table 1 presents the bounds used in the three last reviews by the UN-CDP.

Table 1: Changes in the bounds used in the min-max procedure

	2009 Review Bounds		2012 Review Bounds		2015 Review Bounds	
Components	Min	Max	Min	Max	Min	Max
Undernourishment	2.5	65	5	65	5	65
Under Five Mortality	10	240	10	175	10	175
Secondary School Enrolment	5.7	100	10	100	10	100
Literacy rate	15	100	25	100	25	100

Source: Source: united Nations Committee for Development Policy (UN-CDP).

Even if these methodological changes remain marginal, the analysis of trends in human capital requires the calculation of retrospective series with a constant definition over time and time series that are updated and comparable over time. This is recognized by the UN-CDP that has recently opened StatPlanet Graphical Interface, a visual and retrieval tool for 2006, 2009, 2012 and 2015 data. The UN-CDP then explains that "The calculations of all indicators are based on the definitions of LDC criteria applicable to the corresponding year (…). Data is not comparable between the individual triennial reviews due to data revisions, changes in data sources, methodological changes and changes in composition of composite indices." [34]

The construction of HAI retrospective series was done previously after the 2009 review by Korachais (2011) and after the 2012 review by Closset et al. (2014).[35] Retrospective series of the HAI have been used by, among others, Guillaumont (2009, 2011, 2013, 2015), Guillaumont and Wagner (2012), Guillaumont, MacGillivray and Wagner (2013), Wagner (2014), Assaf et al. (2015), Kaya (2016), Kilama (2016), Gnangnon (2016, 2017), Cerra and Woldemichael (2017), Ritzel and Kohler (2017). They are also referenced in a recent and large review of human development indices (Anderson et al, 2015).

The construction of retrospective series faces various challenges. The main one is historical data availability, which is especially weak for some components and some developing countries. Components of the HAI are based on social statistics that are characterized by their scarcity. We then compute a set of retrospective series, for which, to a limited extent, we have used econometric tools to consistently impute missing data. Series are completed with generated values from econometric estimates using explanatory variables such as the GNI per capita, the Gini index, region dummies, country and time effects.[36] Computation details are presented in appendix 1.

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[34] United Nations Committee for Development Policy Secretariat. Triennial review dataset 2000—2015. https://www.un.org/development/desa/dpad/least-developed-country-category/ldc-data-retrieval.html

[35] A similar exercise is done regularly for the Economic Vulnerability Index, see Cariolle and Goujon (2013) and Feindouno and Goujon (2016).

[36] In a small number of cases, we were not able to use imputation methods. Due to missing data on some components, HAI is missing over some years for Solomon Islands (1990-1991); Palau and Federated States of Micronesia (1990-1992); Marshall Islands (1990-1994); Tuvalu (1990-2000); Nauru (1990-2005). Only one year is available for DPR of Korea (2009) and Turkmenistan (2014) and HAI is missing over the entire period for Singapore and South Sudan.

II - 2) Main results of the HAI retrospective series

As a first relevance check, we compare the scores of the official UN-CDP HAI released at the triennial review of 2015 with the scores of our retrospective HAI for the year 2013 (this corresponds to the year of the data used by the UN-CDP 2015 review). Figure 2 shows a high correlation (98.5%) between the scores of both HAI (of 141 countries, excluding DPR Korea, Singapore, South Sudan, Turkmenistan due to missing data). One can observe small differences between UN-CDP and retrospective series of HAI scores. This is the case when the UN-CDP used information from different reports that may not correspond to the year 2013 while we preferably use econometric models to generate data that correspond to every year. Also, our calculations have been done some months after the UN-CDP's ones, with primary data further updated, then creating some other discrepancies.

Figure 3 shows the evolution of the HAI scores over the period 1990—2014 for 135 countries (45 LDCs and 90 non-LDCs[37]). The average score of HAI is significantly higher in non-LDCs than in LDCs. However, since 2000, the slope of the LDCs HAI curve has steepened, substantially reducing the gap with the non-LDCs. As reported in Table 2, the gap between LDCs and non-LDCs is on average about 46 points in 1990 and 34 points in 2014. However, HAI scores in LDCs present a high level of standard deviation, signaling heterogeneity within this group. The level of HAI in African LDCs is lower than in non-African LDCs, and increases less rapidly between 2000 and 2014 (+20 points for African LDCs versus +24 points for non-African LDCs). Figure 4 reports on a world map the levels of the retrospective HAI in 2014.

[37] To get a constant sample over time, we remove 10 countries for which data are not complete over the entire period (see footnote 36): Marshall Islands, Tuvalu, Nauru, Turkmenistan, Palau, Solomon Islands, Singapore, Federated States of Micronesia, South Sudan, DPR of Korea.

Figure 2: Correlation between HAI scores of the UN-CDP 2015 review and the retrospective 2015 HAI database for the year 2013

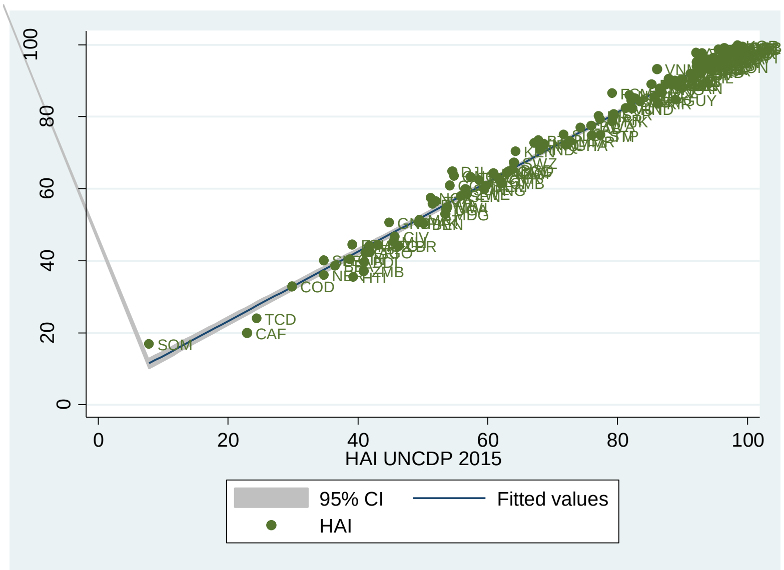


Figure 3: Changes in the retrospective HAI, LDCs versus non-LDCs averages

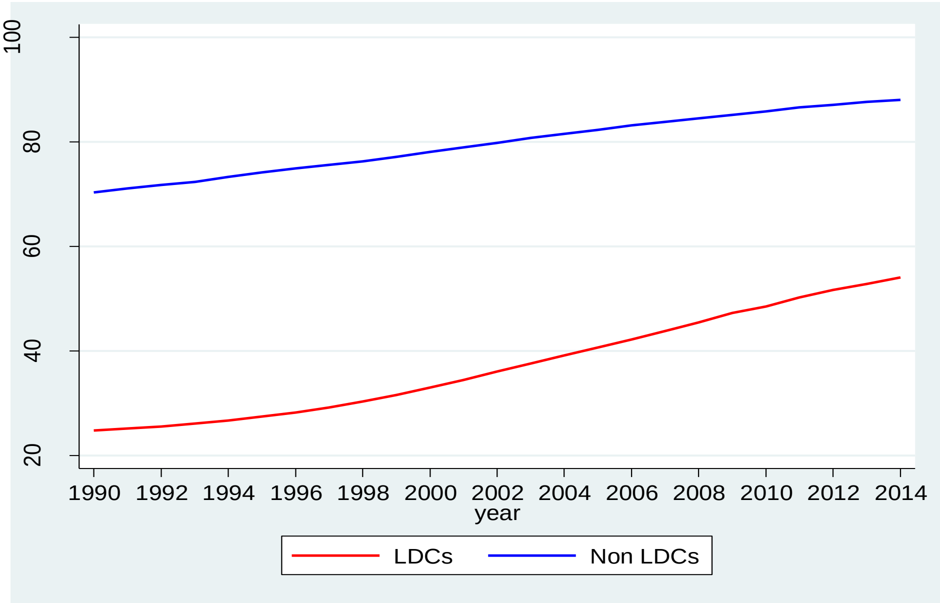


Figure 4: HAI on the MAP in 2014

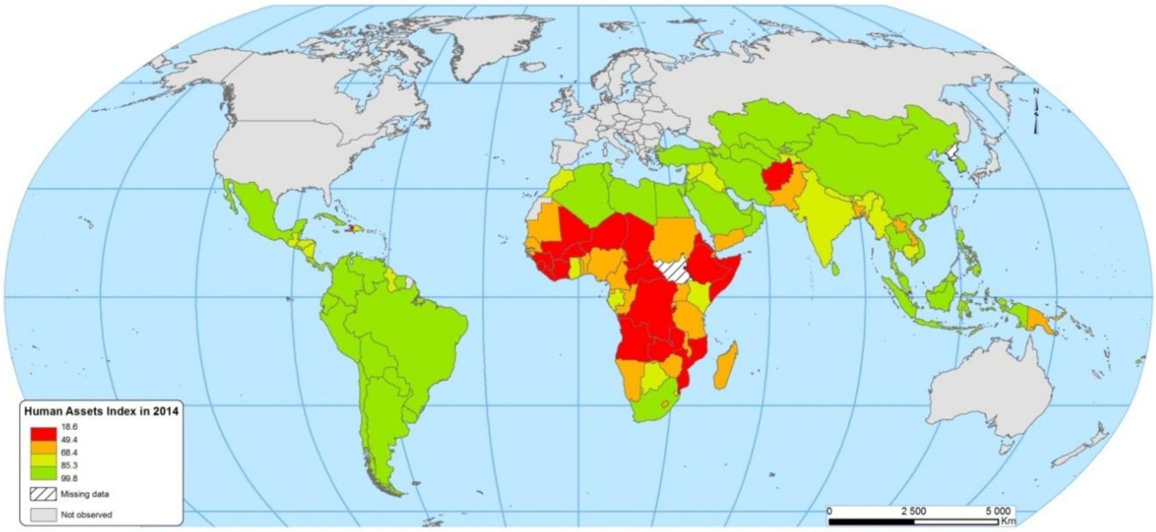


Table 2: HAI average scores by country groups

Country groups	1990	2000	2010	2014
LDCs	24.7 *(14.7)*	33.0 *(15.7)*	48.5 *(15.9)*	54.1 *(15.9)*
Non-LDCs	70.3 *(16.5)*	78.1 *(15.7)*	85.9 *(13.0)*	88.1 *(11.8)*
African LDCs	22.8 *(14.2)*	28.6 *(13.3)*	43.5 *(12.9)*	48.7 *(13.6)*
Non-African LDCs	29.6 *(15.5)*	43.7 *(16.4)*	60.7 *(16.3)*	67.2 *(13.8)*

II - 3) Evolution of the scores of the Retrospective HAI's components

The average index of undernourishment in LDCs has increased (the prevalence of undernourishment has decreased) steadily, from about 50 in 1990 to 70 in 2014.[38] The Figure 5 shows that the gap between LDCs and non-LDCs has decreased over time from 30 in 1990 to 21 in 2014 with a clear relative improvement for LDCs over the 1998—2008 period. The decrease in the index (increase in the prevalence) of undernourishment at the beginning the 1990s is generally attributed to natural disasters such as drought, but also political instability, which brought about hunger and malnutrition, particularly in LDCs. The average figures, however, mask disparities across LDCs. This is reflected in Table 3 by higher standard deviations in LDCs compared to those observed in the non-LDCs group. The level of undernourishment prevalence is higher in African LDCs than in non-African LDCs. Also, it decreases more quickly in non-African LDCs (Figure 5).

[38] Again, we here retain only countries for which data on undernourishment index are available for all years. Nauru, Palau, Marshall Islands and Federated States of Micronesia are then excluded.

Figure 5: Changes in the HAI components, LDCs versus non-LDCs averages

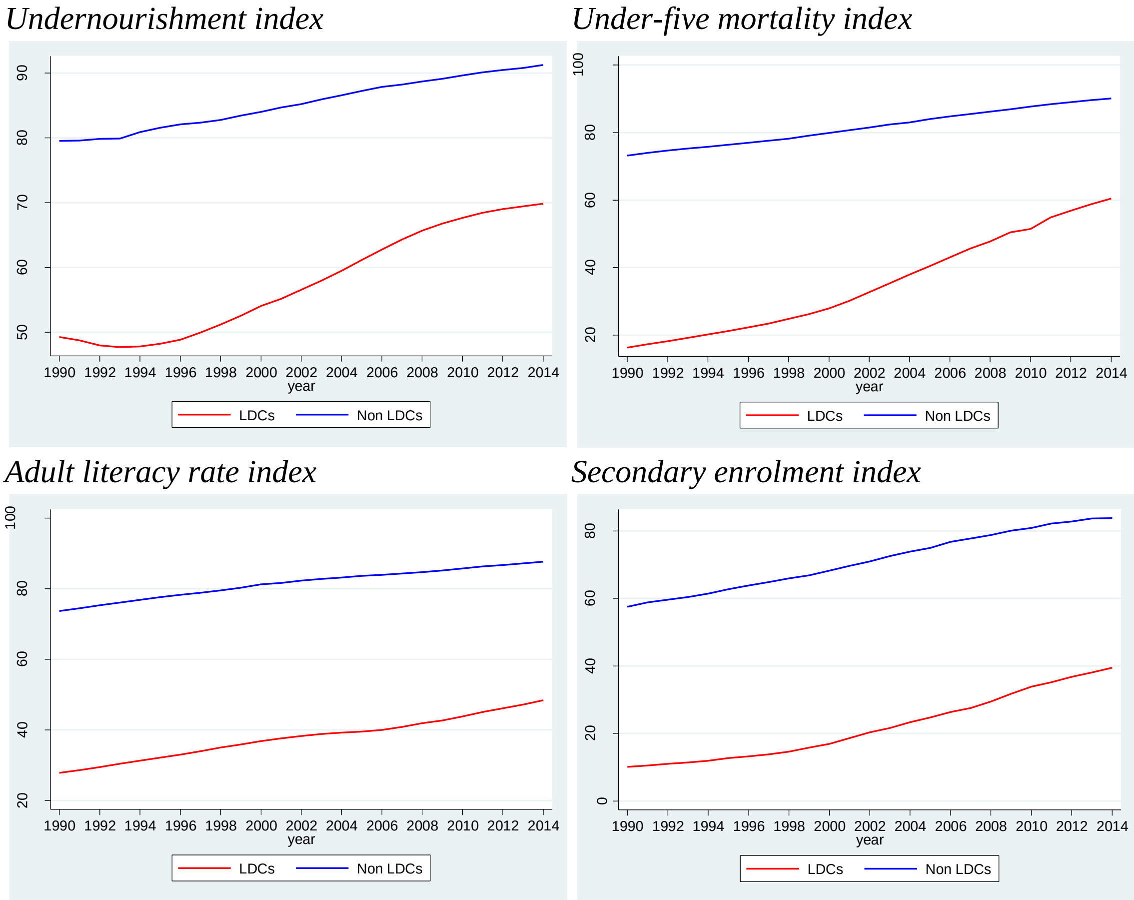


Table 3: HAI Components average scores by country groups

Undernourishment index

Country groups	1990	2000	2010	2014
LDCs	49.3 *(28.6)*	54.0 *(25.8)*	67.6 *(26.0)*	69.8 *(26.8)*
Non-LDCs	79.5 *(21.1)*	84.0 *(17.5)*	89.6 *(14.3)*	91.2 *(13.7)*
African LDCs	47.8 *(27.8)*	51.6 *(25.1)*	63.3 *(27.8)*	65.7 *(28.6)*
Non-African LDCs	52.6 *(30.8)*	59.4 *(27.3)*	77.1 *(19.0)*	78.8 *(20.3)*

Under-five mortality index

Country groups	1990	2000	2010	2014
LDCs	16.3 *(22.3)*	27.8 *(25.4)*	51.4 *(23.2)*	60.5 *(19.7)*
Non-LDCs	73.2 *(21.2)*	79.8 *(21.0)*	87.7 *(14.8)*	90.1 *(12.4)*
African LDCs	8.2 *(13.9)*	15.8 *(17.7)*	44.1 *(19.7)*	53.3 *(18.3)*
Non-African LDCs	34.2 *(27.0)*	54.3 *(18.9)*	67.7 *(22.4)*	76.3 *(11.9)*

Adult literacy rate index

Country groups	1990	2000	2010	2014
LDCs	27.8 *(27.4)*	36.8 *(26.5)*	43.8 *(25.1)*	48.5 *(24.5)*
Non-LDCs	73.7 *(21.1)*	81.2 *(17.2)*	85.8 *(15.2)*	87.7 *(14.1)*
African LDCs	26.8 *(28.2)*	33.8 *(26.5)*	39.1 *(24.9)*	43.3 *(24.3)*
Non-African LDCs	30.3 *(26.1)*	44.4 *(25.9)*	55.7 *(22.2)*	61.5 *(20.5)*

Secondary enrolment index

Country groups	1990	2000	2010	2014
LDCs	10.1 *(13.1)*	16.9 *(15.9)*	33.8 *(18.5)*	39.4 *(20.5)*
Non-LDCs	57.4 *(26.1)*	68.2 *(23.3)*	80.9 *(18.7)*	83.7 *(18.2)*
African LDCs	7.6 *(8.7)*	11.8 *(10.4)*	26.5 *(13.8)*	31.4 *(16.5)*
Non-African LDCs	15.3 *(18.8)*	27.7 *(20.2)*	49.3 *(17.8)*	56.6 *(17.8)*

Notes: Standard deviations are indicated in brackets under the means

Despite a significant improvement in socio-economic and sanitary conditions in DCs over the last decades, the average under-five mortality is still higher (and accordingly the average Under-five mortality index is lower) in LDCs than in non-LDCs despite a substantial relative progress, in particular since 2000. In LDCs, the average score increases from 17 in 1990 to 60 in 2014 while in non-LDCs, it increases from 74 in 1990 to 90 in 2014, reducing the gap from 57 points in 1990 to 30 points in 2014. There are significant disparities within the group of LDCs. For instance, the average index score is considerably higher in non-African LDCs than in African LDCs, but the later benefit from a faster improvement.

The gap in Adult literacy index between LDCs and non-LDCs average has remained large over time: it equals to 46 points in 1990 and 39 points in 2014. Compared to the two health and nutrition components of the HAI, progress in Adult literacy is very slower signaling an expected high degree of inertia despite efforts of developing countries' authorities and of the international community (e.g. the United Nations Literacy Decade launched in 2003 and the inclusion of "Education for all" in the Millennium Development Goals). As shown by high standard deviations, the Adult literacy index is heterogeneous across the LDCs group. The average score is clearly lower in African LDCs than in non-African LDCs since 2000 although the two groups had almost the same level in 1990.

The secondary enrolment index is higher in LDCs than in non-LDCs and the difference between the two groups has not declined significantly since 1990 (a gap of 47 points in 1990 versus 44 in 2014). Despite a real improvement, the secondary enrolment index remains very low in LDCs (39 versus 84 in non-LDCs for the year 2014) and the index is even lower for the group of African LDCs. Table 2 shows that in 2014, the LDCs' average score is still lower than the one of non-LDCs in 1990, while non-African LDCs' score is almost the same. Table 3 also reports large standard deviations for both groups. Heterogeneity in African LDCs is lower than in non-African LDCs but tends to increase over time.

This first exploration has shown that the four components of the HAI have different patterns of levels, distribution and trends. This puts into question their relative contribution, their weights and importance in the composite index.

III - Inside the HAI

We now explore different questions thanks to the use of retrospective series over 1990—2014. The first one is whether all of the 4 components evenly contribute to the progress in HAI, which is observed in DCs on average. Second, whether the HAI and components' distributions follow the same trend over time, signaling convergence or divergence between countries. Third, we compare the progress in health and education and their correlation over time within the group of developing countries.

III - 1) Relative contribution of components to the average change in HAI, DCs and LDCs

We compute the average contribution of the 4 components to HAI change between 1990 and 2014 for 135 DCs of which 45 LDCs. It is equal to the change in component multiplied by 0.25. Contributions are reported for the change in HAI average for the DCs and LDCs groups in Table 4. Regarding DCs, the four components contribute to the average HAI increase. The Health and Education dimensions have a similar contribution but that is rather pushed by the under-five mortality index and the secondary enrolment index respectively.

Regarding the group of LDCs, the higher progress in HAI is explained by higher increases in the four components, but more significantly from Under-five mortality index.

Table 4: Contribution of components to change in HAI average

Index and Components	1990	2014	change	Contribution	in percent
	Developing countries				
HAI	55.1	76.8	21.7	21.7	100.0
Undernourishment	68.7	84.0	15.3	3.8	17.5
Under5mortality	53.3	80.1	26.8	6.7	30.9
Literacy	57.8	74.5	16.7	4.2	19.4
SecondaryEnroll	40.6	68.4	27.8	7.0	32.2
	Least developed countries				
HAI	24.7	54.1	29.4	29.4	100.0
Undernourishment	47.7	68.9	21.2	5.3	18.0
Under5mortality	14.0	59.5	45.5	**11.4**	**38.8**
Literacy	28.4	49.3	20.9	5.2	17.7
SecondaryEnroll	8.8	38.5	29.7	7.5	25.5

Notes: Component's contribution to HAI change = 25% x change in component.
Constant sample of 135 DCs o.w. 45 LDCs over 1990—2014, excluding 3 LDCs (Solomon Islands, South Sudan, Tuvalu) and 7 non-LDCs (DPR Korea, Marshall Islands, Federated States of Micronesia, Nauru, Palau, Singapore, Turkmenistan).

III - 2) Changes over time in the distribution of the HAI and its components

The variance in the HAI scores and in the four components for the DC group has decreased between 1990 and 2014. However, this is not the case for the variance in the HAI scores for the LDC group, probably because of a larger variance in the Secondary enrolment rate that is not compensated by the other components (Table 5).

Figure 6 reports the distribution density for the HAI and its 4 components, for the years 1990, 2000 and 2014, for 45 LDCs and 90 non-LDCs. The shapes of distributions and their deformation over time are different across components. As expected, because of fixed maximum values over time, distributions tend to shift to the right and agglomerate nearby 100. This is particularly the case for undernourishment, under-five mortality and literacy indices, and for the group of non-LDCs. LDCs' backwardness is visible, but more on education than on health. Distributions are more flat, signaling heterogeneity, for LDCs and the literacy index particularly.

Table 5: Changes in standard deviations, HAI and components

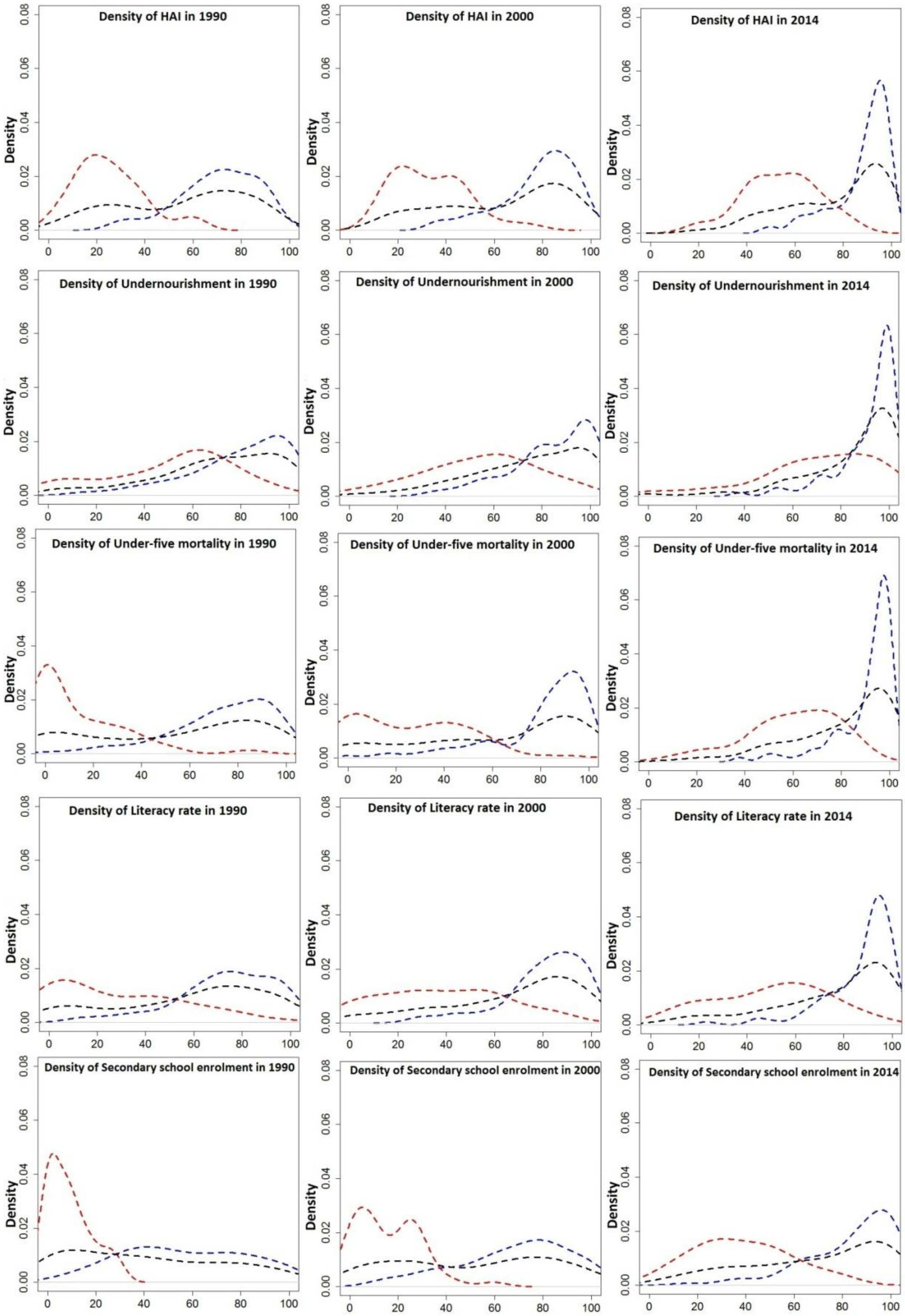
	1990	2014	change
Developing countries			
HAI	26.4	20.7	–5.7
Undernourishment	26.4	20.6	–5.7
Under5mortality	34.8	21.1	–13.8
Literacy	31.1	25.3	–5.8
Secondary Enroll	31.2	28.5	–2.7
Least developed countries			
HAI	14.6	15.6	+1.0
Undernourishment	26.2	25.7	–0.4
Under5mortality	18.8	19.6	+0.7
Literacy	27.1	23.8	–3.2
SecondaryEnroll	9.0	20.4	+11.4

III - 3) Education versus health progresses and their correlation

The following figure plots Education (computed as the simple average of Adult literacy rate index and Gross secondary school enrolment ratio index, x-axis) against Health (computed as the average of under-five mortality index and percentage of population undernourished index, y-axis) for the 135 countries in 1990 (red) and 2014 (blue). A somewhat expected positive association appears between education and health in both years, in terms of levels and trends.

The magnitude of relationship seemed to vary over time: the correlation is higher in 2014 than in 1990 (spearman rank's correlation of 79.5% versus 73.2%). From 1990 to 2014, the sample of countries tends to shift to the above-right, but improvements are not uniform across countries. Some countries do not follow the general trend as highlighted in Figure 7.b. For instance, Bhutan, Rwanda, Cambodia and Timor-Leste have made enormous strides in terms of education but even more on health. Tajikistan, despite a high score in education has not made progress in health.

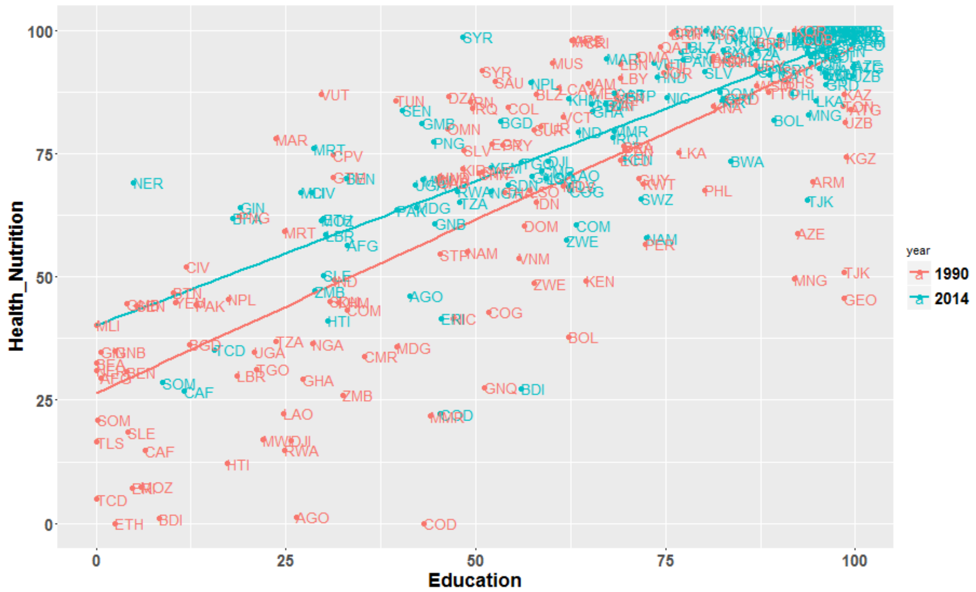
Figure 6: Distribution density of HAI and its components over time



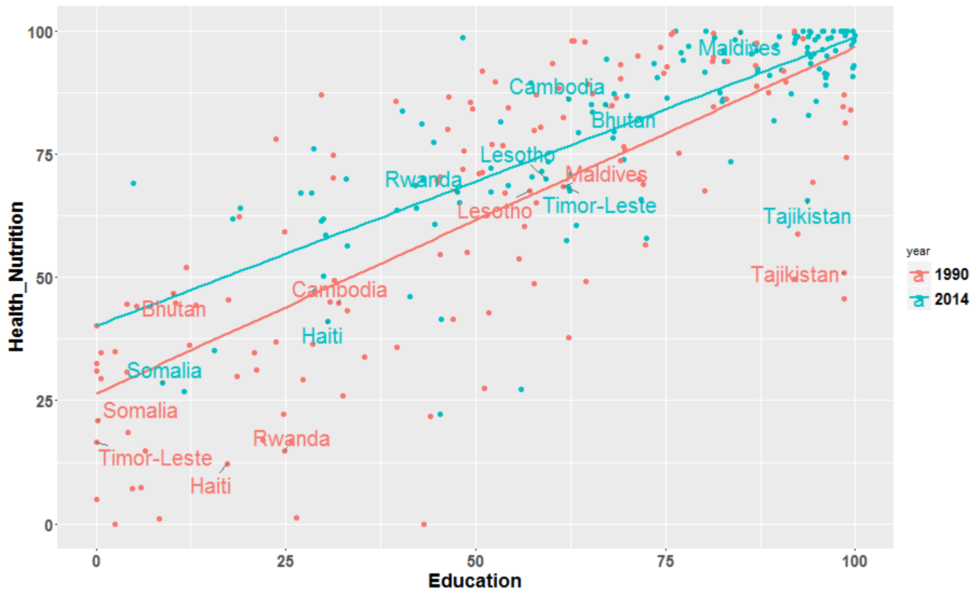
Notes: Constant sample of 135 DCs o.w. 45 LDCs.

Figure 7: Education (x) and Health (y) in 1990 (red) and 2014 (blue)

a



b



Notes: Constant sample of 135 DCs o.w. 45 LDCs over 1990—2014, excluding 3 LDCs (Solomon Islands, South Sudan, Tuvalu) and 7 non-LDCs (DPR Korea, Marshall Islands, Federated States of Micronesia, Nauru, Palau, Singapore, Turkmenistan).

In view of the above, under-five mortality and secondary enrolment rate were the least achieved dimensions for the majority of the developing countries in the initial period (1990). There have been large improvements in the two indices over time, thus becoming the main contributors in the official equally-weighted HAI. If we consider the group of LDCs, secondary enrolment rate remains the only component for which the standard deviation increased drastically between 1990 and 2014. This clearly indicates an extremely wide range of contributions of this component.

Even though each component is weighted equally after converting the raw components into indices, the above analysis has shown that these indices have not the same importance in explaining the dynamics of the HAI. Given these caveats, we adopt a methodology based on the correlated sensitivity analysis to derive weights that ensure equal importance of components in the HAI.

IV - Weight versus importance of components in the HAI: a sensitivity analysis

Numerous questions can arise in the construction of a composite index like the HAI, like weights, standardization, and aggregation techniques; because these choices can be subjective and influence the countries' level and ranking. The choice of equal weighting for the 4 components of the HAI made by the UN-CDP aims to build a simple composite index, in which all components are assumed to be equally important. However, the real importance of components depends on the characteristics of the statistical distribution of the components and their correlation (Paruolo et al, 2013). The correlations between components are thus closely associated with the issue of weights.

Let CI be a composite index. It is defined as:

$$CI = \sum_{i=1}^{n} w_i x_i \qquad (1)$$

Where n is the number of components, w_i is the weight attached to indicator i, and x_i the score on component i.
The variance of this composite is calculated as:

$$\sigma_c^2 = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + \sum_{i=1}^{n} \sum_{j \neq i} w_i w_j \operatorname{cov}(x_i, x_j) \qquad (2)$$

Leading to the following:

$$\frac{\partial \sigma_c^2}{\partial w_i} = 2w_i\sigma_i^2 + 2\sum_{j\neq i} w_j \operatorname{cov}(x_i, x_j) \tag{3}$$

So an exogenous increase in weight w_i leads to an increase in variance, providing $w_i\sigma_i^2 + \sum_{j\neq i} w_j \operatorname{cov}(x_i, x_j) > 0$.

Generally this will be the case, as some countries tend to score well across most indicators (that is, $\operatorname{cov}(x_{i,} x_j) > 0$ for most (i, j)).

It might be argued that one is only interested in the increase in the relative weight attached to component i. This is trivial to accommodate, by dividing each weight by a scaling factor:

$$W = \sum_{i=1}^{n} w_i \tag{4}$$

Then:

$$\sigma_c^2 = \left\{ \sum_{i=1}^{n} w_i^2\sigma_i^2 + \sum_{i=1}^{n}\sum_{j\neq i} w_i w_j \operatorname{cov}(x_i, x_j) \right\} / W^2 \tag{5}$$

And

$$\frac{\partial \sigma_c^2}{\partial w_i} = \frac{2}{W^2}\left\{ w_i\sigma_i^2 + \sum_{j\neq i} w_j \operatorname{cov}(x_i, x_j) \right\}\left(1 - \frac{w_i}{W}\right), \tag{6}$$

It should be argued that equal weights are appropriate where the components within the composite CI are uncorrelated. Or components could be highly correlated, but less so where some are correlated and some are not.

We apply a sensitivity analysis to the HAI following the approach provided by Becker et al. (2017), in which the importance of each component of a composite index is quantified using sensitivity indices which measure the contribution of each component to the composite's variance. This analysis allows derivation of alternative weighting patterns for the HAI if importance is interpreted as a linear, or nonlinear, dependence. We then show the implications as regards country rank changes. The sensitivity analysis is applied to the data for the year 2014 of the retrospective series of HAI[39].

[39] We use the year 2014 given the similarity between our retrospective data and the UN-CDP HAI values for 2014 (see section 2). The sensitivity analysis that follows can be applied to a different year of the retrospective data, and can be done by the authors on request.

IV - 1) A new weighting scheme

If x_i is the i^{th} component and y the composite, the first order sensitivity index, denoted S_i, measures the (possibly nonlinear) influence of each component on the composite. It can be computed using the formula of Karl Pearson's correlation ratio defined as:

$$S_i = \frac{Var_{x_i}\left[E_{X_{\sim i}}(y|x_i)\right]}{Var(y)} \tag{7}$$

Where $X_{\sim i}$ is defined as the vector containing all components of the composite except the component x_i; $E_{X_{\sim i}}(y|x_i)$= $f_i(x_i)$ is the conditional expectation of y, given x_i. It may be linear or nonlinear in x_i. If $f_i(x_i)$ is linear in x_i, S_i is equivalent to R_i^2, the square of the correlation between y and x_i. In the nonlinear case, $f_i(x_i)$ is a nonlinear trend line through the scatter plot of y against x_i. So, in this case, S_i is calculated using an appropriate nonlinear regression method and by taking the variance of this curve. S_i captures both the effect of the component x_i alone, but also the effect of the other variables with which it is correlated. Consequently, different variances and correlations of the components can prevent the weights from corresponding to the components' importance in the composite index. To check the impact of the correlation between the components, and to measure the "net" effects of the component x_i on the composite, Becker et al. (2017) break down S_i into 2 parts: the uncorrelated part (S_i^u) and the correlated part (S_i^c).

In the case of a large correlated part, the weights need to be adjusted, to more closely match the intended importance of each component in the composite. For this, the optimized weights w_{opt} can be obtained by minimizing the following objective function:

$$w_{opt} = argmin_w \sum_{i=1}^{d} (\tilde{S}_i^* - \tilde{S}_i(w))^2 \tag{8}$$

Where $\tilde{S}_i$ is the normalized correlation ratio of x_i ($\tilde{S}_i = S_i / \sum_{i=1}^{d} S_i$), and $\tilde{S}_i^*$ is the target normalized correlation ratio. It is assumed that $\tilde{S}_i^* = w_i$, w_i being the weights assigned by the UN-CDP to each component of the HAI (25%). $w = \{w_i\}_{i=1}^{d}$.

IV - 2) Application to the HAI

Figure 8 displays the relationship between the HAI and its components using 2 kinds of nonlinear regression: Local linear regression (Loess) and Penalized splines regression. The results from the 2 methods are very similar. In the work described below, the penalized splines regression has been used because of its multiple advantages mentioned in the literature (Wood, 2006; Crainiceanu et al, 2005). The chi-square tests reported in Table 6 show that the relationships between the HAI and its components are nonlinear, because the difference in the deviance relative to the difference in degrees of freedom between the linear and nonlinear models is significant. So, the nonlinear relationships between the HAI and Undernourishment, Under-five mortality, and Literacy rate cannot be rejected, especially for Under-five mortality.

The results presented in Table 7 show that the 4 components have an unbalanced impact on the variance of HAI. Secondary school enrolment has the highest impact on HAI, and Undernourishment appears to be the least important (these findings are consistent with those presented in section 2 for HAI change over time). Re-calculating after setting the variance of Secondary school enrolment at zero would reduce the variance of the HAI scores by 88 %.

Table 6: Nonlinearity Tests from deviance

	Regression of the HAI on			
	Undernourishment	Under-five mortality	Literacy rate	Secondary school enrolment
Deviance in linear regression	28589	12042	13128	6692
Deviance in nonlinear regression	26815	9666.5	12259	5941.7
Difference in deviance	1774.7	2375.9	869.13	750.57
Chi-square test	0.008677 **	3.453×10^{-5} ***	0.005909 **	0.01755 *

Notes: The levels of significance: *** p<0.01, ** p<0.05, *p<0.1. The table contains deviances for the linear and nonlinear (splines) relationship between the HAI and its components. The p-values of the tests are calculated using the χ^2 distribution. The null hypothesis assumes that there is a linear relationship between the HAI and its components.

Figure 8: Local linear regression fit vs Penalized splines regression fit

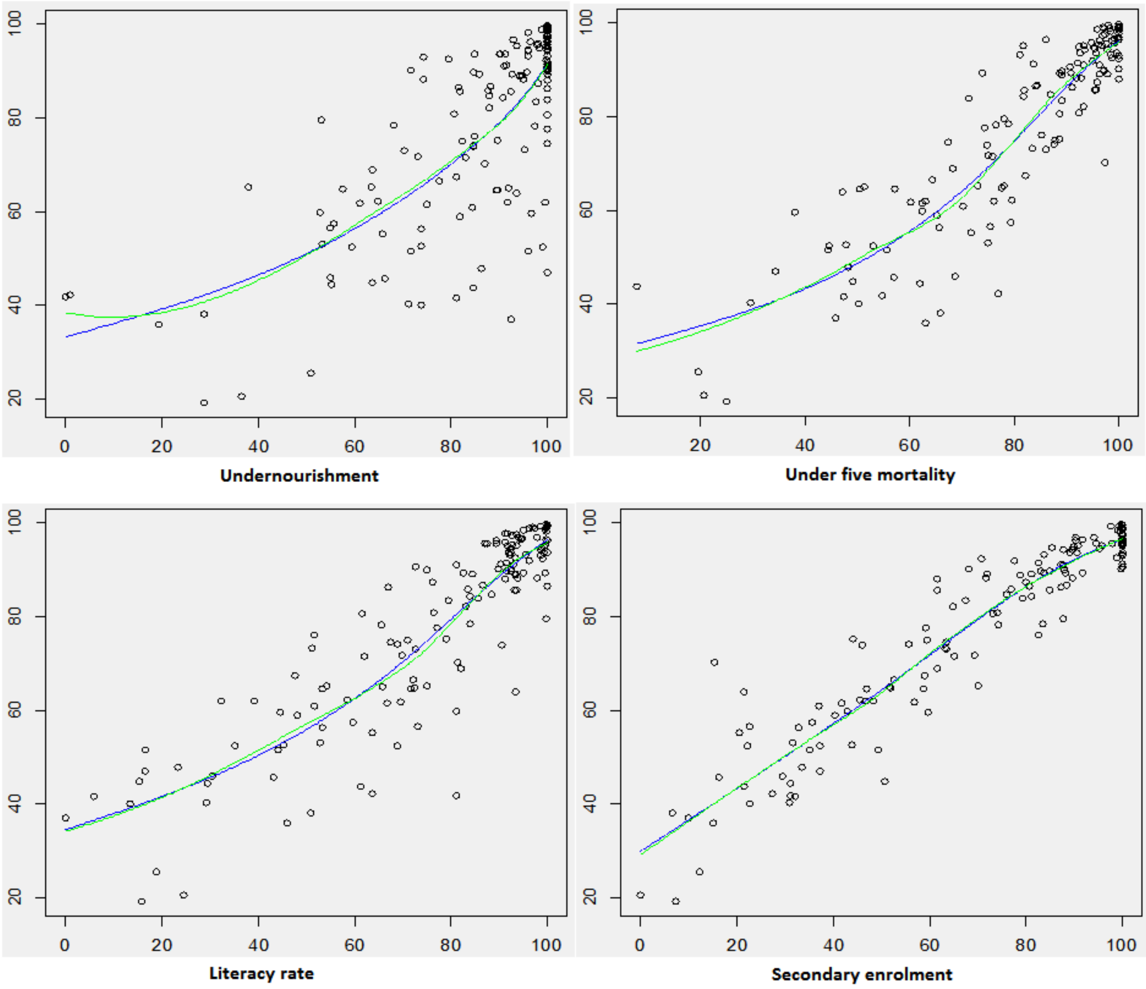


Table 7: Estimates of S_i broken down into 2 parts: correlated and uncorrelated

	w_i	R_i	$S_{i,linear}$	$S_{i,spline}$	$S^u_{i,spline}$	$S^c_{i,spline}$
Undernourishment	0.25	0.71	0.51	0.54	0.26	0.28
Under-five mortality	0.25	0.89	0.79	0.81	0.26	0.55
Literacy rate	0.25	0.88	0.77	0.78	0.19	0.59
Secondary school enrolment	0.25	0.94	0.89	0.88	0.07	0.82

Notes: w_i = Prior weight assigned to each component of the HAI by UN-CDP. R_i = Pearson correlation coefficient between component i and HAI. $S_{i,linear}$ = correlation ratio linear, which is equal to the square of R_i. $S_{i,spline}$ = correlation ratio spline. $S^u_{i,spline}$ = the uncorrelated part of $S_{i,spline}$. $S^c_{i,spline}$= the correlated part of $S_{i,spline}$.

However, our results show that almost all the influence of the Secondary school enrolment stems from the effects of the other components (undernourishment, under-five mortality, literacy rate) with which the index is correlated. In Figure 9, which shows the correlation between the 4 components of the HAI, the components have correlations which range from 0.42 to 0.79, with an average bivariate correlation of 0.65. The fact that S_i is close to S_i^c for

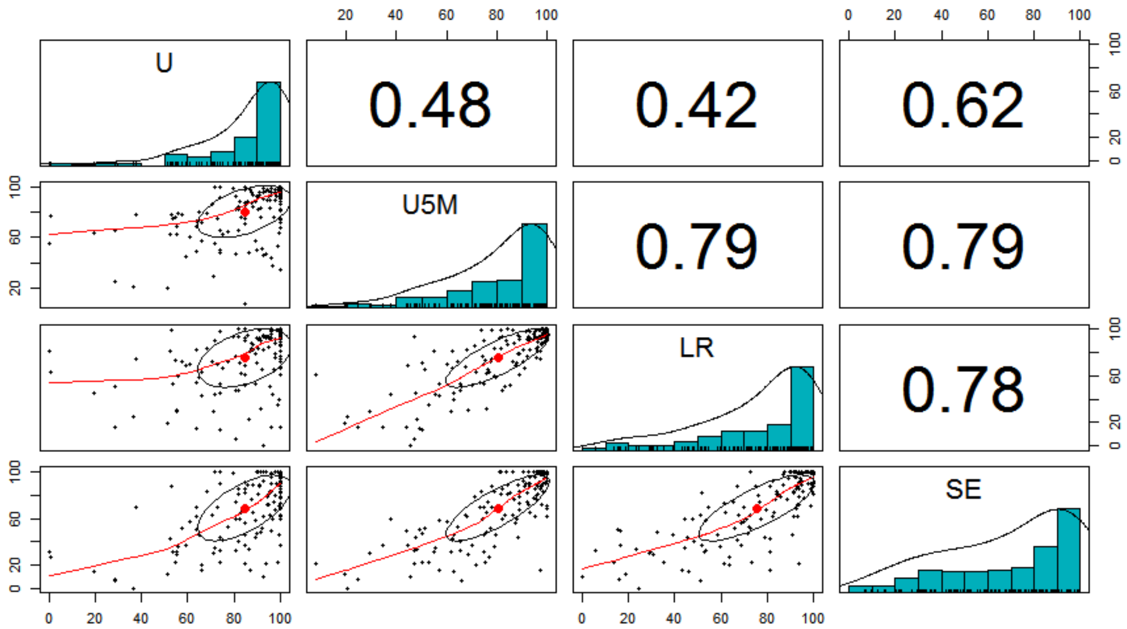
Secondary school enrolment implies that it may have a negligible influence on the final outcome. In other words, secondary enrolment is redundant.

An optimized weighting system should neutralize the part of the correlation caused by the other components, in order to avoid double-counting. With the exception of Undernourishment (for which the correlated and uncorrelated parts contribute equally to S_i), the correlated part of S_i largely dominates the uncorrelated part for the 3 other components (more than twice for Under-five mortality, more than three times for Literacy rate, and more than 11 times for Secondary school enrolment).

The optimized and UN-CDP weights are shown in Figure 10. Without the constraint of having positive weights, the optimization procedure gives the weights 0.50 for undernourishment, 0.17 for under-five mortality, 0.34 for literacy rate and –0.01 for secondary school enrolment. The negative weight of secondary school enrolment is due to its strong correlations with the other 3 components (Becker et al, 2017, also give examples of resulting negative optimized weights for composite indices). The optimization procedure with the constraint of positive weights does not significantly differ from the unconstrained procedure. So, our findings would show that the Secondary school enrolment component could be omitted. This would result in an alternative HAI composed of only 3 components: a component for nutrition outcome (percentage of population undernourished) with a weight of 0.5 (or 1/2), a component for health outcome (mortality rate for children aged 5 years or under) with a weight of 0.16 (or 1/6), and a component for education outcome (literacy rate) with a weight of 0.34 (or 1/3). In a statistical sense, this alternative HAI provides enough information on measuring human capital. Beyond this result drawn from a statistical analysis, the finding is that nutrition and health dominate the education dimension in the HAI, which is conceivable given the importance of nutrition and health for the quality of education and their role for the overall human capacity building. The quality of education is also better measured by the literacy outcome, so it is unnecessary and confusing to use indicators for both literacy and school enrolment in the composite index. The use of only three components may appear as a simplification, but with different weights of the components. Our result may also feed the debate since a change in the HAI structure may also affect country ranking.

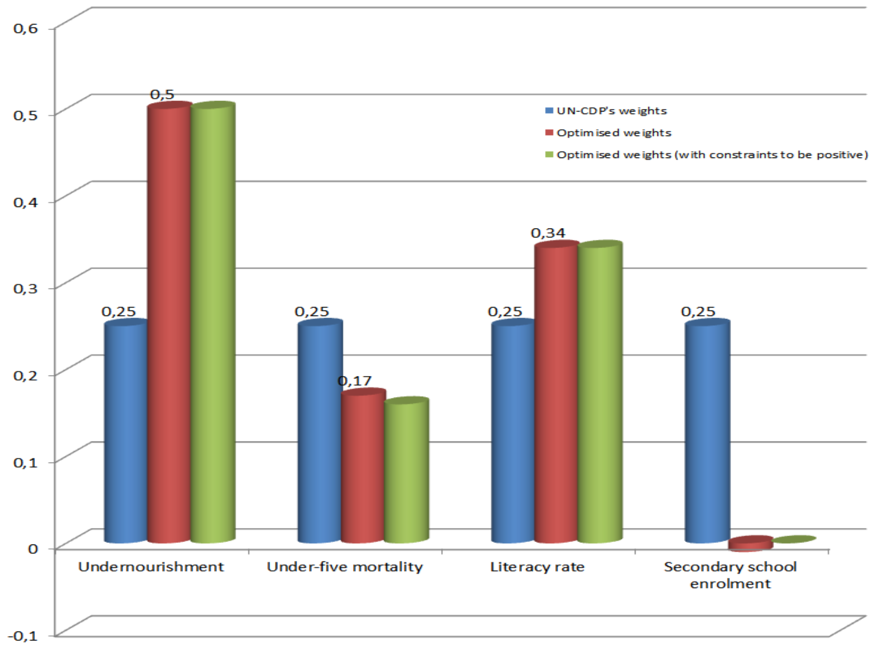
The strong correlation between the UN-CDP weight HAI, and the weight-optimized HAI, which is 95.6 %, conceals significant change in country ranking. At the top of the ranking, Cuba and the Republic of Korea are first and fourth with the official HAI, but rank second and first with the weight-optimized HAI. Figure 11 presents the largest changes, upwards and downwards, in country ranking between the UN-CDP weight HAI and the weight-optimized HAI. The countries which show the biggest upward changes from the UN-CDP HAI to the weight-optimized HAI are Maldives (41 ranks), Lebanon (37 ranks), Jordan (31 ranks), Equatorial Guinea (28 ranks), Samoa (27 ranks). On the other hand, the countries which show the biggest downward changes are Sri Lanka (33 ranks), Antigua and Barbuda (33 ranks), Namibia (27 ranks), Grenada (27 ranks), China (23 ranks).

Figure 9: Correlation between the four components of the HAI



Note: U refers to Undernourishment index; U5M refers to Under-five mortality index; LR refers to Literacy rate index and SE refers to Secondary school enrolment index.

Figure 10: HAI weights for each component



V - Conclusion

The concept of human capital has many dimensions, implying that its measurement requires the use of a composite indicator. Many researches and organizations have produced measures of human capital, relying on a variety of approaches. The most sensible approach is to focus on a narrower range of variables related to education and health. The two variables as well as overall level of income per capita influence the ability of countries to respond to shocks. In that spirit and, because human capital is a critical characteristic impacting on structural vulnerability, the UN-CDP has designed a composite index called the Human Assets Index (HAI).

The Human Assets Index, a composite index of health and education outcomes, offers a revealing picture of human capital in developing countries. This chapter details the methods used to build retrospective series of the Human Assets Index, and its 4 components, which cover 145 countries for the period 1990—2014. Developing countries achieve differing patterns of HAI by dimension and component. The LDCs made big progress during the period 1990—2014, but with a lot of within-LDC heterogeneity. Under-five mortality and Secondary enrolment rate are the main contributors to the HAI's change over this period. But for the LDC group, the standard deviation of the HAI index score was markedly higher in 2014 than in 1990.

In order to improve the quality of the existing HAI, some of the remaining statistical and methodological challenges should be addressed. While collecting and modeling retrospective series of socio-economic data in developing countries still remains a big challenge, controversies usually arise in the selection of the weighting pattern for a composite index such as the HAI. A new weighting could be proposed by determining the true influence of each component in the overall index, via the structure of correlation ratio and taking account of nonlinearity in the data relationships. We apply this analysis and derive an optimized weighting scheme for the HAI. Our results show that the Secondary school enrolment component is redundant and suggest an alternative HAI with only three components with different weights: Undernourishment rate (1/2), Literacy rate (1/3), and Under-five mortality (1/6). Our result implies that the HAI may reduce to three components, which can be viewed as an advantage, but that are not equally weighted, which can be viewed as an inconvenient, given the preference for equal weights in the construction of such indices. Moreover, this alternative results in significant ranking changes for some countries that should be discussed for their political implications. The structure of a synthetic index such the HAI is subject to a continuous discussion in order to improve its ability to measure human capital. Our result may be used in these discussions and be useful in the view of further reforms of the HAI.

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Appendices

Appendix 1: Methods for constructing retrospective series

A.1. Percentage of population undernourished

A.1.1 Definition

The percentage of population undernourished is computed and regularly reported by the Food and Agriculture Organization of the United Nations (FAO). It estimates the proportion of the population with a calorie intake below the minimum necessary for an active and healthy life. The FAO uses the cutoff of 1800 calories as the average minimum energy requirement per person per day[40].

A.1.2 Calculation principles of the Undernourishment index retrospective series

Primary data on the prevalence of undernourishment is retrieved from the official dataset FAOSTAT (data available at http://faostat3.fao.org/home/E). Data are complete over all the 25 years except for 28 countries for which there is no information available on undernourishment, which represent 19% of the sample[41]. To deal with this, we resort to econometric regressions to predict undernourishment prevalence from available information on strong correlates, income distribution measured by the Gini index, and gross national income per capita (GNIpc).

Method 1: using GNIpc, Gini and region fixed effects

This method is used to impute missing data on undernourishment to countries with complete series on GNIpc and Gini. The first step consists in estimating the following OLS regression on the sample of countries/years for which undernourishment, GNIpc and Gini data are available, which also exploit region fixed effects:

$$U_{1it} = \alpha_1 + \beta_1 * \ln(GNIpc_{it}) + \gamma_1 * \ln(Gini_{it}) + \delta_1 * t_t + \mu_{1i} * region + \varepsilon_{1it}$$

[40] The exact requirement is determined by a person's age, body size, activity level and physiological conditions such as illness, infection, pregnancy and lactation. Therefore, many nutritionists set a cutoff of 2100 calories as the minimum energy requirement per person per day to maintain a healthy, active lifestyle.

[41] Antigua and Barbuda, Burundi, Bahrain, Bahamas, Bhutan, Democratic Republic of the Congo, Comoros, Dominica, Eritrea, Federated States of Micronesia, Equatorial Guinea, Grenada, Saint Kitts and Nevis, Libya, Saint Lucia, Marshall Islands, Nauru, Palau, Papua New Guinea, Qatar, Sudan, Singapore, Somalia, South Sudan, Seychelles, Syria, Tonga, Tuvalu.

With U undernourishment, FAO primary data; GNIpc Gross national income per capita, World Development Indicators - World Bank; Gini: Gini index, World Development Indicators – The World Bank; region: a set of dummies Middle East and North Africa (MENA), Sub Saharan Africa (SSA), South Asia (SA), East Asia and Pacific (EAP), Latin America and Caribbean (LAC) and Europe and Central Asia (ECA).

Coefficient are taken out and used to calculate values for countries where data on U are missing but data on GNIpc and Gini are available:

$$\widehat{U_{1it}} = \hat{\alpha}_1 + \hat{\beta}_1 * \ln(GNIpc_{it}) + \hat{\gamma}_1 * \ln(Gini_{it}) + \hat{\delta}_1 * t_t + \hat{\mu}_{1i} * region$$

Data have been generated using this method for Burundi, Comoros, Democratic Republic of Congo, Papua New Guinea, Federated States of Micronesia (for the 1993—2014 period), Saint Lucia, Seychelles, Syria (1990—2007) and Sudan (2008-2014).

Method 2: using GNI and region fixed effects

This method is used to impute missing data on undernourishment to countries-years for which only series on GNIpc are available. The first step consists in estimating the following OLS regression:

$$U_{2it} = \alpha_2 + \beta_2 * \ln(GNIpc_{it}) + \delta_2 * t_t + \mu_{2i} * region + \varepsilon_{2it}$$

Coefficient are taken out and used to calculate missing values:

$$\widehat{U_{2it}} = \hat{\alpha}_2 + \hat{\beta}_2 * \ln(GNIpc_{it}) + \hat{\delta}_2 * t_t + \hat{\mu}_{2i} * region$$

This Method 2 has been used to produce data for Antigua and Barbuda, Bhutan, Dominica, Equatorial Guinea, Eritrea (for the 1994—2011 period), Grenada, Libya (2001—2014), Marshall Island (1995—2014), Palau (1993—2014), Saint Kitts and Nevis, South Sudan (2010—2014), Tonga and Tuvalu (2001—2014).

Special cases

For some countries, the use of methods 1 and 2 is not possible because data on Gini and GNIpc are missing. Thus:

- Data for Somalia are obtained from the 2012 retrospective series of Undernourishment; and extrapolated on 2012-2014.
- Former Sudan data prior to 2008 are used for Sudan and South Sudan;

- Data for Nauru are obtained from the source indicated by the UN-CDP (from Statistics for Development Division-Secretariat of the Pacific Community: http://www.spc.int/nmdi/poverty).

After the use of these imputation methods, only 27 data are still missing, representing 0.7% of the sample of 145 countries over 1990—2014: Marshall Islands (1990—1994), Federated States of Micronesia (1990—1992), Nauru (1990—2005), and Palau (1990—1992).

A.1.3 Normalization and Bounds

Undernourishment, which is negatively related to human assets, is normalized through the following inversed formula (the higher the undernourishment, the lower the index):

$$U_{Index} = \begin{cases} 100 * \dfrac{Max - x}{Max - min} & if\ min < x < max \\ 0 & if\ x > Max \\ 100 & if\ x < min \end{cases}$$

With x is the country/year undernourishment prevalence value

Lower bound (Min): 5 Upper bound (Max): 65

A.2. Under-five mortality index

A.2.1 Definition

As explained in UN-DESA definitions, the Under-5 mortality rate "expresses the probability of dying between birth and age five. It is expressed as deaths per 1,000 births". The under-five mortality rate provides comprehensive information on the health impact of social, economic and environmental conditions in a country. It is influenced by poverty, education; by the availability, accessibility and quality of health services; by environmental risks including access to safe water and sanitation; and by nutrition. Following the UN-CDP, we use the under-five mortality rate from the United Nations Inter-agency Group for Child Mortality Estimation (CME), CME Info, available from http://childmortality.org.

A.2.2 Calculation principles of the Under-five mortality index retrospective series

The estimates of Under-five mortality rates from the United Nations - CME are generated with a regression model for assessing levels and trends for all countries in the world over a long time period (Alkema and New, 2014). Thus, primary data on under-five mortality rates are fully complete over 1990—2015.

A.2.3 Normalization and Bounds

The Under-five mortality rate, which is negatively related to human assets, is normalized so as to get the index to enter the HAI through the following inversed formula (the higher the under-five mortality rate, the lower the index):

$$U5M_{Index} = \begin{cases} 100 * \dfrac{Max - x}{Max - min} & if\ min < x < max \\ 0 & if\ \ x > Max \\ 100 & if\ x < min \end{cases}$$

With x under-five mortality rate value.

Lower bound (Min): 10 Upper bound (Max): 175

A.3. Adult literacy rate index

A.3.1 Definition

As defined by the UN-DESA, the adult literacy rate "measures the number of literate persons aged fifteen and above expressed as a percentage of the total population in that age group. A person is considered literate if he/she can read and write, with understanding, a simple statement related to his/her daily life"[42]. The indicator shows the accumulated achievement of primary education and literacy programs in imparting basic literacy skills to the population, thereby enabling them to apply such skills in life, contributing to the economic and socio-cultural development. The adult literacy rate is regularly reported by the UNESCO Institute for Statistics at http://www.uis.unesco.org/.

[42] "Literacy" also encompasses "numeracy", the ability to make simple arithmetic calculations (Source: UNESCO Institute for Statistics glossary).

A.3.2 Calculation principles of the Adult literacy index retrospective series

Despite significant improvement in terms of data coverage, a large number of missing data still exist in the adult literacy rate database provided by the UNESCO Institute for Statistics. For our sample of 145 countries over 1990—2014, 3160 data out of 3625 are missing (about 87%). We first resort to simple linear interpolation and extrapolation to estimate data for countries where intermediate, beginning or end-of period data are scarcely missing (no more than 5 missing data). After this step, 992 missing data remain (about 27%), as the interpolation method is not relevant for 18 countries for which data are widely missing. We then rely on econometric methods of imputation.

Method 1: using GNI and country fixed effects

This method is used for countries for which data on LR exist but are too scarce to use simple inter or extrapolation. It is based on a regression that links Literacy rate to GNI per capita, time and country fixed effects (using the within estimator):

$$LR_{1it} = \alpha_1 + \beta_1 * \ln(GNIpc_{it}) + \delta_1 * \; t_t + \; \mu_{1i} \; + \varepsilon_{1it}$$

With $GNIpc$: Gross national income per capita, World Development Indicators

Literacy rate is then generated by:

$$\widehat{LR_{1it}} = \; \hat{\alpha}_1 + \; \hat{\beta}_1 * \ln(GNIpc_{it}) + \hat{\delta}_1 * t_t + \; \hat{\mu}_{1i}$$

This method is used to generate data for Solomon Islands over 1992—2014.

Method 2: using GNIpc and region fixed effects

This method is used for countries which have only one observation over the period 1990—2014. For these countries, it is not relevant to run country fixed-effects estimates using within estimator. Therefore, we introduce region fixed effects and provide estimates using OLS estimator:

$$LR_{2it} = \alpha_2 + \beta_2 * \ln(GNIpc_{it}) + \delta_2 * \; t_t + \; \mu_{2i} * Region_i + \varepsilon_{2it}$$

With $GNIpc$: Gross national income per capita, World Development Indicators- World Bank; $Region$: dummies Middle East and North Africa (MENA), Sub Saharan Africa (SSA), South Asia (SA), East Asia and Pacific (EAP), Latin America and Caribbean (LAC) and Europe and Central Asia (ECA)

The predicted value for Literacy rate is then:

$$\widehat{LR_{2it}} = \hat{\alpha}_2 + \hat{\beta}_2 * \ln(GNIpc_{it}) + \hat{\delta}_2 * t_t + \hat{\mu}_{2i} * Region_i$$

This method is used to generate data for Djibouti over 1992—2005, and over the entire period for Bahamas, Barbados, Dominica, Fiji, Grenada, Israel, Kiribati, Marshall Islands, Federated States of Micronesia, Korea Republic, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines and Tuvalu.

Special cases

Due to incomplete data on GNIpc, both imputation methods are not applicable for a couple of countries:

- For Somalia, we use data from the last previous retrospective series;
- To complete data for Djibouti (2006—2014), we use data from the last previous retrospective series; and extrapolated over 2012—2014.

After the use of these imputation methods, only 20 data are still missing, representing 0,6% of the sample of 145 countries over 1990—2014: Marshall Islands (1990—1994), Federated States of Micronesia (1990—1991), Solomon Islands (1990—1991), Tuvalu (1990—2000).

A.3.3 Normalization and Bounds

The Adult literacy rate, which is positively related to human assets, is normalized using the following min-max formula (the higher the literacy rate, the higher the index; the literacy index is merely the adult literacy rate multiplied by 100):

$$LR_{Index} = \begin{cases} 100 * \dfrac{x - min}{Max - min} & if\ min < x < max \\ 100 & if\ x > Max \\ 0 & if\ x < min \end{cases}$$

With x Adult literacy rate value.

Lower bound (Min): 25 Upper bound (Max): 100

A.4. Gross secondary school enrolment ratio index

A.4.1 Definition

The secondary education, which is one of the greatest challenges in poor countries, is usually measured by the gross secondary school enrolment ratio. As defined by the UNDP-DESA-DPAD, this indicator "measures the number of pupils enrolled in secondary schools, regardless of age, expressed as a percentage of the population in the theoretical age group for the same level of education"[43]. It provides information on the share of population with the level of skills deemed to be necessary for development. The indicator is regularly reported by the United Nations Educational, Scientific and Cultural Organization (UNESCO), Institute for Statistics (available at http://www.uis.unesco.org).

A.4.2 Calculation principles for the retrospective series of the Gross secondary enrolment ratio index

The raw data downloaded from the UNESCO website are missing for 1406 observations out of 3625 (39%). For intermediate and end-of period missing data, when no more than 5 data are missing, we use linear interpolation and extrapolation to fill them. After this step, 511 missing data remain (14%). For the other cases, we use imputation based on econometric regression.

Method 1: beginning of period, using GNIpc and country fixed effects

This method is used for values missing at the beginning of the series. We use the following model which includes income level, one year lead value of gross secondary school enrolment ratio, and time and country fixed effects. The within estimator is used:

$$SE_{1it} = \alpha_1 + \beta_1 * \ln(GNIpc_{it}) + \gamma_1 SE_{i,t+1} + \delta_1 * \ t_t + \ \mu_{1i} \ + \varepsilon_{1it}$$

The gross secondary school enrolment ratio is then generated, anti-chronologically and year after year:

[43] A high secondary enrolment rate generally indicates a high degree of participation, whether the pupils belong to the official age group or not. A rate approaching or exceeding 100% indicates that a country is, in principle, able to accommodate all of its school-age population, but it does not indicate the proportion already enrolled. The gross enrolment rate can exceed 100% due to the inclusion of over-aged and under-aged pupils because of early or late entrants, and grade repetition (Source: UNESCO Institute for Statistics glossary).

$$\widehat{SE_{1it}} = \hat{\alpha}_1 + \hat{\beta}_1 * \ln(GNIpc_{it}) + \hat{\gamma}_1 SE_{i,t+1} + \hat{\delta}_1 * t_t + \hat{\mu}_{1i}$$

This method has been used sporadically to generate data for some countries, but more widely for Equatorial Guinea (2006—2014); Gabon (2003—2014); Cambodia (2009—2014); Bahrain (2007—2014); Guinea-Bissau (2007—2014); Haiti (1990—2014; Kiribati (2009—2014); Palau (1990—2002), Nauru (1990—1999); Federated States of Micronesia (2006—2014); Marshall Islands (1990—1998;2010—2014); Libya (2007—2014); Maldives (2005—2014); Timor-Leste(1990—2000); Trinidad and Tobago (2005—2014); Tuvalu (1990—2000); United Arab Emirates (2000—2014).

Special cases

Due to missing data on SE and GNIpc, data remain missing for the entire period for Singapore, South Sudan, Turkmenistan (except the year 2014), and Democratic People's Republic of Korea (except for the year 2009). This represents 98 data or 2.7% of the sample.

A.4.3 Normalization and Bounds

The gross secondary school enrolment ratio, which is positively related to human assets, is normalized using the following min-max formula (the higher the gross secondary school enrolment ratio, the higher the index):

$$SE_{Index} = \begin{cases} 100 * \dfrac{x - min}{Max - min} & if\ Min < x < max \\ 100 & if\ x > Max \\ 0 & if\ x < min \end{cases}$$

With x Gross secondary school enrolment ratio value.

Lower bound (Min): 10 Upper bound (Max): 100

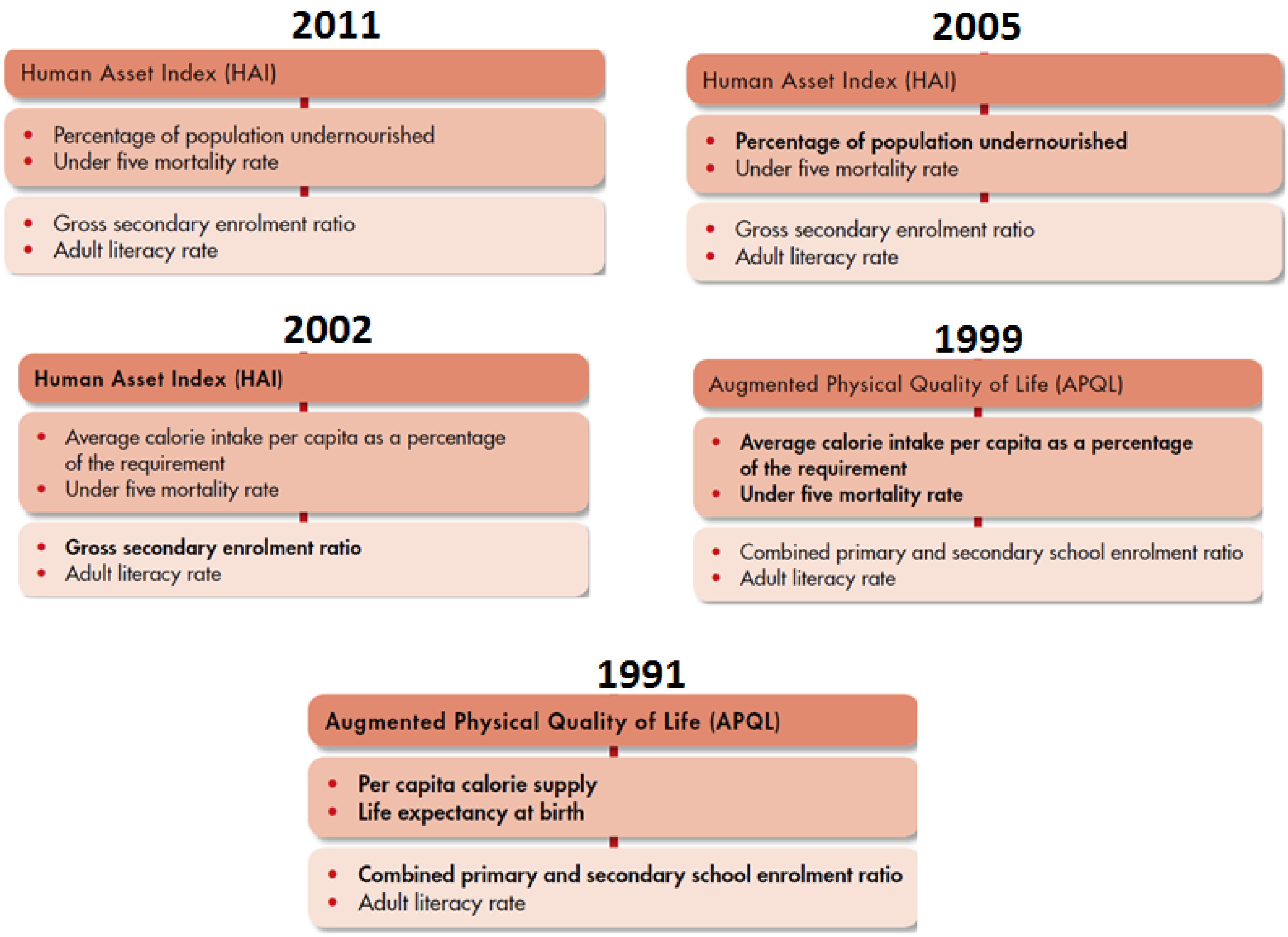
Appendix 2: Ranking differences between the UN-CDP HAI and the Weight-optimized HAI for the year 2014

Country	ISO	UNCDP HAI		Weight-optimized HAI		Difference in ranking [A]-[B]
		Value	Rank [A]	Value	Rank [B]	
Afghanistan	AFG	44,74	129	45,07	135	-6
Angola	AGO	43,77	131	64,42	114	+17
United Arab Emirates	ARE	97,82	15	97,07	28	-13
Argentina	ARG	98,90	9	98,84	11	-2
Armenia	ARM	98,88	10	98,78	13	-3
Antigua and Barbuda	ATG	93,19	44	86,57	77	-33
Azerbaijan	AZE	96,46	22	97,69	21	+1
Burundi	BDI	41,72	133	36,14	137	-4
Benin	BEN	51,45	124	60,78	121	+3
Burkina Faso	BFA	39,99	136	49,65	132	+4
Bangladesh	BGD	67,40	97	69,89	106	-9
Bahrain	BHR	96,99	18	97,97	17	+1
Bahamas	BHS	96,29	24	97,93	18	+6
Belize	BLZ	87,48	67	90,30	60	+7
Bolivia	BOL	85,60	73	85,85	79	-6
Brazil	BRA	96,41	23	95,83	37	-14
Barbados	BRB	99,50	2	99,69	3	-1
Brunei Darussalam	BRN	98,52	12	98,35	15	-3
Bhutan	BTN	76,01	85	73,68	95	-10
Botswana	BWA	78,59	82	75,19	93	-11
Central African Republic	CAF	19,18	142	23,75	142	0
Chile	CHL	99,05	8	98,73	14	-6
China	CHN	96,70	20	94,53	43	-23
Côte D'Ivoire	CIV	47,76	125	58,83	125	0
Cameroon	CMR	65,06	101	76,47	92	+9
DR of the Congo	COD	52,44	121	60,14	122	-1
Congo	COG	64,83	102	65,74	111	-9
Colombia	COL	95,58	29	93,69	48	-19
Comoros	COM	61,84	109	63,73	117	-8
Cabo Verde	CPV	89,41	58	88,93	66	-8
Costa Rica	CRI	99,22	6	98,96	10	-4
Cuba	CUB	99,82	1	99,89	2	-1
Cyprus	CYP	99,49	3	99,55	4	-1
Djibouti	DJI	58,86	114	67,74	109	+5
Dominica	DMA	95,17	32	96,15	35	-3
Dominican Republic	DOM	84,80	74	87,90	69	+5
Algeria	DZA	90,76	52	89,22	65	-13
Lebanon	LBN	88,18	66	97,02	29	+37
Liberia	LBR	44,34	130	47,54	134	-4
Libya	LBY	95,73	27	94,29	46	-19
Saint Lucia	LCA	89,77	56	89,25	64	-8
Sri Lanka	LKA	90,31	53	82,35	86	-33
Lesotho	LSO	64,63	103	77,28	91	+12
Morocco	MAR	80,78	80	85,18	81	-1
Madagascar	MDG	53,15	119	56,61	128	-9
Maldives	MDV	92,36	46	99,47	5	+41
Mexico	MEX	94,42	36	97,02	30	+6
Marshall Islands	MHL	91,36	49	89,84	62	-13
Mali	MLI	47,04	126	61,31	119	+7
Myanmar	MMR	73,97	90	85,06	82	+8
Mongolia	MNG	88,37	64	84,99	83	-19
Mozambique	MOZ	45,59	128	56,91	126	+2
Mauritania	MRT	52,30	122	70,03	105	+17
Mauritius	MUS	95,60	28	95,26	39	-11
Malawi	MWI	56,33	117	65,53	112	+5
Malaysia	MYS	90,15	54	97,45	23	+31
Namibia	NAM	65,18	100	56,82	127	-27
Niger	NER	37,00	138	53,77	129	+9
Nigeria	NGA	59,63	113	69,63	107	+6
Nicaragua	NIC	80,82	79	81,11	87	-8
Nepal	NPL	73,28	91	78,54	90	+1
Nauru	NRU	86,61	69	88,24	67	+2
Oman	OMN	95,74	26	96,25	33	-7
Pakistan	PAK	51,61	123	59,77	124	-1
Panama	PAN	85,64	72	93,18	50	+22
Peru	PER	94,69	35	94,61	41	-6
Philippines	PHL	89,39	59	89,34	63	-4
Palau	PLW	98,78	11	99,12	8	+3
Papua New Guinea	PNG	60,87	111	71,14	102	+9
Paraguay	PRY	91,19	50	91,98	54	-4
Qatar	QAT	99,25	5	99,00	9	-4
Rwanda	RWA	57,52	115	60,81	120	-5
Saudi Arabia	SAU	97,42	17	97,07	27	-10
Sudan	SDN	61,48	110	70,20	104	+6

Country	ISO	UNCDP HAI		Weight-optimized HAI		Difference in ranking [A]-
Ecuador	ECU	93,64	41	91,12	58	-17
Egypt	EGY	86,27	70	87,39	71	-1
Eritrea	ERI	42,17	132	34,28	140	-8
Ethiopia	ETH	45,90	127	48,90	133	-6
Fiji	FJI	91,53	48	95,89	36	+12
Micronesia	FSM	86,87	68	87,04	74	-6
Gabon	GAB	77,67	84	88,18	68	+16
Georgia	GEO	98,37	13	97,64	22	-9
Ghana	GHA	74,53	88	83,75	84	+4
Guinea	GIN	41,54	134	50,24	131	+3
Gambia	GMB	62,05	108	73,28	98	+10
Guinea-Bissau	GNB	52,66	120	59,97	123	-3
Equatorial Guinea	GNQ	63,86	105	86,01	78	+27
Grenada	GRD	92,57	45	87,24	72	-27
Guatemala	GTM	75,13	87	79,35	89	-2
Guyana	GUY	84,35	75	86,95	75	0
Honduras	HND	82,27	78	87,13	73	+5
Haiti	HTI	35,83	139	35,29	138	+1
Indonesia	IDN	89,75	57	93,19	49	+8
India	IND	71,48	94	74,74	94	0
Iran	IRN	91,11	51	93,02	52	-1
Iraq	IRQ	73,13	92	73,64	96	-4
Israel	ISR	97,93	14	97,21	26	-12
Jamaica	JAM	89,15	62	91,54	55	+7
Jordan	JOR	92,09	47	97,86	19	+28
Kazakhstan	KAZ	99,15	7	99,42	6	+1
Kenya	KEN	71,75	93	72,19	100	-7
Kyrgyzstan	KGZ	94,94	33	97,71	20	+13
Cambodia	KHM	74,19	89	79,79	88	+1
Kiribati	KIR	84,02	76	90,54	59	+17
Saint Kitts and Nevis	KNA	93,74	40	92,36	53	-13
Republic of Korea	KOR	99,37	4	100,01	1	+3
Kuwait	KWT	96,56	21	98,15	16	+5
Lao PDR	LAO	66,59	98	73,57	97	+1

Country	ISO	UNCDP HAI		Weight-optimized HAI		Difference in ranking
Senegal	SEN	62,06	107	69,13	108	-1
Solomon Islands	SLB	75,25	86	85,79	80	+6
Sierra Leone	SLE	40,13	135	50,30	130	+5
El Salvador	SLV	85,84	71	87,50	70	+1
Somalia	SOM	20,39	141	29,91	141	0
Sao Tome and Principe	STP	78,39	83	83,25	85	-2
Suriname	SUR	88,30	65	94,26	47	+18
Swaziland	SWZ	68,84	96	70,61	103	-7
Seychelles	SYC	89,24	61	94,45	44	+17
Syrian Arab Republic	SYR	70,24	95	86,74	76	+19
Chad	TCD	25,39	140	35,11	139	+1
Togo	TGO	64,59	104	72,02	101	+3
Thailand	THA	93,39	42	96,22	34	+8
Tajikistan	TJK	79,61	81	72,77	99	-18
Turkmenistan	TKM	89,29	60	95,66	38	+22
Timor-Leste	TLS	65,21	99	61,92	118	-19
Tonga	TON	93,78	38	94,60	42	-4
Trinidad and Tobago	TTO	94,37	37	96,45	32	+5
Tunisia	TUN	90,05	55	91,13	57	-2
Turkey	TUR	97,73	16	97,40	24	-8
Tuvalu	TUV	88,84	63	93,14	51	+12
Tanzania	TZA	56,49	116	64,31	115	+1
Uganda	UGA	55,34	118	65,96	110	+8
Uruguay	URY	96,93	19	99,23	7	+12
Uzbekistan	UZB	95,25	31	96,85	31	0
S^{t} Vincent and the Grenad.	VCT	95,97	25	95,19	40	-15
Venezuela	VEN	95,27	30	97,34	25	+5
Viet Nam	VNM	93,75	39	91,25	56	-17
Vanuatu	VUT	83,41	77	90,15	61	+16
Samoa	WSM	94,82	34	98,79	12	+22
Yemen	YEM	62,10	106	65,05	113	-7
South Africa	ZAF	93,27	43	94,30	45	-2
Zambia	ZMB	37,95	137	42,08	136	+1
Zimbabwe	ZWE	59,73	112	63,77	116	-4

Appendix 3: HAI and its components over time



Notes: New components in bold. Prior to 1991, the index of human capital of the UN-CDP contained a single variable which was the adult literacy rate. The first attempt to design a composite index has been done in 1991 under the name of "Augmented Physical Quality of Life (EDI)". The name Human Assets Index (EVI) was given at the first time in 2002 in preparation of the 2003 triennial review.

Source: Source: united Nations Committee for Development Policy (UN-CDP).

CHAPTER 3: STRUCTURAL VULNERABILITY TO CLIMATE CHANGE*

I - Introduction

Climate change is one of the greatest challenges facing humanity. Global warming, demographic changes and the effects of globalization mark the beginning of tremendous upheaval. In most countries, the effects of temperature changes on health, livelihoods, food production, water availability and security are already being felt. The 2015 year agenda was exceptional with the adoption of the new Sustainable Development Goals, for the fight against climate change (COP 21 Summit in Paris) and for risk disaster management (negotiations on the post-Kyoto framework agreement). In the preparation of these events, the risk, vulnerability and resilience concepts have frequently been recalled[44], as well as the complexity of their design and assessment. For instance the International Panel on Climate Change (IPCC) report of the working group II (2014) has defined vulnerability index as "a metric characterizing the vulnerability of a system. A climate vulnerability index is typically derived by combining, with or without weighting, several indicators assumed to represent vulnerability". Behind this broad definition encompassing all aspects of vulnerability, there

* Sections 1 to 5 of this chapter are summarized elements of a published working paper "A Physical Vulnerability to Climate Change Index: Which Are the Most Vulnerable Developing Countries?" co-authored with Patrick Guillaumont, Catherine Simonet and Mathilde Closset. The remaining sections are original work.

[44] cf. the Outcome document of the United Nations' Open Working Group on Sustainable Development Goals for instance.

does not seem to be an agreement on how these notions should be incorporated in the framework of the Sustainable Development Goals.

In all areas of human, environmental and economic activity, it is therefore necessary to take the best possible liability provisions leading to a search for resources for financing mitigation and adaptation. It is in this spirit that one of the decisions of the Paris Agreement in December 2015 was to seek a balance between mitigation and adaptation over time, with financial resources channeled to supporting low-carbon growth and helping the most vulnerable countries to adapt to the effects of climate change. While raising funds for mitigation and for adaptation meet similar problems, their allocation between countries cannot be ruled by the same criteria. For the concessional funds devoted to adaptation, allocation criteria should specifically reflect the adaptation needs of the recipient countries (beside their level of income and their capacity to effectively use the funds). An appropriate indicator of vulnerability to climate change is then required for guiding the allocation of adaptation resources. Not any existing indicator of vulnerability to climate change can fit this purpose.

Recent years have seen a proliferation of indices[45] of vulnerability to climate change, despite the complexity of the phenomenon. The development of the majority of them is based on the IPCC's three keys aspects of vulnerability[46]. They aggregate a wide variety of variables that combine economic, social, physical and political dimensions, making lose sight of the objective assigned to them. The IPCC's specification does not establish a clear relationship between the three elements of vulnerability. Furthermore, there is an overlap between sensitivity and adaptive capacity. The distinction between the two elements is not easy to implement in the construction of indices because they use similar variables. The vagueness remains particularly on what must constitute the adaptive capacity. This element refers to the resilience and combines institutional, governance, infrastructure, food security, health,

[45] For example the Disaster Risk Index of the United Nations Development Programme (UNDP, 2005), the quantitative assessment of vulnerability to climate change index of the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT, 2009) and the University of Notre Dame's Global Adaptation Index.

[46] Exposure, sensitivity and adaptive capacity are the IPCC's three aspects of vulnerability. Exposure pertains to the nature, magnitude and rhythm of climatic variations to which a country is or will be exposed, according to IPCC scenarios. Sensitivity refers to the size of the effects (both negative and positive) of climate stimuli in a given country. And adaptive capacity concerns the intrinsic ability of a country's authorities to adapt in order to mitigate the impacts of climate change.

water resources, economy, human resources and environmental variables. Indicators of adaptive capacity are often different from one study to another, confusing decision-makers.

Existing indices of vulnerability to climate change, do to their complexity, are difficult to relate to a clearly defined public policy objective. The methodology used can lack transparency, which can make it difficult to reproduce the outcomes. In the same way, the social data used to highlight the adaptive capacity come from household surveys that are subject to significant measurement errors, especially in developing countries.

The search of an appropriate indicator of vulnerability to climate change can draw lessons from the past experience of development economics and policy. A relevant experience is that of the least developing countries (LDCs), designed as the poor countries facing most severe structural handicaps to development, and thus threatened to be locked into a poverty trap. A main structural handicap retained for their identification is a high structural economic vulnerability, captured in an index called Economic Vulnerability Index (EVI) (United Nations, 2015), which has been covered in Chapter 1 of this thesis.

Here, with the aim at combining the allocation of resources for poverty reduction and for adaptation to climate change in a consistent manner, we propose an index of physical vulnerability to climate change built on principles similar to those of the UN Economic Vulnerability Index. As the EVI captures the “structural” economic vulnerability and supposed to be exogenous, the index of vulnerability to climate change should capture the “physical” vulnerability to climate change and thus exogenous. Such a vulnerability to climate change, independent of the present political will of the countries, is expected to identify countries needing the most adaptation assistance, regardless of their political choices, and is likely to be used as a criterion for the allocation of adaptation resources. This index could then be combined with other indicators to determine an optimal allocation of these resources (Guillaumont 2015b).

The assessment of the vulnerability to climate change that is proposed is thus focused on the vulnerability which depends only on physical factors, factors which do not depend on the present will or policies of the countries, and are essentially geo-physical. This “Physical Vulnerability to Climate Change Index” (PVCCI) should offer a quantitative and comparative assessment of the vulnerability of developing countries in a synthetic way. It relies on a few components, both relevant and reliable, which are available for the whole set of developing countries, and which are easily understandable, so that the index can be used in a transparent manner. Once calculated, this index of physical vulnerability to climate change shows a high degree of heterogeneity among countries, even within the same regional area or continent.

Recent research has speculated that vulnerability to climate change might spark violent conflicts in a number of regions around the world. Climate change is a phenomenon that unfolds over long periods of time. However, most of the research on the link between climate variability and conflict examines rainfall and temperature variability as proxies for the kinds of longer-term changes that might occur due to climate change. This is difficult to conceive of as climate change; for instance, studying the effects of a persistent period of high temperatures could yield imperfect outcomes. The PVCCI in its design captures a long-term change in the physical vulnerability and appears to be appropriate to this kind of analysis. Consequently, we examine the association between the PVCCI and civil conflict.

The remainder of this chapter is organized as follows. Section 2 presents the concept of vulnerability to climate change and the associated terminology. Section 3 presents the key features of an index of physical vulnerability to climate change likely to be used for operational purposes and differing from other various concepts of vulnerability in climate change research. In Section 4, we provide a description of the components of the PVCCI. Next, we present the specific methodology used to build the PVCCI in Section 5 and, the results for developing countries, not forgetting the robustness analysis. In Section 6, we propose to investigate the effect of the PVCCI on civil conflict after doing a brief review of the literature on the link between climate change and conflict. We also conduct several robustness tests of our baseline results. Section 7 concludes the chapter with potential policy implications and directions for future research.

II - Vulnerability to climate change: An elusive concept

Despite several attempts of researchers, there is not a coherent conceptual framework to define the concept of vulnerability. The definitions of vulnerability vary from one study to another and the term is used to mean different things by different authors[47] causing confusion among researchers in the literature (Brooks, 2003; Burton et al., 2002; Cutter, 1996; Kelly et Adger, 2000; O'Brien et al., 2004). Even the IPCC, the genuine scientific authority in the field of climate change, in its Third Assessment Report exhibits some discrepancies in its two definitions of vulnerability. Foremost, the IPCC considers the vulnerability of a "system" as a function of its sensitivity and clearly refers to biophysical vulnerability while in chapter 18 of the same report vulnerability is viewed as a subset of sensitivity and only refers to social vulnerability.

In their article *"What's in a word?, Conflicting interpretations of vulnerability in climate change research"*, O'Brien et al. (2004) drew attention to the danger of multiple frameworks and definitions and argue that "…the two definitions not only result in two different diagnoses of the climate change problem, but also two different kinds of cures…". Depending on the sector on which the effects are observed, it is possible to thematically classify the different aspects of vulnerability to climate change. It is easy to understand the difficulty of performing a comprehensive list of thematic to be addressed in a diagnosis of vulnerability. Nevertheless, several researchers explicitly recognize that vulnerability to climate change is not only a result of biophysical events alone but is also influenced by the contextual socio-economic conditions in which climate change occurs. Accordingly, vulnerability is most of time divided into biophysical (or natural) vulnerability and social (or socio-economic) vulnerability (Füssel 2007).

II - 1) Social vulnerability to climate change

Governments, academia, nongovernmental organizations, media are increasingly aware that climate change is a serious problem against which rapid response is required. Populations in function of their characteristics experience climate change impacts. Some populations are

[47] Many definitions and approaches to vulnerability can be found in Adger (1999). By the same token, the methods for the improvements of vulnerability assessment in Europe (MOVE) suggest seven types of vulnerability.

particularly vulnerable to climate and may have less capacity to cope with climate-related hazards and effects. Such populations of “low status” are more vulnerable when catastrophic environmental, social, and economic events occur.

According to the IPCC report on the regional impacts on climate change (2007), Africa appears as the most vulnerable to the impacts of projected changes because of multiple stresses of poor infrastructures, poverty and governance. The importance of agricultural activities (65 % of employment and contribute to 32 % to GDP, FAO 2015) combined with the long period of droughts and floods make countries in the region particularly vulnerable to climate change. A lack of economic diversification increases vulnerability when the main sector is directly influenced by climate.

Literature focused on natural hazards provides a number of definitions of social vulnerability within disaster context. Cutter and Finch (2008) defined social vulnerability as a measure of both the sensitivity of a population to natural hazards and its ability to respond to and recover from the impacts of hazards. The United Nations Development Program (2000) defined it as “… the degree to which societies or socioeconomic groups are affected by stresses and hazards, whether brought about by external forces or intrinsic factors (internal and external) that negatively impact the social cohesion of a country” (UNDP 2000).

Social vulnerability to climate change is inextricably linked to other causes of vulnerability. It is partially the product of social inequalities. For instance, countries with high knowledge, skills and experience could be less vulnerable to climate change because of their increased capacity to address it. Wall and Marzall (2006) pointed out that the lack of social networks and connections make complicated collective action and communication. Hence the fundamental role of public authorities to provide an efficient education system and high performance social standards to vulnerable populations (Gamble et al., 2008). Social vulnerability could also be influenced by place inequalities pertaining to the level of urbanization, growth rates and economic vitality.

To describe social vulnerability, most of authors (Cutter, 2002; Tierney et al., 2001; Putnam, 2000; Blaikie et al., 1994) used the individual characteristics of people (age, race, health, income, employment …). The two demographic groups most affected by disasters are children and the elderly because they are frail and physically limited individuals.

II - 2) Biophysical vulnerability to climate change

Recently, an abundant literature examines biophysical science that is related to the causes and effects of climate change. Biophysical vulnerability concerns the vulnerability views in terms of the amount of potential damage to a biophysical system by harmful climatic event (Jones and Boer, 2003). It refers to the physical and environmental aspects that can contribute to increase (or decrease) the vulnerability of a system. Therefore, the biophysical vulnerability depends on the characteristics of the natural system itself; it has fewer implications on policy making since variables like temperature and precipitation are beyond the immediate control of the policy makers. The concept of biophysical vulnerability is frequently defined as the exposure of an ecosystem (or human systems) to natural hazard (Burton et al., 1993; Hilhorst and Bankoff, 2004; Macchi et al., 2008). Focusing on the characteristics of the hazard, Burton et al. (1993) determined seven dimensions of hazardous events: magnitude, frequency, duration, speed, geographical extends, spatial dispersion and temporal spacing.

The IPCC in its fourth assessment report, Climate Change 2007, presents vulnerability as a function of three overlapping elements: the exposure, sensitivity and adaptive capacity. Exposure is defined as “the nature and degree to which a system is exposed to significant climate variations”. Sensitivity is “the degree to which a system is affected, either adversely or beneficially, by climate-related stimuli. The effect may be direct (e.g., a change in crop yield in response to a change in the mean, range or variability of temperature) or indirect (eg., damages caused by an increase in the frequency of coastal flooding due to sea level rise)”. Adaptive capacity is “the ability of a system to adjust to climate change (including climate variability and extremes), to moderate potential damages, to take advantage of opportunities, or to cope with the consequences”. The biophysical approach corresponds most closely to sensitivity in the IPCC concept and terminology; it is also associated with the risk assessment and risk management (Alwang et al., 2001).

The overall vulnerability is mainly the result of the interaction between social and biophysical vulnerabilities. Likewise, social vulnerability is intricately related to biophysical vulnerability, particularly for communities that are dependent on environmental resources for their livelihoods (Adger, 2003). For this reason Brooks (2003) finally argued that “social vulnerability may be viewed as one of the determinants of biophysical vulnerability”. In contrast, Cutter (1996) considered that the biophysical dimension and social dimension of vulnerability are independent. Finding and building appropriate indicators for vulnerability assessment become a high challenge.

II - 3) Existing studies and indices for measuring the vulnerability to climate change

The recognition of climate change as a global environmental threat led to the production of many indices of vulnerability and adaptation to climate change: Disaster Risk Index (UNDP, 2005), Natural Disaster Hotspots (World Bank/ Columbia University, 2005), Predictive Indicator of Vulnerability (Adger et al., 2004), Social Vulnerability Index (Cutter et al., 2003)…..Most of these indicators measure the magnitude of the threat posed by the climate change as a means of determining the need for the implication of policy makers to limit that threat.

The national level is mostly used for quantitative measure of vulnerability and the selection of indicators at this scale is driven by the current exposition and capacity of country. This allows making the indicators comparable across nations and providing a relevant tool to negotiate the allocation of resources for adaptation (Fermann, 1997; Cooper, 2000; Klepper and Springer, 2003). In doing so, Eriksen and Kelly (2007) showed how national level vulnerability indices can provide an "objective comparison of levels of vulnerability between countries […] as a way of allocating priorities for funding and intervention, for example, in the context of the Adaptation Fund set up under the United Nations Framework Convention on Climate Change" (p.496). These indices generally incorporate a wide variety of indicators, such as GDP, the mortality resulting from extreme weather events (floods, storms, drought…) so that countries wind up on international assistance. Among the national level indices of vulnerability to climate change, we can notice: Vulnerability Resilience Indicators (Moss et al., 2001), the Environmental Sustainability Index (Esty et al., 2005), the Environmental Vulnerability Index (Kaly et al., 2004), the Global Distribution of Vulnerability Index (Yohe et al.,2006).

Sometimes, the national level is not an appropriate scale for vulnerability analysis. Indeed, due to the heterogeneity of the biophysical environment and socio-economic context within the same country area, national indicators might mask local differentiation in vulnerability. Studies at a local level are often conducted by universities and scientific laboratories as part of research projects with the cooperation of regional and local authorities. The indicators mainly concern specific risks associated with the study area including the use of mapping tools. It is therefore difficult to extrapolate the methods and results to other contexts. For example, Abuodha and Woodroff (2010) developed a Coastal Sensitivity Index (CSI)[48] to assess vulnerability to sea level rise in Southeast Australia. Cutter et al. (2000) analyzed the vulnerability of Georgetown County (in South Carolina) by selecting specific indicators.

The most common approach to derive climate change vulnerability indicators is driven by the IPCC vulnerability definition including components of exposure, sensitivity and adaptive capacity. But there is no consensus about how to aggregate the variables. The methods of aggregation may differ a lot from one study to another. In the Global Distribution of Vulnerability Index (Yohe et al., 2006), the vulnerability depends on exposure and adaptive capacity. Exposure is characterized by an increase in temperature trends under different climate change scenarios while adaptive capacity is evaluated by a sub-index from Vulnerability-Resilience Indicator model (designed by Brenkert and Malone, 2005).

The vulnerability to climate change concerns potential future damages. So, the vulnerability indicators to climate change should have a forward-looking component. However, most of the existing indicators take stock of the state of the vulnerability based on past data. The few studies that include a prospective component are often based on IPCC scenarios (Block et al., 2006) or provide early-warning systems for prevention (Ho et al, 2012). In Figure 1, the diagram given by Füssel (2010) helps to understand what in the IPCC definition concerns structural vulnerability and what does not: here "social impacts" should be understood as "vulnerability to climate change". This approach is reformulated by the Special Report on Managing the Risks of Extreme (IPCC, 2012) presenting a risk management approach and by the IPCC WGII Report (IPCC, 2014a). The vulnerability is defined as "The propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts including sensitivity or susceptibility to harm and lack of capacity to cope and adapt".

[48] This is a semi quantitative indicator based on several physical variables, such as typology of the coast, relief, geology, with the aim of assessing the vulnerability to sea level rise of the southeast coast of Australia.

Figure 1: Vulnerability to climate change framework, the reading of IPPC definition by Füssel (2010)

<table>
<tr><td>Regional
climate change
(+)</td><td>Biophysical
sensitivity
(+)</td><td rowspan="2">Socio-economic
Exposure
(+)</td><td rowspan="2">Socio-economic
capacity
(-)</td></tr>
<tr><td colspan="2">Biophysical impacts
(+)</td></tr>
<tr><td colspan="4">Social impacts</td></tr>
</table>

III - Required features of the new index of vulnerability to climate change

Beginning with the main definitions of vulnerability to climate change, this section tries to define physical vulnerability to climate change. The "vulnerability of systems to climate change" is examined in what has been a rapidly growing literature, relying on various fields of research, such as climate science, disaster management and development economics. It illustrates the "necessary greater synergy between ecologists and economics" (Wam, 2009).

III - 1) General economic vulnerability versus structural economic vulnerability

The word 'vulnerability' has been used with various meanings and by many researchers in food security, natural hazards, disaster risk, public health, global environment, climate change or development economics (for a sample of applications of the concept of vulnerability in these various fields, see: Timmerman, 1981; Blaikie, 1994; Cutter et al., 1996; Guillaumont and Chauvet, 2001; McCarthy, 2001; UNEP, 2002 chapter 3; Prowse, 2003; Turner et al., 2003; Miola et al., 2015). In development economics, the notion of vulnerability has been used mainly at the microeconomic level (see for instance Dercon et al., 2005; Yamano et al., 2005). It has also been used at the macroeconomic level, with the search for measurable and comparable indices (this literature is reviewed in Guillaumont, 2009a, b).

In the macroeconomic context, the vulnerability of a country is taken as "the risk of being harmed by exogenous, generally unforeseen, events or shocks" (Guillaumont, 2009a). Based on several decades of research (in particular on export instability), this macro vulnerability is now widely considered to be an impediment to growth. Economic vulnerability can be seen to consist of three main components: shock, exposure and resilience. Shocks are exogenous and generally unforeseen events (external e.g. the instability of exports, or natural, e.g. typhoons, hurricanes, earthquakes, droughts…). Exposure corresponds to factors on which the direct impact of shocks depends. Resilience is the capacity to react to shocks. A weak resilience is a part of the general vulnerability (Miller et al., 2010).

Assessments of vulnerability retain some or all of these three components. When the three elements are considered, a general or overall vulnerability is assessed. When only the size of the exogenous shocks and the extent of exposure to these shocks are the only components considered, the vulnerability considered is essentially a "structural" vulnerability. Resilience, even if it may include some structural elements, is often related to policy factors. Structural economic vulnerability is the kind of vulnerability captured by the Economic Vulnerability Index (EVI), used by the United Nations to identify the Least Developing Countries (LDCs). This index intends to reflect the likely size of recurrent external or natural shocks, and the main structural factors of the exposure to these shocks, using a small number of indicators in a transparent manner. It refers mainly to vulnerability in low-income and lower middle-income countries (see UN-CDP website and Guillaumont 2007, 2009a, 2009b). The level of income per capita is indeed a major factor of economic resilience, but since this level is taken into account separately both officially for the identification of the LDCs and most often for the allocation of Official Development Assistance (ODA), it is not usually included in the measurement of structural economic vulnerability.

III - 2) Structural or physical vulnerability to climate change: can it be identified?

Vulnerability to climate change is a vulnerability to environmental shocks resulting from climate change. These shocks are here considered as the physical expression of climate change. They essentially appear through the increase in the number and intensity of droughts, floods, and storms, as well as through the rise in sea level for low-lying coastal areas; they are reflected by the change in the mean values of climatic variables (such as temperature or rainfall), and by related changes in the instability of these variables.

There has been a rich recent literature on vulnerability to environmental change and more specifically to climate change, as well as, partly overlapping, on vulnerability to natural hazards. Not surprisingly, there is no universally accepted definition of vulnerability to climate change.

To identify the structural or physical vulnerability to climate change, it is useful to refer to the three usual components of economic vulnerability (size of the shocks, exposure to the shocks, resilience), and to consider that structural vulnerability is mainly captured through the shock and exposure components, while resilience is more related to policy or to other variables likely to be considered separately as the level of income per capita.

III - 3) From analysis to measurement of vulnerability to climate change

The impact of climate change is not homogeneous within a country. Some effects will impact only a certain area in a given country, while others will have the same impact in the neighboring countries of a particular region. Although the choice of a national scale for the index does not correspond to homogeneous climate change characteristics, it can be used at the national level for the construction of the index from more disaggregated data. As noted at the beginning of this chapter, the proposed index should be likely to be used as a criterion for the allocation of adaptation resources between countries, leading to allocate more resources to countries which are on average more vulnerable to climate change. For this reason, the choice of scale for the analysis is the country.

Another issue to be addressed is the heterogeneity of the source of vulnerability among countries. What matters for a country is not the simple average of the various sources of vulnerability, but its vulnerability to the source likely to have the highest impact in its case. For this reason, as we will see later, the indicator of the vulnerability to climate change resulting from various sources of vulnerability should be designed so that it can reflect a high vulnerability resulting from a specific factor.

The time frame of the index also raises an important issue. To what extent can the indicators rely on past trends and characteristics to assess vulnerability to future shocks? Components can be calculated as forecasts, i.e. on a purely ex-ante basis or ex-post, from the observation of current trends. It seems possible to rely on forecasts only when data are available and reliable (e.g. likelihood of sea level rises). Other components should be calculated ex-post from past trends and levels.

IV - Components of the Physical Vulnerability to Climate Change Index

The IPCC WGII report defines the climate change as “a change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer”. This definition calls for a distinction between two kinds of consequences and related risks: the risks of progressive shocks and the risks of increasing recurrent shocks. These two categories of risk roughly correspond to the first and the second categories of hazard identified by Adger et al. (2004).

Starting from the distinction between the risk of progressive shocks and the risk of an increase of the recurrent shocks, we try to identify reliable indicators that are good candidates to compose an index of physical vulnerability to climate change. Since it is unavoidably debatable to assess the final economic and social impact of climate change, indicators should rely on measurable intermediary consequences, estimated either directly or by the means of proxies. Thus, differing from other attempts to assess vulnerability to climate change, our assessment only considers the expected impact of climate change on physical variables. These variables are of course likely to have socio-economic consequences, but they are not socio-economic variables. Using physical indicators means using only objective or neutral data. It avoids reference to indicators partly influenced by policy or resilience factors.

In any case, the set of indicators presented below should be considered as tentative. They try to capture the main channels through which climate change is a factor of vulnerability. It should be remembered that a good index should use a limited number of components, transparent and focused on the most relevant issues. We present what would represent the physical vulnerability, focusing only on physical dimension of vulnerability to climate change.

IV - 1) Risk of progressive and durable shocks

The risk of progressive shocks (or continuous hazard) refers to possible persistent consequences of climate change at the country level. The two main types of such risks, as identified in the literature, are rise of the sea level, which may lead to flooding, and increasing aridity, which may lead to desertification.

IV - 1 - a) Risk of flooding from the rise of sea level: shock and exposure

The vulnerability of a country to the rise of the sea level is essentially the risk of this country being flooded. Its assessment involves making a distinction between the size of the shock (magnitude of the rise of the sea level) and the exposure to this shock (altitude). An assessment of the vulnerability of zones likely to be flooded then depends on the two following factors:

- The exposure to sea level rise depends on the relief, since it influences the likelihood of flooding, so that the indicator should take into account the distribution of the heights of arable lands or the distribution of the population according to the height of occupied lands;

- The shock could be estimated by the distribution of the likelihood of a sea level rise in t future years.

The combination of the exposure and potential shocks allows for the assessment of the likelihood of flooding resulting from the sea level rise (in t years).

The measurement of the exposure component does not raise insuperable difficulties. Its assessment relies on a good knowledge of the geographical configuration of countries. If the index refers to the distribution of the heights of land, a possible matter of debate is the kind of area to be considered. If the distribution of the height of population location is referred to, a debate might arise about the expected change in this distribution over time. However since the future change may itself depend on the adaptation policy, there is a rationale in considering only the present distribution. Indeed the present structural vulnerability should not really depend on this change.

It is more difficult to assess the risk of the sea level rise, for two reasons. First, there is still some degree of uncertainty about the rise of the sea level on a given time horizon. Secondly, the probability distribution is changing over time with rising average sea level and increasing dispersion. Let us suppose that we know the probability distribution of the sea level rise for each of the next t years. The impact on the expected percentage of flooded areas is consequently changing. This impact can be considered at a given future time (for instance +30 years or +50years …) or all over given number of years. In this case should it be expressed as a present value, using a discount rate? This might be done for two reasons. The uncertainty of estimations is increasing as the time horizon is extending, although this growing uncertainty can be already captured by the increasing dispersion of the probability of the sea level rise. When the each year sea level rise is expressed only as an average level, then it would be legitimate to discount for this reason alone. A second reason would be the "pure time preference": the disadvantage generated by a given sea level can be considered higher the earlier it occurs; the later it occurs, the higher the capacity of a country to face it. So a logical indicator would be the present value of the likelihood of flooded areas over the next t years.

$$SLR_i = \int^{t}\int^{j} \frac{h_{ijt}}{(1+r)^t} \times s_{ij} \tag{1}$$

With: *SLR*: sea level rise indicator;
i, country indicator and *j*, the meters of sea level rise;
h_{ij}, probability that the sea level rises by *j* meters for the *i* country;
and s_{ij} the part of arable lands below *j* meters in country *i (or the share of population living below j* meters in country *i*)*;*
t: number of years from now;
r: discount rate.

The discount rate can be the same for all countries. Indeed, as far as it reflects a pure time preference, it could differ across countries, but differences cannot be reliably assessed and they would then reflect differences in the capacity to adapt, a component of vulnerability which is not really "structural" and cannot clearly be considered for the allocation of adaptation resources.

Anyway one can consider arbitrary to apply any discount rate. Then, taking $r = 0$, a simplified indicator could be the likely part of flooded areas in t years (the time horizon of t years being also arbitrary):

$$SLR_{ix} = \int^{j} h_{ijx} \times s_{ij} \tag{2}$$

IV - 1 - b) Risk of increasing aridity: assessment from past trends in temperature and rainfall, and from initial conditions

The literature on the consequences of climate change shows the risk of some arid countries (in particular Sahelian countries) being threatened by extreme aridity (see for instance IPCC

2014b). The risk depends both on the present level of temperature and rainfall (exposure) and on their trends (shock).

Proxies for the exposure to the risk of an increasing aridity can be either the actual average level of rainfall in the country, or preferably the actual part of drylands in the country, which better fits the risk of desertification. The lower the rainfall level or the higher the drylands percentage in a country, the more exposed the country to a long term decrease of rainfall or increase in temperature.

As for the size of the shocks, it seems relevant to use the past trend (appropriately estimated) in annual average temperature over the past two or three decades, supposing it will go on. A similar and complementary proxy of the shock measurement for the risk of increasing aridity can also be found in a decreasing trend of the average rainfall level. At the country level, the progressive shock resulting from climate change, and evidenced in a rising trend in temperature or a decreasing trend in rainfall, is thus captured by exploiting past trends.

IV - 2) Risk of increasing recurrent shocks

Climate change is also likely to generate more frequent or more acute natural shocks, such as droughts, floods, and typhoons (IPCC, 2014a). Here again the only variables to be considered should be unambiguously linked to climate and its change, such as the rainfall and temperature increasing variability, and the frequency of typhoons as well.

The vulnerability to increasing recurrent rainfall and temperature shocks has two main kinds of components, corresponding to the previous distinction between exposure and shocks. The exposure components are here given by the average frequency of past (rainfall, or temperature, or storms) shocks, which reflect the local climate, but not its change: this average frequency during previous years can be taken as a proxy for the exposure. The shock components, more forward-looking, are drawn from the trend in the frequency and intensity of the shocks, assuming this trend is determined by climate change, likely to go on in the future. These two kinds of components are considered in the same way for rainfall, temperature, and storms.

IV - 2 - a) Average present frequency as an indicator of exposure

When the Economic Vulnerability Index (EVI) was developed at the United Nations by the Committee for Development Policy (CDP) for the identification of the Least Developed Countries, the risks of natural shocks were assessed ex-post by a measure of shock incidence over past years. Among the components of the EVI, indirect and synthetic indicators were used likely to capture highly heterogeneous natural shocks (floods, typhoons, droughts, hurricanes, and earthquakes) with highly unequal intensity and consequences. The two related indicators of the EVI were an index of the instability of agricultural production (IA), and initially an index of the percentage of homeless population due to natural disasters[49](HL), replaced since the 2012 triennial review by an indicator of the percentage of population killed or affected by natural disasters.

The instability of agriculture production was a square deviation of the agricultural production with regard to its trend. These two indicators were averaged in a natural shocks index: $NSI = (IA+HL)/2$.

Within the EVI, this natural shock index, although calculated ex-post, is considered as reflecting a risk for the future, due to the recurrent nature of the related shocks: the average past level is taken as a proxy for the risk of future shocks. This index is indeed likely to change over time, but a high past level can simultaneously be considered as generating a handicap to future economic growth.

As for the vulnerability to climate change, the present approach is different. First, the average level of past shocks is related to rainfall and temperature, two variables clearly linked to climate, while the instability of agriculture production or homelessness (or the percentage of population killed or affected by natural disasters) also depends on shocks which are not all related to climate. Thus, the index of exposure to climate change, relying on past average levels of rainfall or temperature instabilities, is unambiguously physical, and by no way influenced by policy or resilience factors. To measure instabilities, two methods can be applied. A simple way consists to use the absolute deviance of climate variables (rainfall or temperature) from their long-term trend. But, this method does not have good mathematical properties and is not widely used. Our preferred measurement is the

[49] The latter index comes from the Center of Research on Epidemiological Diseases which also produces other indicators, such as the percentage of population affected by natural disasters.

instability calculated as square root of square deviation of climate variables from their long-term trend. For instance, the index of rainfall instability IR should be:

$$IR = \sqrt{\sum \frac{(R_t - \hat{R}_t)^2}{R_t}} \tag{3}$$

With $\hat{R}_t$ the trend level of R_t.

Second, the past average level of shocks is considered as an indicator of the exposure to an increase in the frequency and size of these shocks, which is captured by a specific index of the size of the shocks, as explained below.

IV - 2 - b) Trend in the intensity of past shocks as a proxy of future shocks

The risk of increasing recurrent shocks associated with climate change is here assessed in a look back manner. We assume that the more significantly the shock intensity has been increasing in the past, the more likely is a shock increase in the future. In other words, if rainfall and temperature shocks have increased due to climate change, they are assumed to remain increasing in the future. The proxy used will then be the trend in the size of instability.

For instance, the proxy for the risk of increasing rainfall shocks will be the (positive) trend in the absolute (or squared) deviation of the yearly average of rainfall from its own trend. For instance, supposing a linear trend, the indicator may be measured from:

$$\sqrt{\sum \frac{(R_t - \hat{R}_t)^2}{R_t}} = \alpha.t + \beta \tag{4}$$

With α being the trend in the intensity of rainfall instability. Assuming a non-linear trend, the measurement may be:

$$\sqrt{\sum \frac{(R_t - \hat{R}_t)^2}{R_t}} = \alpha_1.t + \alpha_2.t^2 + \beta \tag{5}$$

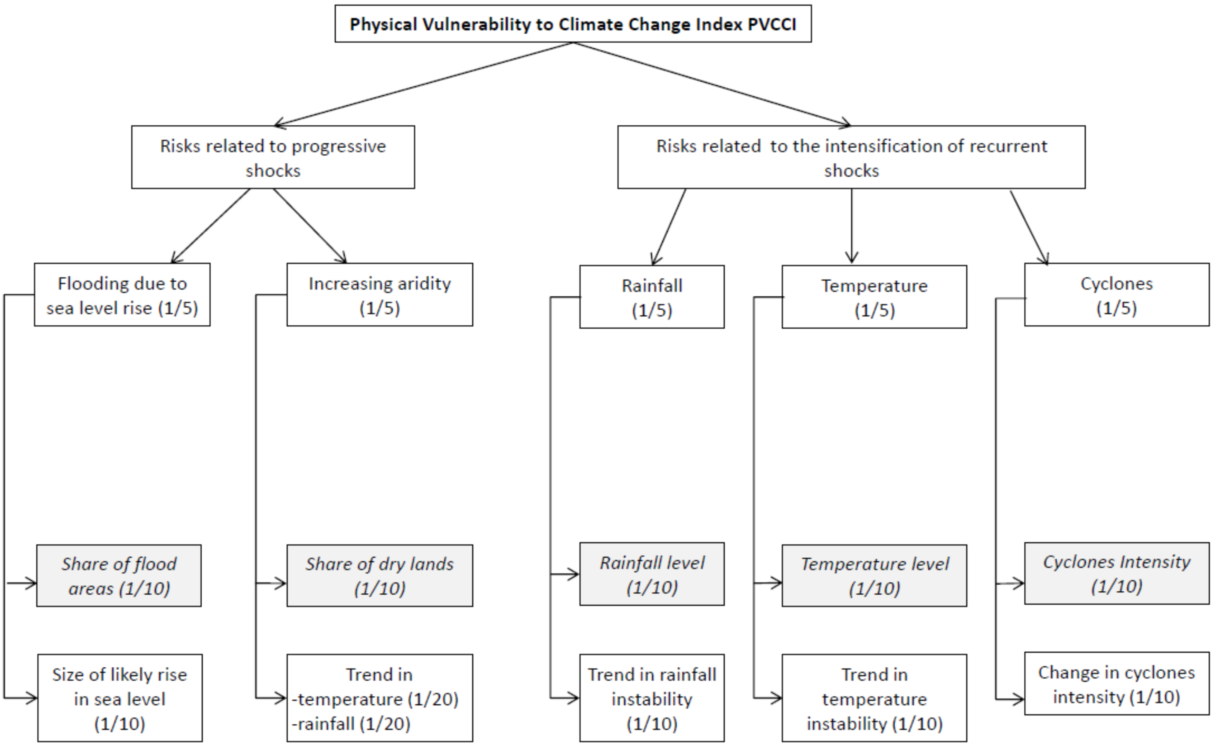
The index of the size of future (rainfall) shocks then will depend on the time horizon selected, as is the case for the rise of the sea level, as well as on the shape of the trend.

In the same way, it is possible to estimate an index of the size of future (temperature) shocks from the trend in the intensity of temperature instability (α’).

It is also possible to build an indicator of the change in the frequency of rainfall or temperature significant shocks, or typhoons as well, by designing significant shocks from given thresholds in the level of "bad events", what could seem more arbitrary, but may appear more dicriminatory. We come back to this option when calculating the index.

As presented in the Figure 2, the physical vulnerability to climate change index gathers ten sub-components into five components reflecting two kinds of shocks (progressive ones and increasing recurrent ones), following a unified framework.

Figure 2: Structure of the Physical Vulnerability to Climate Change Index



NB. The boxes corresponding to the two last rows of the graph respectively refer to exposure components *(in italics)* and to size of the shocks components

V - Construction of the index

The physical vulnerability to climate change index has been calculated from data beginning in 1950, covering sixty four years. The index can be updated and calculated regularly.

V - 1) Measurement of components: Data and methodology

V - 1 - a) Risk of flooding

It has not been possible to calculate the risk of flooding due to sea level rise according to the formula previously proposed because of a lack of agreed data on the evolution of the average sea level rise, and even more on the probability distribution of this rise. However, data allowed us to calculate the exposure to sea level rise, supposing a rise up to 1 meter. So, a convenient proxy for the risk of flooding due to sea level rise would be the index of the "relative part of country affected by a rise of 1 meter of the sea level". Furthermore, we investigate the robustness of this indicator by assessing the impact of choosing an elevation threshold of 2 meters. It appeared that a possible choice of the elevation threshold of 2 meters instead of the one of 1 meter would not change results significantly. The Spearman's rank correlation between the two measures is strongly significant and stands at 99.2 %.

Countries with low elevated coastal zones are obviously the most exposed to the risk of flooding due to sea level rise. Nevertheless, it should not be forgotten that some of the most devastating floods occur when glacial lakes overflow, in particular when the so-called Glacial Lake Outburst Floods (GLOFs) take place. The spectacular retreat of mountain glaciers is one of the most reliable evidence of climate change. Glacier-outburst floods represent the highest and most far-reaching glacial risk with high potential of disasters and damages (Richard and Gay 2003). For instance, in Bhutan, according to the International Centre for Integrated Mountain Development (ICIMOD) annual report 2002, glaciers have been retreating and thinning at an average rate of 30-40 meters per year since the mid-1970s. A similar situation is observed in Nepal. A large part of these two countries are covered by the Himalaya Mountains which concentrate the bulk of outbursts from moraine-dammed lakes. This type of country needs a specific treatment in the measurement of the risk of flooding due to climate change. Otherwise Bhutan and Nepal which are landlocked would be given a minimum score of 0, thus appearing non vulnerable because of their lack of access to the open sea. So in order to take into account of the serious risk of ice melting to which they are exposed, but which cannot be presently measured, their initial zero score has been replaced by the value standing at the top quartile of the full sample.

V - 1 - b) Share of dryland areas

Database on the exposure of drylands are based on the definition of dryland of the United Nations Environment Program[50]. Our indicator is the part of dryland areas, considered to be the arid, semi-arid, and dry sub-humid zones (three of the world's six aridity zones), as a percent of the country's (non desertic) total land area. For consistency's sake, we exclude deserts (which are classified as hyper-arid areas) in both the dryland area and the country's total land area. We use CRU TS 3.22 database to calculate the ratio[51] of average annual precipitation to potential evapotranspiration (P/PET), from which the definitions of areas according to the degree of aridity are drawn.

V - 1 - c) Rainfall and temperature: levels, trends and instabilities

Rainfall and temperature data come from the Climate Research Unit (CRU TS version 3.22 – University of East Anglia); currently one of the most frequently used dataset, particularly by recent works on climate change. This version of database covers the period from 1901 to 2013. Monthly time series of temperature or rainfall are globally gridded to 0.5 x 0.5 degree spatial resolution on land areas[52].

To calculate the trend of temperature and rainfall, we use the OLS approach, respecting fundamental principles of the OLS that there should not be autocorrelation between observations. The estimated coefficients obtained by the OLS from the monthly climatic data (especially monthly temperature data) might indeed be erroneous, since monthly temperature data violate the hypothesis of no dependence between observations: monthly data of temperature are not independent, hot months tending to follow hot months and cold months to follow cold months. This autocorrelation increasing the uncertainty in the trend may lead to spurious estimates of the trends.

To deal with this issue and assuming a linear[53] trend, we apply a simple and consistent approach as follows[54]:

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[50] UNEP definition of Arid, semiarid and sub humid areas: Areas, other than the polar and subpolar regions, in which the ratio of annual precipitation to potential evapotranspiration falls within the range from 0.05 to 0.65.

[51] This ratio makes it possible to highlight the "degree of aridity" of a territory. Hyper-aridity (desert) is observed when the ratio P/PET is less than 5 percent.

[52] For countries where kriging points are not exactly in the country (13 countries), we use buffering technique and couple the point closest to the country in the country where data are missing.

[53] For simplicity, we assume a linear trend. One can check the validity of this assumption. For instance, in the previous version of the PVCCI, a squared trend was also added in checking the robustness.

- for each country and per month of year, we regress the temperature (or rainfall) on the time variable covering the 1950—2013 period using the following equations:

$$Temp_{ij} = \alpha + \beta t + \varepsilon_j \qquad (6)$$

where $Temp_{ij}$ is monthly temperature of country i in the month *j* since 1950; t time variable and ε error term.

- for each country, we recover the twelwe estimated coefficients β (one by month);
- finally, the trend indicator is measured by the arithmetic mean of estimated coefficients by country.

The same approach is implemented to monthly rainfall data even if these are less subject to the autocorrelation of observations.

The level of temperature and the level of rainfall are determined by the annual average of each of the two variables over the period 1950—2013, respectively.

Trends in shocks are determined by the regression of the residuals (in absolute value) obtained from the equation (6) on the time variable. In the benchmark PVCCI, we only take into account the negative shocks for rainfall and only the positive shocks for temperature. These trends in the absolute values of the negative rainfall shocks and in the positive temperature shocks are supposed to be related to climate change, with a potential impact all the more significant that the country is more arid.

V - 1 - d) Cyclones intensity*

The literature on climate change seems to agree that storms are likely to become more intense. Differing from a previous version of PVCCI, this version includes a component of storm intensity. Data on storm duration and categories[55] are obtained from the National Oceanic and Atmospheric Administration – National Climatic Data Center – International Best Track Archive for Climate Stewardship (IBTrACS), version v03r06. From the perimeter of land area provided by this database, we compute the territory's land area affected by the

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[54] One can reduce the number of data points of the series, focusing on the number of independent observations. The final effective sample size is determined by $N_{eff} = N(1-r_1)/(1+r_1)$, where N is the original sample size, r_1 the lag-1 autocorrelation coefficient. The main harmful aspect of this technique is that it is burdensome and consumer of data.

*In the published working paper Feindouno, Goujon and Santoni (2017) "Un indicateur d'intensité cyclonique au niveau pays", FERDI WP n°210, we present the building of this index in details. The release of the English version of the document should be forthcoming.

[55] These categories correspond to Saffir-Simpson scale rating from 1 to 5. We also add the category of "other minor storms" to which we assign the rate equal to 0.

storms using the ArcGIS software. We use data from 1970 to 2014, period for which storms events are exhaustively recorded.

If a country is affected by several storm events during the same year, we add them. Thus, the storm intensity in a country i for the year t is computed as follows:

$$IC_{it} = \sum_{j=0}^{n}\sum_{k=0}^{5} \propto_k \times D_{kjit} \times S_{kjit} \quad (7)$$

Where j is a given storm event (total equal to n) observed in the country i at the periode t, k the category of storm (6 categories ranking from 0 to 5), D the duration by storm category (in hours) of the event j, S the share of territory affected by storm category (expressed as a percentage of the total country area).

For each country, we compute the arithmetic mean of the storms intensity for each year over the 1970—2014 period, then the change in storms intensity. Storms being random phenomena with some countries experiencing them more than others, it may be difficult to highlight a consistent linear trend for each country. For this reason, we divide data into two periods. The first time period examined runs from 1970 to 1992 and the second from 1993 to 2014. The average storms intensity of each period has been computed for each country. The difference of the average storms intensity between the second period and the first period could be considered as a proxy of the trend in storms intensity.

V - 2) Averaging the components

Each component is first normalized following the max-min method:

$$CN = \frac{(C - min_C)}{max_C - min_C} * 100 \quad (8)$$

With
CN : normalized component
C: value of component

V - 2 - a) Aggregation: choosing a quadratic rather than arithmetic average

Each of the previous component indicators gives information which can be used independently from each other. Making available the measurement for each component and sub-component will allow researchers to use them separately or to combine them in an aggregated index. Indeed a synthetic index is also required, in particular, as underlined above, for aid allocation. The aggregation of the components, once they have been expressed as indices on a common scale, raises several issues.

The structure of the index can be presented in two ways. The first one, illustrated by the Figure 2, distinguishes between risks related to progressive shocks and risks related to more intense recurrent shocks, both considered as resulting from climate change. The risks related to progressive shocks cover those due to (i) the sea level rise and (ii) the trends in average rainfall and temperature. The intensification of recurrent shocks corresponds to the increasing intensity of (iii) rainfall shocks, (iv) temperature shocks and (v) cyclones. The shocks are thus grouped into five components, each of them including both an exposure index (in italics) and a shock index has been computed. Another way of presenting the structure of the index, still starting from the distinction between risks related to progressive and recurrent shocks, is to split up the later into two mains sub-components: (a) the past average level of rainfall instability, temperature instability and cyclones intensity, a proxy for exposure, and (b) the trend in the instability of rainfall and temperature and the change in cyclones intensity, a proxy for the shock itself.

The way by which the values of the components are averaged is also an important issue. The usual averaging practice for the calculation of synthetic indices is the arithmetic one (as it is done for the Human Development Index between 2005 and 2010 or for the EVI). However, any of the main components of a vulnerability index may be of crucial importance for a country, more or less independently from the level of the other components. In that case, it is relevant to use an averaging method reflecting a limited substitutability between components (as already examined for the EVI in Guillaumont, 2009a). It can be obtained either by a reverse geometric average (as done in Ibid.), or, what is finally retained here, a quadratic average[56] of the components, defined in the following way:

$$G' = \sqrt{\frac{1}{n}\sum_{k=1}^{n} A_k^2} \tag{9}$$

with A_k the index value of the k component.

[56] Here, we prefer the quadratic average. Since each component varies from 0 to 100 because of normalization, the multiplicative nature of the geometric average would reduce to zero the vulnerability of any country having a value of zero for at least one component irrespective of the values of the country in the others components.

The choice of the quadratic mean instead of the arithmetic mean is based on the concept that the vulnerability of a country may critically depend on the levels of only one or two components, whatever the level of the others. While all components bring some information about the vulnerability of a country, their variance should also be considered as an additional factor of vulnerability to climate change. The quadratic mean gives greater weight to larger values (and is equal to or greater than the arithmetic mean[57]). As an example, an island with a very large share of area likely to be flooded and an arid country suffering from a highly increasing trend in the instability of the level of temperatures are both highly vulnerable. But each of these two countries, due to a specific component close to 100, may be considered as highly vulnerable even if it is not vulnerable with respect to other components of the index. Thus a high vulnerability to climate change will be better evidenced by using the quadratic average, rather by an arithmetic average. A quadratic average evidences the vulnerability of each country in its specificity. The quadratic mean is used at two levels:

- for the calculation of the PVCCI by averaging the five components of shocks;

- although it may seem less necessary, for the calculation of each component by the quadratic average of the indices of the exposure to the shock and the size of the shock.

V - 2 - b) Weighting the components

A traditional aggregation issue is related to the weight given to each component. Since the components are forward-looking, it is not possible to determine the weights from an econometric estimation of the expected respective impact of each component on a global indicator of development. Even for the structural economic vulnerability the respective impact of the EVI's components on economic growth appeared quite difficult to apply (Guillaumont 2009a). A simple and usual, although arbitrary, solution is to use equal weights. We propose here to attribute equal weigths (1/5) to the five components. A higher implicit weight is nevertheless assigned to the highest vulnerability component through the use of a quadratic average.

[57] It depends on the variance of the components according to the relationship:

$$(\text{Quadratic mean})^2 = (\text{Arithmetic mean})^2 + \text{Variance}$$

Other simple weightings are conceivable. Since the five components fall into two categories of risk (risks related to progressive shocks and risks related to more intense recurrent shocks), it may be valuable to attribute equal weight to the two kinds of risk. In other words, this amounts to assign weights of 1/4, 1/4, 1/6, 1/6 and 1/6 respectively to flooding due to the sea level rise or ice melting, increasing aridity, and to the intensification of rainfall shocks, temperature shocks and cyclones.

Or since rainfall and temperature are two important climatic factors affecting agricultural production, especially in the context of climate change, it may be legitimate to aggregate the intensification of rainfall shocks and temperature shocks considering the interdependance between the two variables, although rainfall seems more important than temperature for crop yield. One could then assign weights of 1/4, 1/4, 1/8, 1/8, 1/4 respectively to flooding due to the sea level rise or ice melting, increasing aridity, rainfall, temperature and cyclones.

These different choices of weighting could be applied considering all shocks of temperature and rainfall (symmetrical shocks) or just positive shocks of temperature and negative shocks of rainfall (asymmetrical shocks). Several options are possible and we report and discuss some of them in the Appendix 2.

V - 3) Results

The PVCCI is calculated for a complete set of 191 (developed and developing) countries[58]. The normalized scores are between 0 (the least vulnerable) and 100 (the most vulnerable). However, it is important to note that no country has a score equal to 0 or 100. The benchmark PVCCI exhibits a minimum value of 37.0 and the maximum value of 68.2, bringing a statistical range of 31.2. This would mean that all countries are facing climate change somehow, being vulnerable with respect to one or other components of the PVCCI. The index serves as a tool for determining to what extent the countries are physically vulnerable to climate change, and by which way they are so. Let us recall that the results presented below only concerns physical vulnerability: other important factors of the social vulnerability, in particular the level of income per capita and human capital, are not considered since they must be taken into account separately in the allocation of

[58] We have decided to include both the developed and developing countries for two reasons. First, all countries are affected by climate change, and it makes sense to provide a comprehensive view of the risks they all face. Second, all countries may well be candidates for assistance in the uncertain.

concessional resources for adaptation, as they are with respect to EVI in the identification of the LDCs.

According to the benchmark PVCCI, the "physically" most vulnerable countries to climate change are Oman (68.2), Marshall Islands (67.9), Jamaica (65.7), the Maldives (64.6), Tuvalu (64.3) and the least vulnerable are New Zealand (37.0), Nauru (38.0), Georgia (39.4), Bosnia and Herzegovina (39.5), Montenegro (39.7). The average score for the entire sample of the PVCCI stands at 51.2 while the median score stands at 50.0, showing that the scores in a few countries are clearly higher than the main part of the sample. The standard deviation indicates the heterogeneity across countries.

In what follows, we group countries under seven categories of particular interest for researchers and policy makers. Table 1 shows that SIDS, African countries are especially very vulnerable to climate change. Already structurally handicapped in their national development process, LDCs are also penalized by the climate change. PVCCI's scores of LDCs presented in the Appendix 1 show that of the 15 most vulnerable countries in LDCs group, 12 are in Africa (all in sub-Saharan Africa). If we look at LDCs and moving from the most vulnerable to the least vulnerable, Tuvalu is ranked first. With the exception of Tuvalu and Kiribati, Sudan, Mauritania, Eritrea, Niger, and Djibouti are at the same time the most vulnerable in LDCs group and African countries group. This is not surprising when we consider the components used in the PVCCI. Agriculture is one of the key vulnerable sectors identified by IPCC (2007b). But agricultural production in (sub-Saharan) Africa is severely compromised owing to the increasing temperatures, the increasing of arid and semi-arid land, the decreasing rainfall trend. Most of African countries are among the most vulnerable in at least three of the five components. This, combined with the quadratic mean used in the aggregation procedure, increase the likelihood of finding African countries among the highest scores of the PVCCI.

The PVCCI's average score of Small Island Developing States is also very high[59]. Given their inherent physical characteristics (small size of country, low elevated coastal zone), SIDS are very prone to natural disasters: floods, earthquakes, tropical and extratropical cyclones, tsunamis, and so on. In many SIDS, the majority of human communities and infrastructure is

[59] In the previous version of the PVCCI, the average score of SIDS was lower than the one obtained in the present version. This is primarily due to the inclusion of the component of storms intensity.

located in coastal zones. They are the most vulnerable countries into the components of cyclones intensity and flooding due to sea level rise or ice melting.

The standard deviation values highlight a high heterogeneity across all country groups. But this heterogeneity is likely to be significantly less for the group of African countries. The PVCCI is relatively highly variable between the group of SIDS LDCs and SIDS Non-LDCs and the vulnerability is likely to be greatest where local environments are already under stress as a result of human activities.

Table 1: Physical Vulnerability to Climate Change Index (PVCCI) by country groups

Country groups	Mean	Median	Standard Deviation	Min	Max
Developing countries (144)	53.0	52.4	6.9	38.0	68.2
LDCs (48)	53.3	51.4	7.2	39.9	64.3
Non LDCs (96)	52.8	52.7	6.8	38.0	68.2
SIDS (36)	54.4	54.2	7.4	38.0	67.9
SIDS LDCs (9)	54.7	54.1	7.4	41.4	64.3
SIDS Non-LDCs (27)	54.3	54.4	7.5	38.0	67.9
African countries (54)	53.6	51.9	6.7	41.4	64.1

V - 4) Robustness and sensitivity analysis

The PVCCI hitherto built is based upon some methodological choices and assumptions, calling for assessing the robustness of the index. Among a wide range of possible configurations, we retain two relevant configurations used to test the robustness of the benchmark PVCCI. We call them: PVCCI2 and PVCCI3. For ease of analysis, let’s rename the five components of the PVCCI introduced earlier in the figure 2.

- Cluster 1 replaces henceforth “Flooding due to sea level rise or ice melting”
- Cluster 2 replaces henceforth “ Increasing aridity”
- Cluster 3 replaces henceforth “Rainfall”
- Cluster 4 replaces henceforth “Temperature”
- Cluster 5 replaces henceforth “Cyclones”

V - 4 - a) PVCCI2

The aim here is to evaluate the impact of using an alternative way to calculate the instabilities. Instead of taking the square root of square deviation, the PVCCI2 uses the simple absolute deviation (of temperature and rainfall from their long-term trend). The rest remains unchanged: we still consider the quadratic mean and maintain the choice of negative shocks of rainfall and positive shocks of temperature.

The scores of the PVCCI 2 for the whole sample range from 33.4 to 67.0, with an average of 50.0, a median of 48.4 and a standard deviation of 7.1. The four most vulnerable countries are identical to those of the benchmark PVCCI: Oman (67.0), Marshall Islands (66.4), Jamaica (65.2), the Maldives (64.8), Cuba (63.1); the least vulnerable countries are Nauru (34.4), New Zealand (34.8), Georgia (38.4), Montenegro (38.5), Papua New Guinea (38.7).

The spearman's rank correlation between PVCCI 2 and PVCCI is 98.2 %. Figure in the Appendix 5 labels the countries with the highest rank changes. Most notably, the changes are very large for Zambia, Turkey, Benin, Burundi which worsen by 55, 45, 34, 28 places (out of 191), respectively; on the other hand, Vietnam, Brunei, Denmark, Tuvalu improves by 37, 32, 19, 18 places. As can be seen in Table 2, compared to the PVCCI, the PVCCI2 lowers the average scores in all groups of countries. However, SIDS, LDCs and African countries are still the most vulnerable groups with a strong heterogeneity within the SIDS Non-LDCs groups.

Table 2: PVCCI2 by country groups

Country groups	Mean	Median	Standard Deviation	Min	Max
Developing countries (144)	51.8	51.6	7.0	33.4	67.0
LDCs (48)	52.4	51.0	6.8	38.8	62.8
Non LDCs (96)	51.5	51.9	7.0	33.4	67.0
SIDS (36)	52.9	52.8	7.8	33.4	66.4
SIDS LDCs (9)	53.0	53.9	7.3	38.8	61.3
SIDS Non-LDCs (27)	52.8	52.4	8.1	33.4	66.4
African countries (54)	52.6	50.8	6.5	38.8	62.8

V - 4 - b) PVCCI3

The intention here is to take into account all types of shocks and not just positive shocks of temperature and negative shocks of rainfall. It is true that the lack of rainfall is harmful to the agricultural production, but too much rain should also be a major concern when it comes to assessing the impacts of climate change on agriculture. Excessive rain can lead to huge problems and make countries more vulnerable: destruction of crops particularly just after germination and emergence, soil erosion mainly sheet erosion, floods and so on.

Likewise, as mentioned before, warmer temperatures cause glaciers to melt with the undesirable risk of flooding. However, in certain limited cases, ice melting attributable to high temperatures could contribute to the well-being of populations in some countries. For instance, ice melting contributes around 15 % of the water resources[60] of La Paz City in Bolivia (Soruco et al., 2015). Even if it is rare cases, avoiding a double standard lead us to consider all positive and negative shocks.

We assign equal weights to all components as having been made in the benchmark PVCCI. The rest remains unchanged.

The PVCCI 3 for whole sample ranges from 35.0 to 67.8. The average score stands at 50.2, the median at 48.7, the standard deviation at 7.5. Marshall Islands (67.8), Oman (67.7), Jamaica (67.0), Sudan (63.9), the Maldives (63.7) appear as the most vulnerable countries while Sweden (35.0), New Zealand (37.4), Montenegro (37.8), Bosnia and Herzegovina (38.3) and Georgia (38.5) appear as the least vulnerable countries in view of the PVCCI 3. The correlation between PVCCI 3 and PVCCI stands at 97.3 %. Some countries experience great variations in their ranking. For instance, Germany, Solomon Islands, Belgium, Ukraine, and Netherlands improve by 64, 49, 40, 35, 33 places, respectively; whilst Albania, Zambia, Chile, Turkey and Laos drop by 68, 37, 33, 30 and 24 places, respectively.

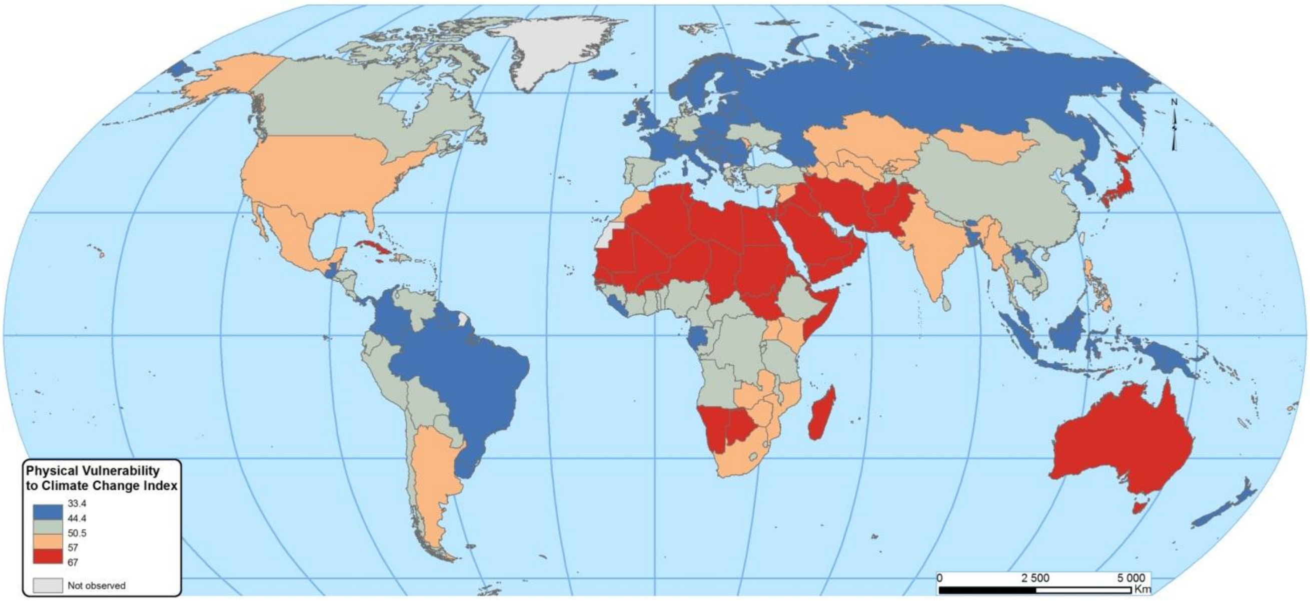
The table 3 shows that African countries, LDCs and SIDS groups highlight a high degree of vulnerability. But the scores are very heterogeneous within LDCs, SIDS groups compared to African countries groups. This is expressed by their relatively high magnitude of standard deviation.

[60] In the same way, a team from a World Bank published at the end of 2009 in the Bulletin of the American Geophysical Union (AGU), a report in which they mention that “70 % of Peru’s electricity comes from hydroelectric dams sited on the glacier-fed rivers.”

Table 3: PVCCI3 by country groups

Country groups	Mean	Median	Standard Deviation	Min	Max
Developing countries (144)	52.2	51.9	6.9	37.8	67.8
LDCs (48)	52.4	49.4	7.2	39.2	63.9
Non LDCs (96)	52.1	52.3	6.9	37.8	67.8
SIDS (36)	53.4	52.4	7.4	39.5	67.8
SIDS LDCs (9)	53.2	54.5	7.5	41.4	63.0
SIDS Non-LDCs (27)	53.5	52.4	7.5	39.5	67.8
African countries (54)	52.9	50.8	6.7	41.4	63.9

Figure 3: PVCCI on the map



Notes: Scores are discretized using the technique of k-means clustering.

In summary, the PVCCI is an instrument designed on the principle of transparency. On the basis of standardized criteria, the index evaluates and compares the structural vulnerability to climate change for 191 UN members' countries. The implications for many developing countries are clearly serious, in particular for LDCs, SIDs and African countries which appear to be the most vulnerable group of countries. Our results are strongly consistent with several options studied.

In line with our findings, the areas particularly vulnerable to climate change are those where people living in places are affected by violent conflict. Climate change thus leads humanity to new challenges by threatening human security. In any case, empirical scientific analyses have sought to investigate mathematical links between certain sudden climate change and increased violence in some areas, regions or countries. With this edict in mind, we take part in the discussion by examining the link between the PVCCI and civil conflict. That is what the next section intends to do.

VI - PVCCI and conflict: An empirical analysis

With growing interest in the environmental consequences of climate change, more and more studies are questioning the link between climate change and conflict. When such a link is mentioned it is largely unsubstantiated by evidence, even if the process-based analysis lies in a wide array of theories and methods. This section assesses the link between vulnerability to climate change, measured by the PVCCI, and civil conflict. The use of the PVCCI as a proxy for climate change confers two advantages. First, the use of very long trends, which are more relevant than simple variations over a few years of temperature and rainfall series as often used in studies. Secondly, it allows taking into account in a single data the various manifestations of climate change. Although each country has its own vulnerability that can be dissolved in a composite index, the component by which vulnerability to climate change manifests itself in each country is still highlighted here thanks to the use of quadratic mean.

We start by a brief review of empirical studies and describe the data used for the estimates. We then present our model and report our results. We conclude the section by evaluating the robustness of our results through several variants proposed at the level of the variables as well as the specification of the model.

VI - 1) Brief overview of literature review

The question of whether climate change is destabilizing for states and societies has been debated for several years now. The effects of climate change on the global physical landscape are changing the geopolitical condition and destabilizing vulnerable regions around the world. The current rate of climate change (sea level rise, melting of glaciers, extreme rainfall variability, increased frequency and intensity of cyclones) confronts humanity with new scenarios and affects the ability of countries to govern themselves and generate conflicts. For example, the former Secretary General of the United Nations (Ki-

Moon) has stressed that the conflict occurring in Darfur was being caused by “an ecological crisis, arising at least in part from climate change”. In the same vein, Werrell and Femia (2013) stated that the “Arab Spring” has been argued to have underlying climatic causes. In the past decade there has been a surge in the number of studies on the possible link between climate change and armed conflict (Boko et al., 2007; Buhaug, 2010; Gleditsch, 2012; Salehyan, 2014; Buhaug, 2015)[61]. Because climate change is likely to have profound effects on agriculture, one group of researchers (Raleigh and Urdal, 2007; Lecoutere et al., 2010; Tir and Stinnett, 2012) argued that climate change will exacerbate resource scarcity, and, ultimately, fuel violent conflicts. These effects are significantly more profound in development countries where agriculture represents an important part of the economy, and by extension more sensitive to environmental stress. In this sense, climate change represents a challenge to the effectiveness of the diverse institutions that already exist to manage relations over these resources. But, offering a different point of view, Dinar et al. (2007) indicated that countries usually prefer to cooperate with each other instead of fighting when facing rivalries to control resources. For the most part, temperature and precipitation are considered as the driving force for the kinds of long-term changes that might occur due to climate change. Also, some authors focused on the relationship between short-term warming and armed conflict (Buhaug, 2010; Koubi et al., 2012; Theisen et al., 2012). Some of them found a weak relationship, some foundd no relationship, and collectively the research does not conclude that there is a strong positive relationship between warming and armed conflict.

The large majority of studies focus on Africa, and, the effects of climate change on violent conflicts are limited and inconclusive. Salehyan and Hendrix (2014) argued that droughts have a pacifying effect on armed conflict because more water enables mobilization. Similarly, Theisen (2012) studied the incidence of conflict in pastoralist communities in Kenya and found that conflict becomes more likely following years when rain is more abundant. Gartzke (2012) examined the effect of the annual global mean temperature on

[61] This explosion of quantitative analyses on the link between climate variability and conflict is due to the growing recognition that climate change is changing; this is coupled with improvements in data quality and computing. On this question, four schools of thought have established the link between climate and conflict. This is the American School represented by Arthur Westing, the Toronto group under the lead of Thomas Homer Dixon. The Swiss School composed of researchers from the Swiss Federal Institute of Technology (Zurich) and the Swiss Peace Foundation (Berne), as part of the Environment and Conflict Project (ENCOP). Finally, the Oslo group including researchers from the International Peace Research Institute (PRIO).

interstate conflict in the last 150 years, but found that climate has not necessarily a causal influence. However, others suggested that the reason of such results is the failing of taking account for non-stationarity of the variables. So, his results are not robust. Using a gridded analysis, Theisen et al. (2010) found no effect of droughts on civil war onset, regardless of whether those droughts take place in sociopolitical contexts that are more prone to violence or not. The same conclusion is drawn by O'Loughlin et al. (2012). They found that droughts have no impact on conflict in Kenya, wetter precipitation deviations reduce conflict, and higher temperatures increase conflict.

Hendrix and Glaser (2007), in studying interannual variability in rainfall as a trigger for conflict, found that positive changes in rainfall are associated with a decreased likelihood of conflict in the following year. Investigating the relationship between civil war and rainfall variability in Africa, Miguel et al. (2004) showed that a decline in rainfall can fuel conflict. But Ciccone (2011) argued that the use of rainfall could account for such a conclusion and that inclusion of rainfall level might be more appropriate.

Hendrix and Salehyan (2012) found that both particularly dry and wet years, as identified by deviations from the long-term annual mean of precipitation, increase the probability of violent conflict. Raleigh and Kniveton (2012) found that extreme dry conditions are conducive to rebel conflict, while extreme wet conditions are conducive to communal violence. Disaggregating at the grid level, Von Uexkull (2014) and Harari and La Ferrera (2013), found that droughts during the growing season increase conflicts. As for Maystadt and Ecker (2014), they emphasized the length and the severity of droughts and argued that longer and more severe droughts contribute to conflict outbreak in Somalia.

The lack of consensus about the linkages between climate change and civil conflict in empirical studies is often caused by the econometric specification and the variables used in the models. The broader point is that there are several physical components of climate change underlying the link between climate and conflict to be examined. We contribute to this empirical work by exploring the relationship between the vulnerability to climate change measured by the PVCCI and conflict. Calculated on long-term trends, the PVCCI is more structural and more relevant to capturing climate change than a simple change in temperature and precipitation for a few years commonly used in the empirical literature.

VI - 2) Data

We use group-level data for 129 developing countries over 1964-2012. The period is divided into 5-year subperiods for a total of 1179 observations. The last subdivision, 2009-2012 contains only four years. The reason to consider 5-year subperiods is that the PVCCI is a structural variable that reveals the climate change over a long period, and the use of yearly data would fail to capture exactly this long-term pattern in the relationship. Using a 5-year subperiods allows at least to focus on medium-term linkages. The one downside of this choice is the lack of availability of a greater number of data, but at the very least prevents us from a bias through serial correlation of the errors[62].

VI - 2 - a) Conflict data

We use armed civil conflict incidence from the annually updated UCDP/PRIO Armed Conflict Dataset (Gleditsch et al., 2002; Harbom and Wallensteen, 2010; Pettersson and Wallensteen, 2015) as our main dependent variable in this analysis. The dataset has a relatively low inclusion criterion. Indeed, an armed civil conflict is defined in the UCDP/PRIO database as a contested incompatibility that concerns government and/or territory where the use of armed force between two parties, of which one is the government of the state, results in at least 25 battle-related deaths. We use a binary indicator of whether there is conflict or peace based on two threshold levels depending on the number of deaths: “minor” (between 25 and 999 battle-related deaths in a given year), and “war” (at least 1,000 battle-related deaths in a given year). We also include a variable of an intermediate level of conflict which takes into account the temporal dimension of the conflict[63]. In total, our dataset has 218 incidences, representing almost 17 % of all country-period observations. As an alternative measure for a robustness check, we include a dummy for a conflict onset which describes the start of a “fresh episode” of war or violence. It takes a value of 1 when a new conflict emerges.

[62] Compared to EVI, the PVCCI is more structural. In the case of EVI, one could support the decision to divide data into 5-years subperiods by conducting a Chow breakpoint test which indicates if there is a structural break in the data.

[63] In early versions of the UCDP/PRIO dataset, the intensity variable of conflict contained three categories: minor, intermediate and war. The intermediate category was defined as “more than 25 battle-related deaths per year and a total conflict history of more than 1000 battle-related deaths, but fewer than 1000 per year.” Thus, the variable included a temporal dimension into the intensity coding.

Other sources of data that are widely used in the literature could also have been used. These include Armed Conflict Location and Event Data Project (ACLED) and Social Conflict Analysis Database (SCAD). Compared to UCDP/PRIO Armed Conflict Dataset we use here, these databases only cover a few areas of the world. ACLED covers Africa, South Asia and South East Asia while SCAD focuses on conflicts in Africa and Latin America. Moreover, conflicts are neither defined nor coded in the same way in the different databases. For example, ACLED and SCAD do not refer to any particular threshold for recoding a conflict, when it is recalled that an event must generate at least 25 deaths in the year to be included in the UCDP/PRIO Armed Conflict Dataset. As a result, it lists fewer events.

VI - 2 - b) Core independent variables and additional variables

Our main independent variable is the PVCCI (and its main components). While omitted variables should not be of great concern, we include a battery of variables for comparison purposes. Quantitative work on armed conflict has identified several factors that affect the incidence (or onset) of conflict. Thus, our baseline analysis includes: logged population (from Penn World Table), logged[64] GDP per capita (from World Penn Table), a dummy for oil/diamond (from Ross, 2011), percentage of mountains terrain (from Fearon and Laitin, 2003), noncontiguity of country territory (from Fearon and Laitin, 2003), and democracy (from Polity IV Project, Marshall and Jaggers, 2014). In order to address issues of simultaneity, political and governance controls as well as GDP per capita and population are measured in the first year of each period. In some specifications, we also use additional controls of governance from Polity IV and Freedom House.

A regression setup allows us to control for various determinants of conflicts. Since our core independent variable of interest (PVCCI) is time-invariant at the horizon of this analysis, a natural starting point is to consider the determinants of whether a country ever had a conflict during the reporting period. The baseline specification is:

$$\sigma_{it} = \beta_1 PVCCI_i + \beta_2 X_{it} + \varepsilon_{it} \qquad i = 1,...,C, \qquad t = 1,...,T, \tag{10}$$

Where X_{it} is a set of controls, ε_{it} is an innovation, and C and T are the number of countries and time periods, respectively. In equation (10), the dependent variable is not directly

[64] The measures of population size and GDP per capita are logged to reduce skewness because some countries are much wealthier and larger than other countries.

observed and could be inferred from its covariates. Considering intensity of conflict as a latent variable that we infer from the realizations of the UCDP/PRIO binary variable, we can directly observe the dependent variable using a standard logit:

$$P(Y_{it} = 1|X) = P(\sigma_{it} > W^{*}|X) = \Phi(X\beta - W^{*}) \qquad (11)$$

Where $X_{it} = (PVCCI, X_{it})$, W^{*} is a threshold that becomes an intercept in Φ, β is the vector of coefficients of interest, including the PVCCI, and Φ is the cumulative distribution function of ε_{it} with symmetric probability density function.

VI - 3) Findings

VI - 3 - a) Baseline findings

Our empirical goal is to estimate the relationship between the PVCCI and civil conflict. The baseline results reveal some interesting patterns and are displayed in Table 4. The columns differ in that we progressively add controls. All estimations are conducted using robust standard errors adjusted for clustering at the country level. Column 1 includes both PVCCI and population measures, and column 2 adds in lagged-dependent variable in order to determine whether incidence is significantly affected by past conflict. Column 3 adds per capita GDP. Column 4 adds natural resources endowment (oil and diamond[65]). Column 5 takes account physical features: mountainous terrain and whether a country has regions separated by land or water. Column 6 accounts for the possibility that ethnolinguistic fractionalization affects the potential for civil conflict. Column 7 adds political and governance controls.

The PVCCI has a positive coefficient and is strongly statistically significant (p-values are less than 0.01 in columns 2, 5 and 6, and are less than 0.05 in columns 1, 3, 4 and 7). This suggests that the probability of civil conflict increases sharply for countries with high scores of the PVCCI. Holding all the control variables at their mean, a one percentage point increase from the PVCCI increases the probability of conflict incidence from 0.204 to 0.212 percentage points, an increase of 3.64 %. A two percentage points increase from the PVCCI

[65] Another possibility is the value of natural resources exports as a percentage of GDP. But this measure does not distinguish among different types of resources because it takes agricultural exports, exports of renewable resources, such as timber, and mineral resources, like oil and metal, as a single category. Moreover, in general, authors seem to agree that oil and diamond are more relevant in the analysis of the relationship between natural resources and conflict.

increases the probability of conflict incidence by 7.37 %. One and two percentage points' decreases from the PVCCI are associated with -3.54 % and -6.99 % decreases in the probability of conflict incidence[66].

Also, lagged dependent variable is positive and highly significant highlighting the inertia nature of the conflict and its likelihood to persist over time. The coefficient of the percentage of mountainous terrain is positive and statistically significant, confirming the results obtained in most of empirical literature. Mountainous countries are likely to experience a higher risk of conflict because rebels find it easier to hide in mountains and forest. This result is consistent with previous researches that found that mountainous terrains are a correlate of civil war (Collier and Hoeffler, 1998, 2004; Fearon and Laitin, 2003). Population size appears to be an important determinant of civil conflict. This is in line with the conclusions of Fearon and Laitin (2003), Hegre and Sambanis (2006), Homer-Dixon (2010), and many other. They argued that a large population implies difficulties in controlling local level activity and increases the number of potential rebels that can be recruited by the insurgents. Also, ethnic fractionalization increases the probability of conflict. The debate on the role of ethnic group in conflict is still very active[67].

In accordance with a common result in all the literature on conflict with cross-country data, per capita income is significantly and negatively correlated with conflict, suggesting that poor countries are more prone to conflict. However, we do not find a direct effect of natural resources on conflict. This result would be contrary to the argument of resource curse, stipulating that civil conflict is more likely in natural resource producers. As well, our political and governance variables are not significant in our regressions. Probably, we should consider the variation of these variables.

[66] This is based on instantaneous rates of change's analysis (also known as marginal effects which are additive approximations of effects in non-additive models). The magnitude of the marginal effect depends on the values of the other variables and their coefficients. Here, we compute the marginal effect at the mean and carry out percentage point variations around the estimated value of the PVCCI. Figures are not reported for all analysis but are available from the author upon request.

[67] See Blattman and Miguel (2010) for a summary of this debate.

Table 4: Baseline specification with conflict incidence

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PVCCI	0.052**	0.045***	0.034**	0.034**	0.045***	0.041***	0.039**
	(0.021)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Population	0.429***	0.278***	0.293***	0.289***	0.205**	0.233***	0.232***
	(0.120)	(0.084)	(0.093)	(0.093)	(0.094)	(0.081)	(0.084)
GDP per capita			-0.405***	-0.411***	-0.479***	-0.359***	-0.347**
			(0.107)	(0.108)	(0.123)	(0.129)	(0.135)
Oil & Diamond				0.117	0.204	0.058	-0.022
				(0.194)	(0.208)	(0.214)	(0.214)
Mountains					0.011**	0.012***	0.011**
					(0.005)	(0.004)	(0.005)
Ncontig					0.800**	0.932***	0.971***
					(0.361)	(0.359)	(0.368)
Ethnic Fract.						1.493***	1.254**
						(0.484)	(0.528)
Democracy							0.078
							(0.354)
Executive cons.							-0.099
							(0.463)
Autocracy							0.118
							(0.317)
Political rights							-0.264
							(0.427)
Civil Liberties							0.451
							(0.470)
Lag conflict		3.048***	2.923***	2.916***	2.847***	2.763***	2.838***
		(0.222)	(0.227)	(0.227)	(0.231)	(0.217)	(0.223)
Constant	-10.597***	-8.920***	-5.387***	-5.318***	-4.315**	-6.124***	-6.102***
	(2.217)	(1.516)	(1.710)	(1.706)	(1.807)	(1.707)	(1.930)
Observations	1,179	1,051	1,033	1,033	1,033	1,033	931
Pseudo R^2	0.282	0.555	0.567	0.567	0.576	0.585	0.602
Log-likelihood	-631.213	-401.749	-390.606	-390.423	-384.731	-379.49	-335.899

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parenthesis.

VI - 3 - b) Robustness tests

We present additional robustness tests that address threats to inference related to (i) the measure of the conflict variable; (ii) the use of onset variable instead of incidence; (iii) the introduction of region and time effects; (iv) the use of other estimation strategies. Further types of robustness check have been carried out in Appendices 7 to 10.

i) Other measures of conflict

We consider several measures of conflict for which we assess the link with the PVCCI. Table 5 provides our results. Column 1 and 2 report our estimates of the effect of the PVCCI on civil war, i.e. the conflict exceeding 1,000 battle-deaths per year. Columns 3 and 4 use a nonbinary measure of intensity based on PRIO dataset: “Peace” is assigned a value of 0; the measure takes on a value of 1 if the number of deaths per year lies between 25 and 999; a value of 2 is assigned to the measure if the overall conflict yields at least 1,000 deaths. These estimates are carried out using the ordered logit. Columns 5 and 6 use a continuous variable of social conflict from the Cross-National Time-Series data archive (CNTS)[68]. The variable used is a weighted average over different conflict measures. Column 7 uses the same variable and time-series cross-sectional (TSCS) estimates with panel-corrected standard error (PSCE) and Prais-Winston (AR1) transformation to reduce serial correlation errors. This is because our analysis includes several explanatory variables that are time-invariant exogenous variables or move slowly across time period. The use of fixed-effects estimator might be problematic in this case.

We find that the PVCCI has a positive and significant effect on conflict no matter how the conflict is measured. In most cases, the effect is slightly higher compared to our baseline estimates. The size of population, mountainous terrain, and noncontiguity of country territory (except the two first columns) remain significantly associated with the likelihood of a civil conflict. Also, the past conflicts have a persistent effect over time and the countries which are more ethnically fractionalized are more prone to conflict. GDP per capita enters with a negative sign and is significant, lowering the probability of conflict. The effects of natural resources and democracy are still surprisingly not significant. We can think that this is due to the use of 5-year periods as the unit of analysis. Indeed, Collier and Hoeffler (2004) also used 5-year periods, and Fearon (2005) demonstrated that their results are not robust to using annual panel data. However, as we have already pointed out, yearly data does not allow capturing the structural dynamic reflected in our analysis. This does not prevent us

[68] The CNTS contains almost 200 variables for over 200 countries and is commonly used by researchers. The data are based on various sources, the main one being The Statesman’s Yearbook for early data, while more recent data are gathered from a number of international sources. The dataset records occurrences of events defined as general strikes, purges, government crises, riots, assassinations, anti-government demonstrations, guerilla welfare, and revolutions.

from concluding that our results appear generally robust to the choice of other measures of civil conflict.

Table 5: Empirical estimates with different conflict variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PVCCI	0.066***	0.066***	0.046***	0.043***	0.103*	0.068*	0.085**
	(0.019)	(0.022)	(0.013)	(0.014)	(0.058)	(0.060)	(0.127)
Population	0.285***	0.237***	0.226***	0.182***	1.478***	1.216***	2.659***
	(0.079)	(0.083)	(0.064)	(0.065)	(0.295)	(0.244)	(0.472)
GDP per capita		-0.477***		-0.298***		-1.253***	-1.498**
		(0.129)		(0.105)		(0.434)	(0.704)
Oil & Diamond		0.124		-0.015		-0.545	-1.279
		(0.327)		(0.183)		(0.808)	(1.669)
Mountains		0.014**		0.010**		0.054***	0.089**
		(0.006)		(0.004)		(0.017)	(0.042)
Ncontig		0.648		0.590**		4.189***	8.893***
		(0.429)		(0.289)		(1.535)	(2.276)
Ethnic Fract.		1.203**		1.343***		3.521**	8.460***
		(0.571)		(0.414)		(1.770)	(1.895)
Democracy		-0.061		0.094		0.094	-1.396
		(0.391)		(0.250)		(0.922)	(1.359)
Lag conflict	3.356***	2.973***	2.265***	2.071***	0.555***	0.514***	-
	(0.274)	(0.268)	(0.159)	(0.160)	(0.036)	(0.038)	
Constant	-11.172***	-7.604***	-	-	-24.840***	-11.298**	-30.690***
	(1.698)	(1.820)			(5.746)	(5.516)	(11.840)
Method	Logit	Logit	Ordered logit	Ordered logit	OLS	OLS	TSCS-PCSE
Observations	1,051	1,033	1,051	1,033	1,040	1,022	1,030
Pseudo R^2	0.549	0.583	0.520	0.539	0.601	0.616	0.297
Log-likelihood	-232.056	-218.643	-556.860	-537.347	-	-	-

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parenthesis.

ii) Onset of civil conflict

In our baseline estimates we have used incidence conflict as our dependent variable. Here, we introduce a usual alternative measure of conflict that is onset (outbreak of the conflict). It is set at 1 for the first year of civil conflict set to missing for the subsequent civil conflict years and at 0 for peace years, making conflict occurrences quite rare. We consider three variables of onset: onset2, onset5 and onset8[69].Table 6 displays our findings. The PVCCI has

[69] Onset2: onset of an intrastate armed conflict exceeding the 25 battle-death threshold. A 1 is assigned if this is a new conflict or there is more than two years since the last observation of the conflict.
Onset5: onset of an intrastate armed conflict exceeding the 25 battle-death threshold. A 1 is assigned if this is a new conflict or there is more than five years since the last observation of the conflict.

a positive and significant effect on the probability of the outbreak of conflict if we only include the PVCCI and population size as controls. However, the last two columns show that the PVCCI has a non-statistically significant effect on the onset of civil conflict when Onset5 or Onset8 are included in a more complete model, suggesting that the PVCCI is not a strong predictor of the onset of civil conflict.

Table 6: Empirical estimates with conflict onset as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
PVCCI	0.041***	0.030**	0.036**	0.035**	0.017	0.022
	(0.016)	(0.015)	(0.014)	(0.017)	(0.015)	(0.015)
Population	0.280***	0.273***	0.247***	0.196***	0.199***	0.189***
	(0.091)	(0.090)	(0.088)	(0.073)	(0.072)	(0.072)
GDP per capita				-0.487***	-0.530***	-0.571***
				(0.122)	(0.119)	(0.120)
Oil & Diamond				0.597***	0.464**	0.487**
				(0.230)	(0.207)	(0.221)
Mountains				0.009**	0.007*	0.007*
				(0.004)	(0.004)	(0.004)
Ncontig				0.806***	0.656**	0.403
				(0.285)	(0.300)	(0.282)
Ethnic Fract.				1.094**	0.987**	0.854*
				(0.489)	(0.493)	(0.490)
Democracy				0.016	0.128	0.171
				(0.280)	(0.284)	(0.290)
Lag conflict	0.590***	0.149	0.126	0.239	-0.217	-0.232
	(0.226)	(0.244)	(0.261)	(0.244)	(0.269)	(0.284)
Constant	-8.552***	-7.930***	-7.869***	-4.063**	-2.851*	-2.646
	(1.757)	(1.615)	(1.644)	(1.882)	(1.617)	(1.619)
Dependent Variable	Onset2	Onset5	Onset8	Onset2	Onset5	Onset8
Observations	922	922	922	906	906	906
Pseudo R^2	0.253	0.232	0.300	0.311	0.288	0.287
Log-likelihood	-363.624	-335.801	-326.952	-339.013	-314.462	-305.833

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parenthesis.

The past onset of conflict is not significant showing that the outbreak of conflict at time $t-1$ does not affect the probability of having a fresh conflict at time t. Of course, it can be argued that using 5-year periods would appear inconsistent in quickly renewed conflict because

Onset8: onset of an intrastate armed conflict exceeding the 25 battle-death threshold. A 1 is assigned if this is a new conflict or there is more than eight years since the last observation of the conflict.

variables are lagged to the beginning of the period. The succession of conflicts may then arbitrarily be coded, depending on whether a period end falls in between. Population size is still significant at the 0.01 level in all cases; ethnic fractionalization is significant at the 0.05 level when we consider Onset2 and Onset5 (and only at the 0.10 level in the case of Onset8). The increasing of the years since the last observation of the conflict contributes to a weakening of the effects of ethnic fractionalization and noncontiguity of country territory. We note, for example, noncontiguity of country territory does not reach the 0.05 level of significance if we use Onset8 as predictor. Per capita GDP is still significant at the 0.01 level with the excepted sign in all cases. The most important change introduced by the use of onset is that the variable capturing natural resources is not significant with the positive sign. This suggests that natural resources play a major role in the outbreak of civil conflict but not affect the incidence. The variable of democracy is still not significant.

iii) Introduction of region and time effects

To provide insights on the possibility that our results could be driven by particular regions, we introduce region[70] and time effects. This exercise is done with the incidence of the conflict as in our baseline regression. Table 7 provides our results.

For comparison purposes only, no effect has been introduced in column 1. Column 2 introduces regional dummies. In columns 3, 4 and 5, we remove African, Asian and Latin American countries, respectively. In column 6, we introduce a time trend in order to mitigate the risk that we are capturing general linear trends in the conflict incidence. Column 7 introduces the interaction between regional dummies and time trend.

In all specifications, the effect of the PVCCI is positive and significant but the significance falls at the 0.10 level when we exclude African countries. Similarly, population size is only significant at the 0.10 level when we introduce regional dummies. We also find that mountainous terrain has a negative but insignificant effect on civil conflict incidence when we exclude African countries. This suggests that the effect of mountainous terrain is driven by African countries. For example, the Darfur conflict took place within the Jebel Marra mountains range, considered as the stronghold of the rebels. In general, compared to our baseline specification, our results are not affected.

[70] We distinguish between three geographical regions: Africa, Latin America and Asia.

Table 7: Empirical estimates with the introduction of Region and Time Effects (incidence)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PVCCI	0.042**	0.044***	0.045*	0.045**	0.051***	0.042**	0.043***
	(0.016)	(0.016)	(0.024)	(0.018)	(0.017)	(0.017)	(0.016)
GDP per capita	-0.386***	-0.640***	-0.673***	-0.342**	-0.399***	-0.404***	-0.528***
	(0.128)	(0.156)	(0.184)	(0.151)	(0.149)	(0.129)	(0.136)
Population	0.230***	0.146*	0.221**	0.206**	0.297***	0.248***	0.166**
	(0.081)	(0.087)	(0.110)	(0.097)	(0.090)	(0.083)	(0.083)
Oil & Diamond	0.085	0.178	-0.024	0.169	0.247	0.110	0.187
	(0.213)	(0.212)	(0.329)	(0.231)	(0.241)	(0.211)	(0.210)
Mountains	0.012***	0.009*	-0.002	0.016***	0.014***	0.013***	0.011**
	(0.004)	(0.005)	(0.009)	(0.005)	(0.005)	(0.004)	(0.005)
Ncontig	0.911**	1.010**	0.918**	0.883**	0.761*	0.876**	0.897**
	(0.362)	(0.396)	(0.433)	(0.441)	(0.420)	(0.374)	(0.382)
Ethnic Fract.	1.461***	2.181***	3.289***	1.460***	1.618***	1.514***	1.931***
	(0.478)	(0.560)	(0.840)	(0.525)	(0.553)	(0.491)	(0.495)
Democracy	0.129	0.195	0.234	-0.122	0.334	0.233	0.227
	(0.280)	(0.287)	(0.416)	(0.301)	(0.306)	(0.280)	(0.291)
Lag conflict	2.761***	2.687***	2.799***	2.707***	2.936***	2.810***	2.746***
	(0.217)	(0.216)	(0.293)	(0.254)	(0.238)	(0.223)	(0.222)
Constant	-5.993***	-2.699	-3.860	-6.091***	-7.754***	-6.755***	-3.954**
	(1.672)	(1.985)	(2.849)	(1.782)	(1.947)	(1.704)	(1.748)
	No	Region dum.	No Africa	No Asia	No Lat.Am.	Time trend	Interaction
Observations	1,033	1,033	687	889	862	1,033	1,033
Pseudo R^2	0.585	0.594	0.650	0.558	0.631	0.593	0.593
Log-likelihood	-379.336	-374.140	-219.541	-318.594	-294.747	-374.426	-374.572

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parenthesis.

iv) Other estimation strategies

We propose here other approaches to investigate the effect of the PVCCI on civil conflict. Our results are shown in Table 8. In column 1, we repeat our baseline specification. Column 2 presents the results obtained when we consider the dependent variable as the average of incidences for each country over the sample and time-dependent variables come from the year 1964. It returns therefore to cross-sectional approach for the present strategy. In column 3, we use penalized likelihood approach to reducing small-sample bias in maximum likelihood estimation[71]. Column 4 presents the results using the linear probability model instead of logit model. Lastly, in column 5 we consider a linear specification with random

[71] The maximum likelihood estimation of the conventional logistic regression is well-known to suffer from data in which events are rare. The degree of bias is strongly dependent on the number of cases in the less frequent of the two categories. King and Zelig (2001) described the problem and proposed an appropriate solution similar to penalized likelihood of logistic.

coefficients. Apart from the cross-sectional strategy carried out in column 2, the coefficient of the PVCCI remains positive and significant. In the same column, we note the significance of the natural resources at the 0.10 level. Per capita GDP, population, mountains, ethnic fractionalization and noncontiguity of country territory are still significant with their signs as in the baseline specification. The coefficients of past conflicts are also positive and significant, which indicates how persistent civil conflicts are. In general, our baseline results remain robust. We also note that for most variables, the coefficients for columns 4 and 5 greatly diminish compared to the three first columns (divided by 10 for PVCCI).

Table 8: Empirical estimates with other estimation strategies

	(1)	(2)	(3)	(4)	(5)
PVCCI	0.042**	0.033	0.042***	0.004**	0.004*
	(0.016)	(0.026)	(0.014)	(0.002)	(0.002)
GDP per capita	-0.386***	-0.572**	-0.380***	-0.040***	-0.046***
	(0.128)	(0.228)	(0.116)	(0.014)	(0.016)
Population	0.230***	0.291**	0.227***	0.027***	0.032***
	(0.081)	(0.140)	(0.070)	(0.010)	(0.011)
Oil & Diamond	0.085	0.718*	0.086	0.001	0.003
	(0.213)	(0.431)	(0.210)	(0.025)	(0.030)
Mountains	0.012***	0.020**	0.012***	0.001**	0.002**
	(0.004)	(0.008)	(0.005)	(0.001)	(0.001)
Ncontig	0.911**	1.466**	0.895***	0.096**	0.134***
	(0.362)	(0.587)	(0.280)	(0.043)	(0.046)
Ethnic Fract.	1.461***	3.144***	1.430***	0.159***	0.204***
	(0.478)	(0.855)	(0.466)	(0.055)	(0.071)
Democracy	0.129	-0.480	0.128	0.013	0.011
	(0.280)	(0.395)	(0.248)	(0.032)	(0.028)
Lag conflict	2.761***		2.714***	0.550***	0.423***
	(0.217)		(0.189)	(0.037)	(0.028)
Constant	-5.993***		-5.929***	-0.287	-0.320
Method	Logit	Ologit (CS)	Penal.logit	LPM	RC
	(1.672)		(1.722)	(0.205)	(0.260)
Observations	1,033	124	1,033	1,033	1033
Pseudo R^2	0.585	0.318	-	0.643	-
Log-likelihood	-379.336	-233.521	-	-	-331.861

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parenthesis.

In view of the various econometric analyses, we conclude that the positive and significant relationship between PVCCI and civil conflict is robust. This is particularly true when we use the incidence for measuring conflict. Whatever the specification rule used, incidence of civil conflict is largely determined by poverty (per capita GDP), country size (population), mountainous terrain and ethnic diversity (Ethnic fractionalization). In contrast, we do not find strong evidence that these factors (except for poverty) affect conflict onset significantly differently.

VII - Conclusion

The issue of climate change is a historical challenge of sustainable development. As often mentioned in the literature, the vulnerability to climate change is a complex concept which should be measured by relevant indicators, the relevance of which should be assessed with regard to their intended use. The conceptual framework of the vulnerability presented here is intended to be a useful tool for the allocation of resources devoted to the adaptation to climate change. It also intended to help in relative comparison of one country's "physical" vulnerability to climate change to another by highlighting the factors that contribute to this vulnerability.

This chapter proposes an index that captures the only physical vulnerability to climate change through its various manifestations in 191 countries around the world. The index differs from the abundant literature on vulnerability to climate change by considering only the part of vulnerability which does not depend on present or future country policy. To this aim, it relies only on physical components. These components are measured from observed trends in physical variables related to climate change and likely to have a socio-economic impact, but without any use of socioeconomic data. It is an index of physical or geo-physical vulnerability to climate change. It then differs from the more general environmental vulnerability indices, which include resilience and policy components, as well as environmental variables other than climate. It also differ from the Economic Vulnerability Index (EVI) used at the UN for the identification of the Least Developed Countries, related only to structural economic vulnerability covering the main kinds of external or natural exogenous shocks likely to affect economic growth.

The components of the PVCCI index capture two types of risk related to climate change: the risks of an increase in the intensity of recurrent shocks (in temperature, rainfall, and storms), and the rather long term risks of progressive shocks (such as flooding due to higher sea level or desertification). The assessment of these risks relies on components referring both to the likely size of the shocks and to the country's exposure to these shocks. To adequately capture the specific vulnerability of each country, the components are averaged by using a quadratic average that enhances the impact of the component(s) reflecting the higher level of vulnerability.

The calculation of the index of physical vulnerability to climate change shows a higher average level for developing countries, in particular for LDCs, SIDS and African countries. However, based on their standard deviations, there is a wide disparity in PVCCI's scores within these groups of countries. This higher physical vulnerability is in many countries amplified by a low structural resilience due to low level of income per capita and human capital.

The PVCCI is a simple, precise, objective, transparent, relevant, measurable, clear indicator and easy to understand. Due to these characteristics, it appears as a suitable indicator for aid allocation. Combined with the UN Economic Vulnerability Index (EVI), the PVCCI can be applied to determine the distribution of concessional adaptation funds, with greater funding going to more vulnerable areas or groups.

After the construction of the PVCCI and discussed its alternative, we have explored the link between the PVCCI and civil conflict. We have shown that the PVCCI has a positive and significant effect on civil conflict. We test the sensitivity of our results to a set of options, among others, the use of other measure of conflict and the introduction of region and time effects. Overall, our baseline model is not affected. Specially, the effect of the PVCCI on civil conflict is unambiguous when we use conflict incidence as dependent variable, but the significance of the link is weak when we consider conflict onset as dependent variable. We also find that conflict risk is generally higher in countries with large populations, in mountainous countries, in ethnically fractionalized countries. By contrast, a relatively high per capita GDP contributes to the decrease of the likelihood of conflict.

This finding should not be considered the last word on the subject matter. Further analysis will have to be conducted with the aim of exploring potential channels for the link between the PVCCI and civil conflict and policy implications thereof. Four keys could be identified: political instability, economic vulnerability, food insecurity, and mass migration.

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Appendices

Appendix 1: PVCCI, PVCCI2 and PVCCI3 for the LDCs

Country	ISO	PVCCI	PVCCI2	PVCCI3
Afghanistan	AFG	58.6	57.9	56.0
Angola	AGO	47.0	47.3	46.4
Burundi	BDI	47.7	49.1	46.0
Benin	BEN	46.6	48.4	46.1
Burkina Faso	BFA	60.0	58.4	59.5
Bangladesh	BGD	45.8	44.3	45.2
Bhutan	BTN	39.9	41.9	39.2
Central African Republic	CAF	47.7	45.7	47.0
Congo, DRC	COD	47.2	47.7	46.2
Comoros	COM	49.9	48.2	48.8
Djibouti	DJI	63.1	62.2	62.1
Eritrea	ERI	63.2	61.8	62.7
Ethiopia	ETH	50.8	48.6	50.2
Guinea	GIN	48.3	46.9	47.5
The Gambia	GMB	60.4	58.9	59.6
Guinea-Bissau	GNB	49.3	47.5	48.7
Equatorial Guinea	GNQ	44.8	42.8	44.2
Haiti	HTI	54.1	53.9	54.5
Cambodia	KHM	46.6	45.4	45.7
Kiribati	KIR	63.6	61.3	63.0
Laos	LAO	45.0	44.1	45.2
Liberia	LBR	43.7	42.3	44.0
Lesotho	LSO	48.9	48.1	46.8
Madagascar	MDG	59.8	58.1	59.3
Mali	MLI	61.8	60.4	60.9
Myanmar	MMR	52.8	51.5	51.7
Mozambique	MOZ	54.3	52.4	53.6
Mauritania	MRT	63.6	62.1	62.9
Malawi	MWI	48.2	46.3	47.2
Niger	NER	63.1	61.5	63.0
Nepal	NPL	48.4	47.4	47.2
Rwanda	RWA	48	50.1	46.2
Sudan	SDN	64.1	62.8	63.9
Senegal	SEN	59.5	58.1	58.8
Solomon Is.	SLB	52.5	51.8	45.7
Sierra Leone	SLE	45.3	43.8	45.2
Somalia	SOM	61.1	59.3	60.5
South Sudan	SSD	57.9	58.4	56.9
Sao Tome & Principe	STP	41.4	38.8	41.4
Chad	TCD	62.1	60.9	61.9
Togo	TGO	50.5	48.0	49.0
Timor-Leste	TLS	59.2	57.7	57.8
Tuvalu	TUV	64.3	59.6	62.1
Tanzania	TZA	50.3	49.1	48.9
Uganda	UGA	52.1	55.3	49.9
Vanuatu	VUT	57.9	58.6	57.0
Yemen	YEM	60.8	59.0	60.2
Zambia	ZMB	46.1	50.6	48.2

Appendix 2: Thorough proposal: building other alternatives to the PVCCI

A.2.1. PVCCI4

In the benchmark PVCCI, we have chosen to attribute equal weight to all the five components. Although, it is quite understood that these components fall into two categories of risk: risks related to progressive shocks and risks related to more intense recurrent shocks. So, the idea behind the PVCCI4 is to assign equal weight to the two risks. This amounts to assign weights of 1/4, 1/4, 1/6, 1/6, 1/6 respectively to the clusters 1, 2, 3, 4 and 5. The rest remains unchanged: we still consider the quadratic mean and maintain the choice of negative shocks of rainfall and positive shocks of temperature.

The scores of the PVCCI4 for the whole sample range from 30.5 to 68.6, with an average of 48.2, a median of 46.4 and a standard deviation of 7.9. The most vulnerable countries are Marshall Island (68.6), the Maldives (66.4), Oman (65.1), Kiribati (62.9), Sudan (62.7); the least vulnerable countries are Nauru (30.5), New Zealand (32.9), Papua New Guinea (36.1), Georgia (36.3), and Montenegro (36.4).

The spearman's rank correlation between PVCCI4 and PVCCI is 98.9 %. The most important rank variations are noted for Canada (+25, thus becoming more vulnerable), Switzerland (+24), Bhutan (+21); Japan (-24, thus becoming less vulnerable), Cuba (-24), Mauritius (-22).

As can be seen in Table A.2.1, compared to the PVCCI, the PVCCI4 lowers the average scores in all groups of countries. However, SIDS, LDCs and African countries are still the most vulnerable groups with a strong heterogeneity within the LDCs and SIDS LDCs groups.

Table A.2.1: PVCCI4 by country groups

Country groups	Mean	Median	Standard Deviation	Min	Max
Developing countries (142)	49.4	48.0	7.8	36.1	68.6
LDCs (48)	50.8	48.2	8.0	36.4	66.4
Non LDCs (94)	48.7	48.0	7.7	36.1	68.6
SIDS (32)	51.0	49.8	7.9	36.1	68.6
SIDS LDCs (10)	51.8	49.2	9.6	36.4	66.4
SIDS Non-LDCs (22)	50.7	49.9	7.3	36.1	68.6
African countries (54)	50.8	48.6	7.3	36.4	62.7

A.2.2. PVCCI5

It is acknowledged that rainfall and temperature are two important climatic factors affecting agricultural production, especially in the context of climate change. Because of the interdependence between the two variables, we assign weights of 1/4, 1/4, 1/8, 1/8, 1/4 respectively to the clusters 1, 2, 3, 4 and 5. The rest remains unchanged.

The PVCCI5 for the whole sample ranges from 26.5 to 67.9, with an average of 44.8, a median of 42.7 and a standard deviation of 8.6. The most vulnerable countries are Marshall Island (67.39), Oman (64.1), the Maldives (63.2), Jamaica (62.0), Japan (61.1); the least vulnerable countries are Nauru (26.5), New Zealand (29.5), Sao Tome and Principe (32.4), Georgia (32.5), and Papua New Guinea (32.5).

The PVCCI5 is correlated with PVCCI at 97.84 %. This level of correlation overshadows some great variations in terms of ranking, particularly for Iceland (+40), Switzerland (+38), Bhutan (+30); Uganda (-26), Brunei (-26), Bahrain (-22).

The average scores shown in Table A.2.2 are lower than those obtained in the PVCCI. On the other hand, we find skyrocketing values of standard deviation for all groups of countries, especially in the group of SIDS. LDCs, SIDS and African countries groups seem to be very vulnerable.

Table A.2.2: PVCCI5 by country groups

Country groups	Mean	Median	Standard Deviation	Min	Max
Developing countries (142)	46.1	44.9	8.4	32.4	67.9
LDCs (48)	47.1	44.4	8.4	32.4	63.2
Non LDCs (94)	45.6	44.9	8.5	32.5	67.9
SIDS (32)	49.4	48.5	9.3	32.4	67.9
SIDS LDCs (10)	49.2	47.2	10.5	32.4	63.2
SIDS Non-LDCs (22)	49.4	48.5	9.0	32.5	67.9
African countries (54)	46.8	44.7	7.7	32.4	61.1

A.2.3. PVCCI6

Here, we follow the weighting system used in the PVCCI4 (1/4, 1/4, 1/6, 1/6, 1/6). We remind that this weighting system aims to assign the same weight to the risks related to progressive shocks and risks related to more intense recurrent shocks. Only this time we implement the procedure by taking account all (positive and negative) shocks, which was not the case in the PVCCI4.

The whole sample scores of PVCCI 6 range between 30.6 to 68.3 with an average of 48.1, a median of 45.9, and a standard deviation of 8.3. The more vulnerable countries are Marshall Island (68.3), Sudan (66.8), the Maldives (65.8), Oman (65.1), Eritrea (63.6) while the least vulnerable countries at Nauru (30.6), New Zealand (32.0), Papua New Guinea (33.1), Sao Tome and Principe (35.8), Colombia (36.2).

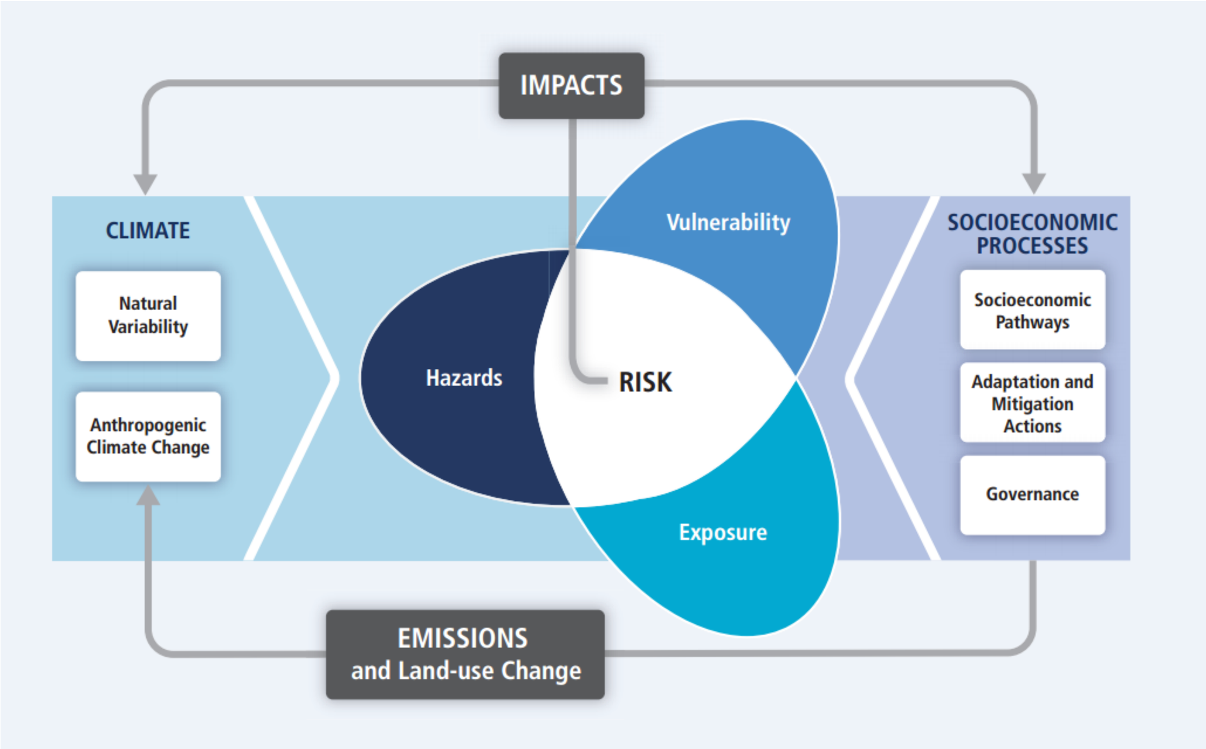
The correlation between PVCCI6 and PVCCI stands at 92.58 %. The great changes in terms of ranking can be seen for Belarus (+71), Switzerland (+53), Estonia (+50); Solomon Island (-94); Rwanda (-56); Burundi (-55).

From Table A.2.3, we can see that African countries group exhibit the highest score of vulnerability. Alongside, LDCs and SIDS which have the same score are also very vulnerable even if we note relatively high values of their standard deviations.

Table A.2.3: PVCCI6 by country groups

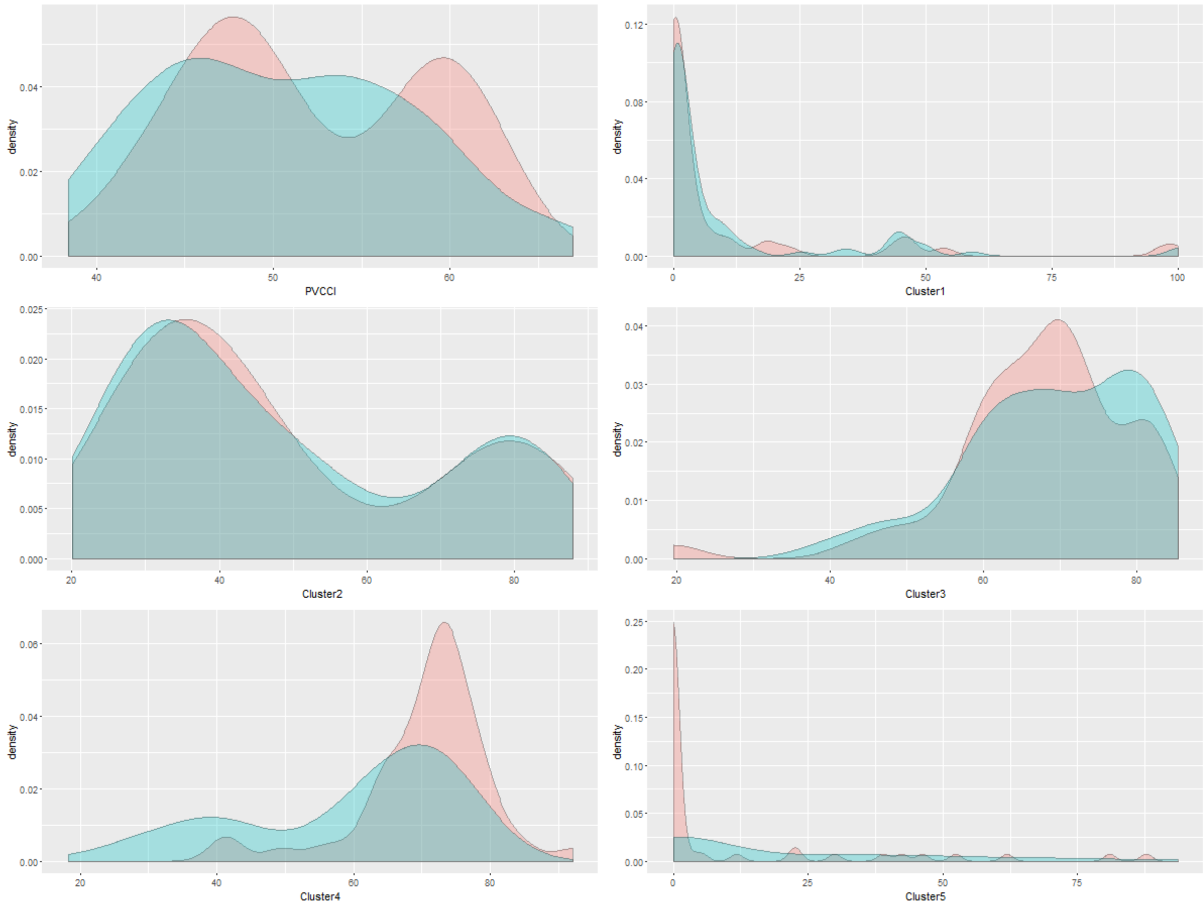
Country groups	Mean	Median	Standard Deviation	Min	Max
Developing countries (142)	49.1	47.8	8.5	33.1	68.3
LDCs (48)	49.9	46.7	9.1	35.8	66.8
Non LDCs (94)	48.8	48.0	8.16	33.1	68.3
SIDS (32)	49.9	48.5	8.4	33.1	68.3
SIDS LDCs (10)	49.4	46.3	10.3	35.8	65.8
SIDS Non-LDCs (22)	50.1	48.9	7.7	33.1	68.3
African countries (54)	50.3	47.8	8.6	35.8	66.8

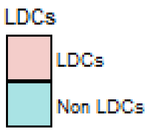
Appendix 3: IPCC framework



Source: IPCC Working Group II report (2014)

Appendix 4: Kernel density of PVCCI and its five main components



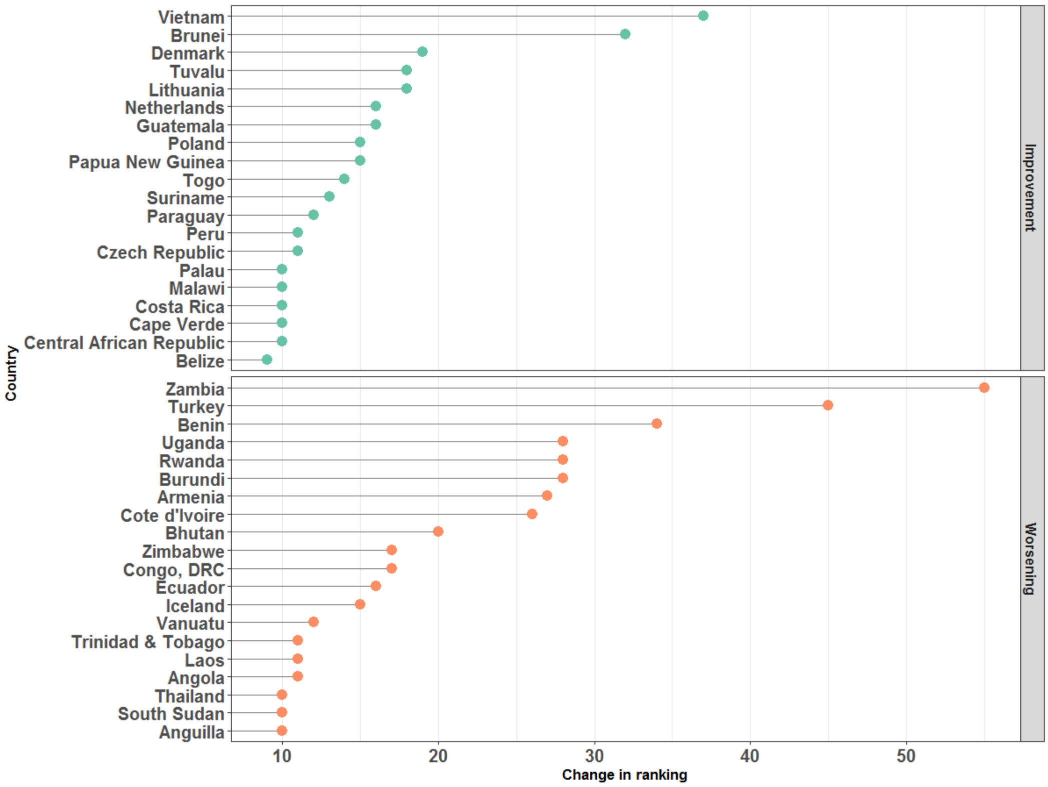


Cluster 1, cluster 2, cluster 3, cluster 4 and cluster 5 refer respectively to “Flooding due to the sea level rise or ice melting”, “Increasing aridity”, “Rainfall”, “Temperature”, “Storms”.

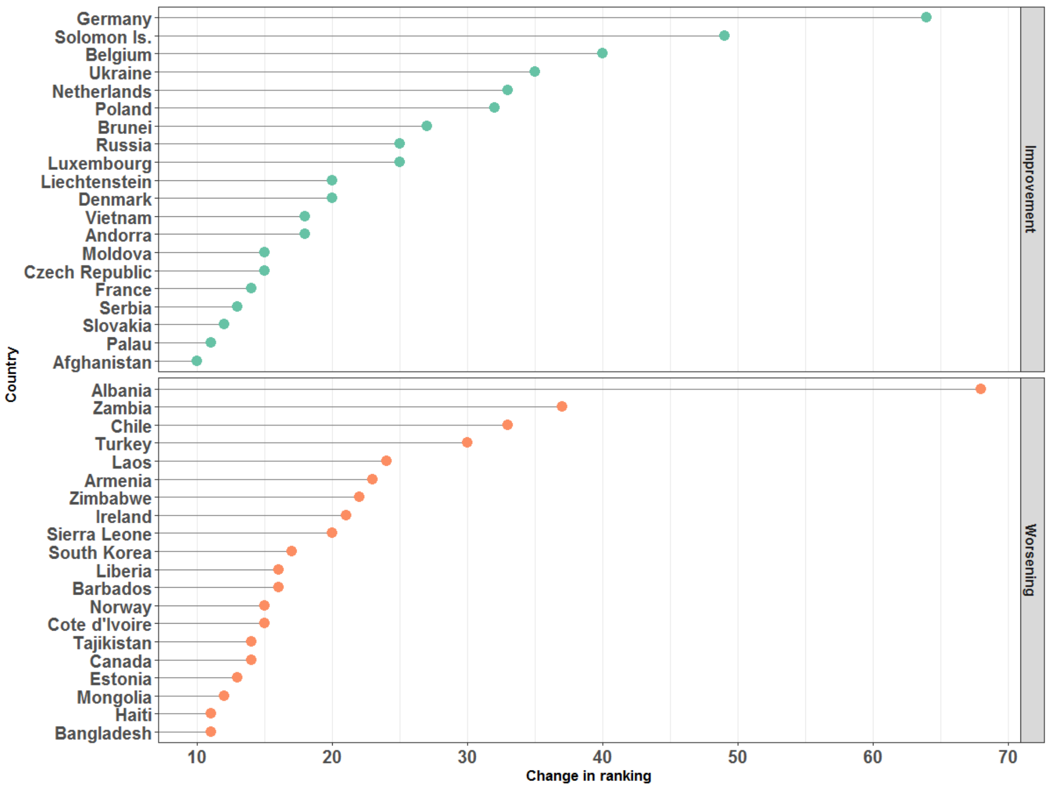
Data used for density refers to those of 142 developing countries: 48 LDCs and 94 Non LDCs.

Appendix 5: Shifts in rank between the benchmark PVCCI and PVCCI2 (a) and the benchmark PVCCI and PVCCI3 (b)

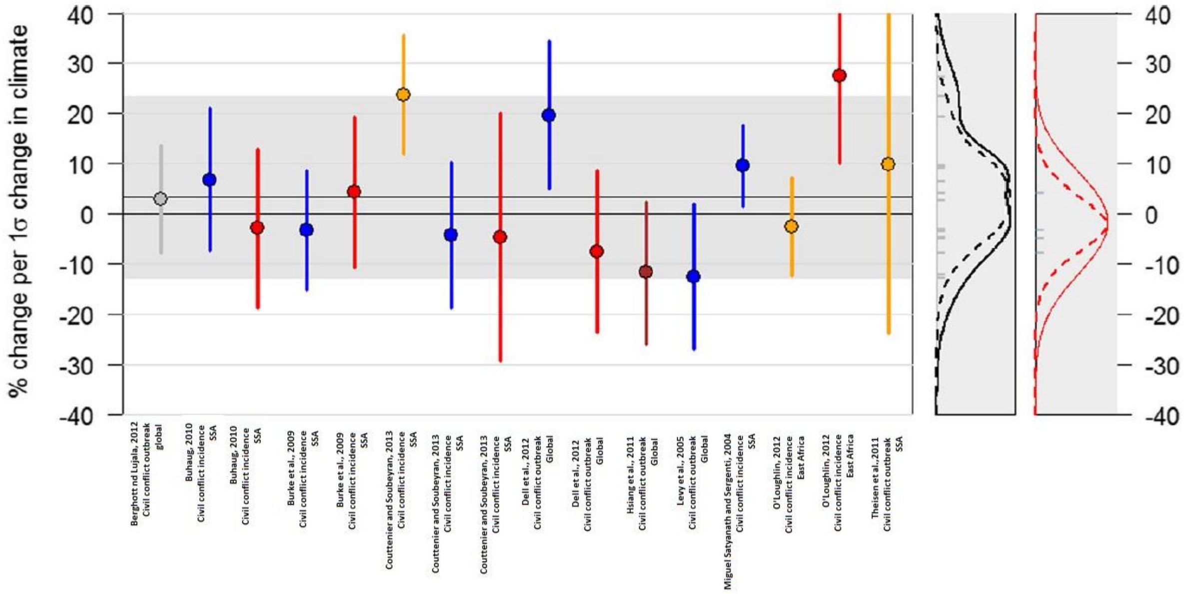
(a)



(b)



Appendix 6: Some empirical estimates for the effects of climate variability on civil conflict



Notes : The markers illustrate the estimated percentage change in conflicts with a 1σ increasein temperature (red), loss of rainfall (blue), increase in drought (orange), El Niño-like conditions (brown) or increase in severity of climatic natural disasters (gray). Whiskers denote the 95 % confidence interval. The solid horizontal line indicates the median climate effect with the 95 % highest density interval in grey, based on a Bayesian hierarchical model. The panels at the right show the distribution of results from all candidate studies (black) or those focusing squarely on temperature effects (red); solid lines represent the variance-weighted distribution while dashed lines depict the Bayesian hierarchical distribution. Studies listed alphabetically.

Appendix 7: Baseline estimates of the alternative PVCCI and its main components (incidence)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GDP per capita	-0.377***	-0.386***	-0.372***	-0.431***	-0.392***	-0.232	-0.376***
	(0.127)	(0.128)	(0.138)	(0.125)	(0.134)	(0.141)	(0.136)
Population	0.230***	0.230***	0.254***	0.240***	0.243***	0.280***	0.249***
	(0.080)	(0.081)	(0.084)	(0.082)	(0.080)	(0.078)	(0.079)
Oil & Diamond	0.087	0.083	0.005	0.046	0.022	-0.030	0.007
	(0.212)	(0.214)	(0.220)	(0.213)	(0.220)	(0.222)	(0.219)
Mountains	0.012***	0.012***	0.010**	0.011***	0.010**	0.016***	0.010**
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)
Ncontig	0.921**	0.929**	0.795**	0.941**	0.833**	0.821**	0.802**
	(0.361)	(0.364)	(0.362)	(0.370)	(0.363)	(0.367)	(0.361)
Ethnic Fract.	1.464***	1.460***	1.627***	1.420***	1.631***	1.307***	1.620***
	(0.473)	(0.477)	(0.487)	(0.478)	(0.488)	(0.495)	(0.478)
Democracy	0.124	0.116	0.008	0.142	0.037	-0.000	0.010
	(0.280)	(0.279)	(0.274)	(0.276)	(0.282)	(0.274)	(0.275)
PVCCI2	0.044***						
	(0.017)						
PVCCI3		0.040**					
		(0.016)					
Cluster1			-0.002				
			(0.008)				
Cluster2				0.014***			
				(0.005)			
Cluster3					0.006		
					(0.012)		
Cluster4						0.033***	
						(0.012)	
Cluster5							-0.000
							(0.005)
Lag conflict	2.764***	2.764***	2.787***	2.763***	2.792***	2.736***	2.788***
	(0.218)	(0.218)	(0.229)	(0.217)	(0.229)	(0.226)	(0.229)
Constant	-6.090***	-5.850***	-4.248***	-4.304***	-4.364***	-7.997***	-4.155***
	(1.686)	(1.657)	(1.578)	(1.515)	(1.605)	(2.001)	(1.492)
Observations	1,033	1,033	1,033	1,033	1,033	1,033	1,033
Pseudo R^2	0.586	0.585	0.579	0.585	0.579	0.585	0.579
Log-likelihood	-379.028	-379.603	-383.443	-379.223	-383.294	-379.325	-383.462

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parenthesis.Cluster1, cluster2, cluster3, cluster4, and cluster5 correspond to “flooding due to sea level rise or ice melting”, “increasing aridity”, “rainfall”, “temperature” and “cyclones”, respectively.

Appendix 8: Baseline estimates of the alternative PVCCI and its main components (Onset2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GDP per capita	-0.466***	-0.472***	-0.465***	-0.497***	-0.483***	-0.366***	-0.463***
	(0.120)	(0.120)	(0.129)	(0.119)	(0.123)	(0.134)	(0.130)
Population	0.182**	0.178**	0.221***	0.188***	0.189***	0.223***	0.196***
	(0.071)	(0.071)	(0.077)	(0.071)	(0.071)	(0.072)	(0.074)
Oil & Diamond	0.610***	0.612***	0.526**	0.573***	0.556**	0.515**	0.534**
	(0.224)	(0.223)	(0.222)	(0.215)	(0.224)	(0.224)	(0.224)
Mountains	0.008*	0.008*	0.008*	0.007*	0.006	0.011***	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Ncontig	0.707**	0.721**	0.570*	0.728**	0.640**	0.544*	0.584**
	(0.285)	(0.285)	(0.295)	(0.286)	(0.293)	(0.324)	(0.297)
Ethnic Fract.	0.966**	0.956**	1.032**	0.952**	1.065**	0.761	1.052**
	(0.476)	(0.477)	(0.481)	(0.481)	(0.490)	(0.513)	(0.470)
Democracy	0.005	0.008	-0.045	0.022	-0.032	-0.053	-0.059
	(0.280)	(0.279)	(0.285)	(0.278)	(0.281)	(0.283)	(0.288)
PVCCI2	0.032**						
	(0.016)						
PVCCI3		0.033**					
		(0.015)					
Cluster1			-0.007				
			(0.006)				
Cluster2				0.011**			
				(0.005)			
Cluster3					0.008		
					(0.011)		
Cluster4						0.025**	
						(0.012)	
Cluster5							0.000
							(0.005)
Lag conflict	0.410*	0.410*	0.455*	0.407*	0.458*	0.402*	0.459*
	(0.233)	(0.232)	(0.252)	(0.237)	(0.247)	(0.241)	(0.252)
Constant	-3.845**	-3.798**	-2.793	-2.585	-2.718	-5.325**	-2.427
	(1.833)	(1.787)	(1.729)	(1.620)	(1.814)	(2.083)	(1.667)
Observations	906	906	906	906	906	906	906
Pseudo R^2	0.314	0.315	0.310	0.315	0.310	0.314	0.309
Log-likelihood	-337.834	-337.661	-339.545	-337.756	-339.658	-337.857	-339.931

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parenthesis.Cluster1, cluster2, cluster3, cluster4, and cluster5 correspond to “flooding due to sea level rise or ice melting”, “increasing aridity”, “rainfall”, “temperature” and “cyclones”, respectively.

Appendix 9: Baseline estimates of the alternative PVCCI and its main components (Onset5)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GDP per capita	-0.523***	-0.526***	-0.526***	-0.544***	-0.509***	-0.431***	-0.525***
	(0.118)	(0.118)	(0.122)	(0.118)	(0.124)	(0.122)	(0.121)
Population	0.202***	0.198***	0.224***	0.203***	0.216***	0.236***	0.209***
	(0.073)	(0.073)	(0.077)	(0.073)	(0.072)	(0.071)	(0.074)
Oil & Diamond	0.454**	0.461**	0.409**	0.442**	0.390*	0.392*	0.414*
	(0.204)	(0.204)	(0.207)	(0.201)	(0.208)	(0.209)	(0.212)
Mountains	0.007*	0.007*	0.007*	0.007*	0.006	0.010**	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Ncontig	0.665**	0.681**	0.610**	0.696**	0.572*	0.568*	0.617**
	(0.298)	(0.297)	(0.292)	(0.301)	(0.307)	(0.304)	(0.297)
Ethnic Fract.	1.009**	0.996**	1.055**	0.992**	1.055**	0.779	1.068**
	(0.494)	(0.495)	(0.488)	(0.492)	(0.493)	(0.514)	(0.465)
Democracy	0.116	0.122	0.098	0.139	0.067	0.092	0.088
	(0.283)	(0.282)	(0.281)	(0.280)	(0.281)	(0.277)	(0.280)
PVCCI2	0.016						
	(0.015)						
PVCCI3		0.019					
		(0.015)					
Cluster1			-0.004				
			(0.007)				
Cluster2				0.007			
				(0.005)			
Cluster3					-0.007		
					(0.011)		
Cluster4						0.024*	
						(0.013)	
Cluster5							0.000
							(0.005)
Lag conflict	-0.112	-0.116	-0.092	-0.121	-0.091	-0.144	-0.090
	(0.243)	(0.241)	(0.252)	(0.244)	(0.251)	(0.246)	(0.250)
Constant	-2.896*	-2.982*	-2.393	-2.289	-1.902	-4.948**	-2.168
	(1.639)	(1.595)	(1.622)	(1.543)	(1.654)	(1.990)	(1.570)
Observations	906	906	906	906	906	906	906
Pseudo R^2	0.287	0.288	0.286	0.288	0.286	0.291	0.286
Log-likelihood	-314.708	-314.495	-315.046	-314.373	-314.974	-313.488	-315.170

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parenthesis. Cluster1, cluster2, cluster3, cluster4, and cluster5 correspond to "flooding due to sea level rise or ice melting", "increasing aridity", "rainfall", "temperature" and "cyclones", respectively.

Appendix 10: Baseline estimates of the alternative PVCCI and its main components (Onset8)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GDP per capita	-0.570***	-0.574***	-0.574***	-0.594***	-0.565***	-0.468***	-0.572***
	(0.121)	(0.120)	(0.128)	(0.122)	(0.129)	(0.129)	(0.126)
Population	0.199***	0.196***	0.228***	0.203***	0.213***	0.240***	0.209***
	(0.075)	(0.075)	(0.079)	(0.075)	(0.074)	(0.074)	(0.077)
Oil & Diamond	0.480**	0.484**	0.415*	0.456**	0.409*	0.398*	0.423*
	(0.222)	(0.222)	(0.225)	(0.220)	(0.226)	(0.225)	(0.228)
Mountains	0.007*	0.008*	0.007*	0.007*	0.006	0.011**	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Ncontig	0.467	0.480	0.398	0.495*	0.383	0.345	0.402
	(0.296)	(0.294)	(0.289)	(0.298)	(0.307)	(0.302)	(0.292)
Ethnic Fract.	0.924*	0.914*	1.000**	0.921*	1.008**	0.693	1.018**
	(0.502)	(0.504)	(0.500)	(0.507)	(0.503)	(0.512)	(0.479)
Democracy	0.164	0.168	0.137	0.184	0.114	0.130	0.123
	(0.290)	(0.289)	(0.290)	(0.285)	(0.290)	(0.287)	(0.288)
PVCCI2	0.023						
	(0.015)						
PVCCI3		0.025*					
		(0.015)					
Cluster1			-0.005				
			(0.007)				
Cluster2				0.009*			
				(0.005)			
Cluster3					-0.003		
					(0.012)		
Cluster4						0.027**	
						(0.013)	
Cluster5							0.000
							(0.005)
Lag conflict	-0.251	-0.253	-0.219	-0.257	-0.217	-0.277	-0.217
	(0.252)	(0.250)	(0.263)	(0.252)	(0.263)	(0.257)	(0.263)
Constant	-2.844*	-2.862*	-2.074	-1.957	-1.669	-4.907**	-1.791
	(1.676)	(1.624)	(1.626)	(1.559)	(1.699)	(2.068)	(1.586)
Observations	906	906	906	906	906	906	906
Pseudo R^2	0.288	0.288	0.285	0.288	0.285	0.291	0.285
Log-likelihood	-305.657	-305.462	-306.393	-305.427	-306.531	-304.583	-306.570

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parenthesis.Cluster1, cluster2, cluster3, cluster4, and cluster5 correspond to “flooding due to sea level rise or ice melting”, “increasing aridity”, “rainfall”, “temperature” and “cyclones”, respectively.

CHAPTER 4: STRUCTURAL ECONOMIC VULNERABILITY AND FOREIGN DIRECT INVESTMENT: EVIDENCE FROM AFRICAN COUNTRIES

I - Introduction

FDI remains one of the most important forms of cross-border capital flows to developing countries. In 2012, FDI flows to developing countries, for the first time ever, exceeded those of developed countries (UNCTAD, 2014); thereby far exceeding the total official development assistance (US $126 billion) provided by the traditional Organization for Economic Cooperation and Development (OECD) donors. However, the share of these FDI flows to Africa is still relatively marginal. For example, in 2012, FDI in Africa accounted for only 7% of total FDI in developing countries with a considerable heterogeneity between African countries. On theoretical and empirical grounds, it is recognized that FDI is a catalyst for economic development, particularly through its contribution to the creation of wealth and the well-being of the host country (Borensztein *et al*., 1998; Bosworth and Collins, 1999). The former United Nations Secretary-General Kofi Annan, in the preface to the 2009 United Nations Conference on Trade and Development (UNCTAD) World Investment Report explained the importance of FDI to the developing countries and argued that "With the enormous potentials to create jobs, raise productivity, enhance exports and transfer technology, foreign direct investment is a vital factor in the long-term economic development of the developing countries". In addition, FDIs can contribute to the prevention of financial crises due to stability in the host countries since they are driven by long-term profit expectations contrarily to short-term or portfolio investments.

Africa has enormous investment needs that the level of domestic savings is unable to finance. The continent should know a substantial increase in external resources to bridge the gap between domestic savings and the investment required for achieving the Sustainable Development Goals. Having given the importance attached to FDI, Africa must therefore learn how to attract greater volumes of FDI. The quality of the investment environment would therefore be decisive in the foreign investors' choice of host countries.

It is pretty hard to say that there is no effort on the part of African countries to attract FDI. Many governments have taken drastic measures to improve their FDI regimes because they associate FDI with the positive effects of economic development and poverty reduction at home. They liberalized large segments of their economies, privatized state-owned companies, strengthened institutional and regulatory frameworks, drastically reduced traditional restrictions on investments, especially on foreign ones, to attract new funds[72]. They engaged simultaneously in the negotiation of free-trade agreements at the multilateral and bilateral levels and unilateral liberalization at national levels. There can be no assurance that these measures will benefit them.

In spite of various reforms, Africa has attracted insignificant proportion of global FDI. Potential investors are still reluctant to come in Africa because of the seemingly negative perception of the continent. We, however, assume that the causes can be more deeply rooted. They can arise from the structural economic vulnerability faced by most African countries, amplifying the expected returns and the risk of investment. Indeed, the structural economic vulnerability is a major handicap to the economic performance of African countries (Guillaumont, 2014). Structural economic vulnerability includes factors that do not marginally depend on current country policy, but are determined mostly by exogenous and

[72]Although it must be acknowledged that some of them have been forced to reform their economy in the context of various structural adjustment programs.

persistent factors. Structural economic vulnerability is the result of the repetition of exogenous shocks such as droughts and commodity price volatility, whether natural or external and exposure to these shocks such as smallness of the country, remoteness and economic structure.). We use in this paper the Economic Vulnerability Index (EVI) as a measure of vulnerability, but we also use the Human Assets Index (HAI) as an additional measure of structural handicaps of developing countries. Both of these composite indicators are used by the United Nations for the identification of least developed countries.

This chapter is in line with several other studies dealing with the determinants of FDI. Furthermore, the link between structural economic vulnerability and FDI was recently investigated by Gnangnon and Lyer (2017) and Razafindravaosolonirina (2016) without fulfilling some econometric issues. Our contribution is threefold. Firstly, early studies have considered only a small number of structural factors as potential candidates explaining FDI. The use of EVI allows us to take into account several structural variables in a single indicator. Although the weights of the variables are different within the EVI, the index gives an overall snapshot of the structural economic vulnerability in African countries. Secondly, unlike many researches on the determinants of FDI in Africa, our study includes 50 African countries in the analysis. As pointed out by Ajayi (2006), only a few numbers of African countries are often included in the analyses, except for the most recent papers (Abdelbagi *et al.*, 2016)[73]. Thirdly, in general, FDI and economic panel data are heterogeneously non-stationary at the country level. Most of the studies do not explicitly investigate the time-series properties of the data, with the undesirable consequences on the reliability of the estimated coefficients and standard errors. Likewise, there are a number of reasons why FDI into a host country may depend on the FDI in neighboring countries. The issue of spatial interdependence has been largely ignored by the empirical studies on determinants of FDI in Africa. Nonetheless, Nwaogu and Ryan (2014) in their paper examined US outbound FDI into Africa, Latin America and the Caribbean, applying a panel spatial autoregressive (SAR) model[74]. But they do not test for stationarity of FDI and regressors. On the other hand, Abdelbagi *et al*. (2016) have dealt with the issue of non-stationary but they have ignored the spatial interdependence by treating the data as non-spatial. In our paper, we apply the spatial error correction model, a

[73]Their study uses a panel dataset of 50 African countries from 1974 to 2013.
[74]Their study includes 37 African host countries and 31 Latin America and Caribbean host countries for the period 1995—2007.

slightly modified version proposed by Beenstock and Felsenstein (2010). The model allows us to take into account both spatial econometrics and non-stationary issues. We investigate the dynamic process in which EVI and FDI are spatially cointegrated and related in the long-run.[75].

Moreover, data analysis tells us that FDI remains unevenly distributed across African countries. For example, the FDI difference between African low-income countries (LIC) and African middle-income countries (MIC) is significant and noticeable. In 2000, FDI stock in African middle-income countries was seven times higher than in African low-income countries. In 2010, the gap remained large, though the ratio was only five times instead of seven. Using the Blinder-Oaxaca decomposition, we decomposed the FDI gap between the two groups of countries into a part explained by the EVI's components and into a residual part, called unexplained part. Firstly, this technique enables us to know if the variables representing the structural economic vulnerability contribute enormously or not to the explanation of this gap. Secondly, the detailed decomposition highlights the contribution of each variable to the explained component.

The remainder of this chapter is organized as follows: In section 2, we briefly review the empirical literature on the driving forces for FDI in developing countries in general and more especially in the African context. In section 3, we present the data sources and variables of interest. The econometric approach based on spatial error-correction is discussed in section 4 while Section 5 reports the main estimation results for the model. The Blinder-Oaxaca decomposition is presented and discussed in section 6 while Section 7 concludes the analysis.

II - Empirical Literature Review

II - 1) A synopsis of the literature in developing countries

Several theories have attempted to develop a broad literature on the determinants that stimulate the attractiveness of FDI. The analysis of FDI's determinants distinguishes internal

[75]The model proposed by Beenstock and Felsenstein (2010) comes much close to Spatial Durbin Model (SDM) where all explanatory variables are spatialized. We opt for a model which spatializes dependent variable (FDI), EVI and error-correction terms.

factors related to the characteristics of the host countries (pull factors) from external factors, linked to economic conditions in the source countries (push factors). Push factors are beyond the control of beneficiary countries. In our case, we focus on the pull factors upon which recipient countries can operate to attract more FDI. According to pull factors theory, a conducive and stable macroeconomic framework is a key condition for attracting FDI. The authors such as Asiedu (2001) and Stiglitz (2002) have largely contributed to the identification of the main determinants of FDI inflows in developing countries. Loewendahl and Ertugal-Loewendahl (2001) and Kamaly (2003) identified more than twenty determinants of FDI's location choice and grouped them into economic, political, institutional and incentive determinants. Lipsey (1999), Truman and Emmert (1999) and Obwona (2001) argued that the most significant determinants of FDI are: market size, macroeconomic factors, and capital stock. In this connection, Charkrabarti (2001) used the analysis based on 135 countries to identify market size and openness to trade of host countries as the most powerful drivers of FDI, followed by wage, net exports, growth rate, tax, tariffs and exchange rate in their order of importance. Helpman (2006) explored a new generation of theoretical studies to better understand the phenomenon of FDI, taking into account the characteristics of economic sectors and the institutional framework of the host countries.

The political environment plays a significant role in the investment decisions of foreign companies. They favour countries that do not suffer from political instability; thus the future of the host countries must be sufficiently predictable. Economic stability cannot be ensured in a climate of high political tension, although political stability does not necessarily imply economic stability. Lehman (1999) and Jaspersen *et al*. (2000) found that countries that are less risky attracting more FDI. Cho (2003) showed that politically stable economies are appropriate to FDI. Some authors such as Morissetand Neso (2002) and Habib and Zurawicki (2002) have looked at corruption and bad governance. They observed that corruption increases administrative costs and therefore discourages FDI inflows. Stein and Daude (2001) confirmed the robustness of political and institutional factors as important determinants of the location of FDI in developing countries. The same observation has been made by Stevens (2000) in Latin America. Using cross sectional data from 1970 to 1997, Jensen (2003) argued that democratic institutional constraints are associated with more policy stability and found that democratic countries attract high levels of FDI. However, Molaie and Ahmadi (2013) found that the effect of democracy on FDI is ambiguous depending on whether recipient countries are developed, developing and least developed. Their analysis includes 36 developed, 68 developing and 34 least developed countries over the period 1995—2010. They showed that democracy has a positive effect on FDI in developed countries, negative effect in developing countries and meaningless in least developed countries. This finding is consistent with a number of other studies. O'Neal (1994) argued that the economy of an authoritarian regime offers higher returns than that of democratic regime in developing countries.

Based on neoclassical theory, it is recognized that factor endowments, geographical location and natural resources influence foreign investors when deciding where to locate their firms. The labor cost is an important determinant of FDI inflows, since many firms relocate to take advantage of the low labor cost in developing countries (Montout and Zitouna, 2005). Other studies have shown the role of human capital (Lucas, 1998). Wang (1990) and Borensztein *et al*. (1998) suggested that human capital is a significant factor contributing to the attractiveness of the host countries. Noorbakhshe *et al*. (2001) pointed out that multinationals are increasingly looking for a highly skilled workforce. Geographical location is a determining factor to attract FDI flows. Krugman (1991) emphasized the positive role of transport costs and the size of the host country on FDI flows. The market size and per-capita income level are important parameters for demand because high per-capita income contributes to high potential demand. Similarly, market growth, access to regional and world markets, and the structure of the economy are also important determinants for attracting investors who are looking for potential markets. In addition, Akinkube (2003) adds the role played by the presence of natural mineral resources such as oil, natural gas, gold, uranium, iron, *etc*. or other raw materials. At the African level, the flows received are mainly concentrated in a few large countries exporting mineral raw materials, including South Africa, Angola, Nigeria and Ghana. Besides, various incentives are taken into account. Indeed, exchange rate strategies are also important for attracting FDI. These strategies concern the level of the real exchange rate and its volatility; both determine the investment decision of foreign companies. Benassy *et al*., (2001) found that host currency depreciation increases FDI while volatility decreases it. However, Brahmasrene and Komain (2001) and

Dewenter (1995) found no statistically significant relationship between the level of the exchange rate and FDI inflows (Ajayi, 2006; Naude and Krugell, 2007). Incentives also include the quality of socio-economic infrastructures and fiscal policy (Drine and Meddeb, 2001; Dabla-Norris *et al*., 2010). Last but not the least, Hermes and Lensink (2003), Alfaro (2004), Kinda (2010) demonstrated that a well-developed financial system fosters FDI flows.

II - 2) The case of Africa: a brief literature review

Many studies have examined the determinants of FDI in Africa. Most of these studies relate only to individual countries or a limited number of countries. Moreover, the variables considered as important determinants in other analyses do not affect the attractiveness of FDI in African countries in the same way. For example, Asiedu (2002) explored whether factors that affect FDI in developing countries affect countries in sub-Saharan Africa (SSA) differently. Using data from 32 African countries for the period 1970—1999, she found that higher return on investment and better infrastructure have a positive impact on FDI to non-SSA countries, but have no significant impact on FDI to SSA. Openness to trade promotes FDI to both SSA and non-SSA countries, although she pointed out that the marginal benefit from increased openness is less for SSA. In another study, she gives the reasons for which, despite economic and institutional reform efforts, SSA attracts few FDI compared to other developing countries. She recommended policies to enhance the SSA's policy environment in both absolute and relative terms. In a recent study, Sichei and Kinyondo (2012) analyzed a large sample of 45 African countries over the period 1980—2009 and identified several numbers of factors that affect FDI flows in Africa as agglomeration economies, natural resources, real GDP growth and international investment agreements.

Bende-Nabende (2002) explored 19 SSA countries over the 1970-2000 period and found that the most dominant long run determinants of FDI in SSA, in order of importance are market growth, a less restrictive export-orientation strategy, FDI policy liberalization, real effective exchange rates, market size and the openness of the economy. Yasin (2005), by using a panel data from 11 SSA countries for the period 1990—2003, found that there is a positive relationship between bilateral Official Development Assistance (ODA) and FDI. Morisset (2000) focused his analysis on 29 SSA countries for the period 1990—1997 and found that both market size and natural resources are the main drivers of FDI in African countries. Asiedu (2006), by using panel regressions for 22 SSA countries over the period 1984—2000 led to the same conclusion. Studies carried out by Musila and Sigue (2006), and Dupasquier and Osakwe (2006) on FDI showed that FDI in Africa is dependent on the development of infrastructure. The role of infrastructure in attracting FDI in Africa is also pointed out by Sekkat and Veganzones-Varoudakis (2007).

In the general case of developing countries, some studies have focused on the link between uncertainty and FDI in Africa. Lemi and Asefa (2003) examined how the uncertainty affects FDI flows to African countries. They showed that, for FDI flows from all source countries and for US FDI flows, both political and economic uncertainties are not significant determinants. Their finding is close to those obtained by Asiedu (2002), Morisset (2000) and Yasin (2005). Kariuki (2015) used data from 1984 to 2010 on a panel of 35 African countries and observed that a high economic risk has a negative and significant risk on FDI inflows while both political risk and financial risks have a negative but insignificant impact on FDI inflows. She also found a positive and significant relationship between FDI and the commodity price index, the good performance of stock markets, the increase in the infrastructure, the increase in openness and amount of FDI received in the previous year by host country.

For specific country studies, Fedderke and Romm (2006) used data in South Africa from 1962 to 1996 and found the factors that either impede or induce FDI flows to be labour, capital ratio, market size, corporate taxation, wage costs, the openness of the economy and the political institutional structure. Using data over the period 1970-2005, Oladipo (2010) stressed the prominent role of the potential market size, the degree of export orientation, human capital, infrastructural facilities and macroeconomic stability in the attractiveness of FDI inflow in Nigeria. A case study in Ghana by Kyereboah-Coleman and Agyire-Tettey (2008) showed the negative influence of the volatility of the real exchange rate on FDI inflow.

III - Data description

III - 1) Data on inward FDI stock

We analyze the evolution of FDI in Africa over the period 1980—2010 compared to the one observed in all developing countries. We focus on inward FDI stock dataset from UNCTAD. FDI stock series are supposed to be more stable than those of FDI flow. It captures more in the long-term relationship between FDI and its determinants (Bloningen and Piger, 2014). Despite this assumption, the stationarity of FDI stock is discussed further in this chapter.

The last three decades witnessed a remarkable progress on inward FDI stock in developing countries, from $294 billion in 1980 to $6,042 billion in 2010. Africa is not standing on the sidelines. Its inward FDI stock increased steadily over time from $41 billion in 1980 to $594 billion in 2010, an increase of 9.3 percent on average per year over the period. The most significant increase took place between 2000 and 2010, the period over which inward FDI stock has almost quadrupled in Africa[76]. This has been fostered by increased liberalization of capital markets, which has led to a profound change in relations between host countries and multinational firms. Nevertheless, Africa's inward FDI stock still very low compared to those of other regions. For example, developing Asia inward FDI stock was estimated at $212 billion in 1980 and at $3,876 billion in 2010. Similarly, developing Latin America's inward FDI stock has increased rapidly from $35 billion in 1980 to $1,080 billion in 2010. Africa's share of FDI to developing countries declined over time, from 14% in 1980 to 12% in 1990 and to 9% in 2000 while it stood at 10% in 2010[77]. This share is in contrast to that of the Latin America, which increased from 12.1% in 1980 to 14.7% in 1990 and to 18.8% in 2002, then to 17.9% in 2010. Although it accounts for a significant share of inward FDI stock in developing countries, Asia saw its share fell from 72.1% in 1980 to 66% in 1990 and to 62.4% in 2000 before experiencing a small increase in 2010, but remains lower than the one observed in 1980.

[76] The dynamics over the period were very positive, with the exception of the year 2008 when the inward FDI stock fell by 1.9% compared to its 2007 level.

[77]Drawing on the empirical literature on the determinants of FDI, Asiedu (2004) provided an explanation for the deterioration in SSA's global (relative) FDI position. The author argued that SSA's share of FDI in developing countries has declined over time, because of the declining attractiveness of SSA for FDI over time, relative to other developing regions. The analysis focuses on three FDI determinants – openness to FDI, good infrastructure and institutional quality – using policy-related measures (since one of the objectives of this paper is to prescribe policies that will enhance SSA's global FDI position) over the 1980—99 period.

Table 1: Total inward FDI stock by country's category

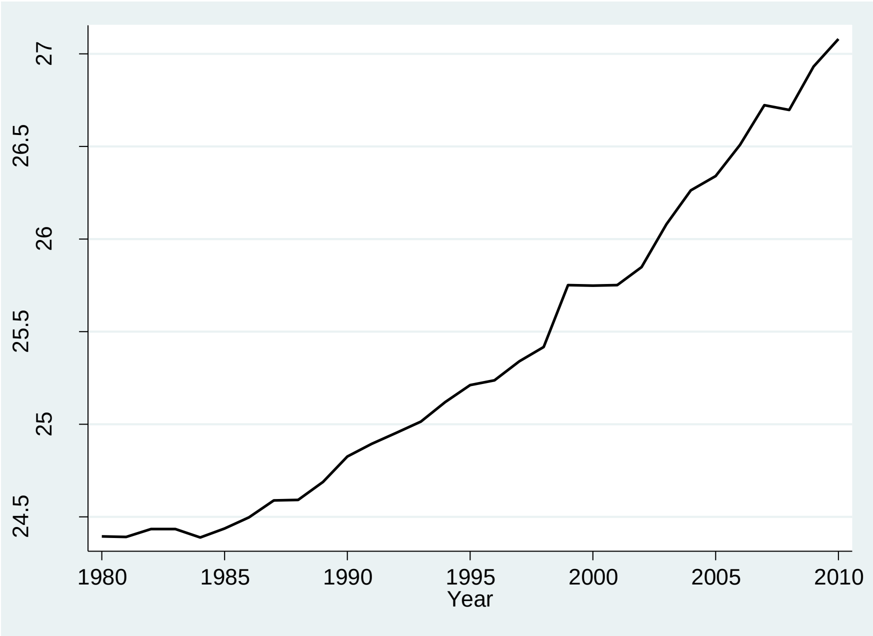
Country Category	Inward FDI stock (million US $)				% of total inward FDI stock to all developing countries			
	1980	1990	2000	2010	1980	1990	2000	2010
Developing	294,499	509,471	1,644,215	6,042,537	100	100	100	100
Africa	41,103	60,678	153,484	594,608	14.0	11.9	9.3	9.8
SSA	30,142	36,945	109,519	409,193	10.2	7.3	6.7	6.8
Africa LIC	3,869	6,694	12,275	52,956	1.3	1.3	0.7	0.9
Africa MIC	14,377	36,713	80,796	282,823	4.9	7.2	4.9	4.7
Developing Asia	212,255	339,675	1,027,614	3,876,876	72.1	66.7	62.5	64.2
Developing Latin America	35,752	74,815	308,949	1,080,750	12.1	14.7	18.8	17.9

Source: Author's calculations based on UNCTADSTAT.

There was a marked disparity between African countries in terms of inward FDI stock. FDI to Africa was concentrated in few countries. For example, in 2010, more than 60% of FDI inward stocks were located in South Africa, Egypt, Nigeria and Morocco[78]. South Africa became the main recipient of FDI in Africa at the end of the 1990s. This was attributed mainly to the beginning of democracy, the return of companies that had relocated to neighboring countries during the liberalization of international trade and the interest of investors in the South Africa large domestic market (Wöcke and Sing, 2013). Africa's aggregated figures also masked the uneven distribution of inward FDI stock across income groups. High-income and mainly middle-income countries have benefited more from the rapid increase of FDI at the expense of low-income countries. In 1980, inward FDI stock was four times higher in African low-income countries than African, Middle-income countries, this gap increased over time. It increased to around 6 times in 1990, 7 times in 2000 and stood at 5 times in 2010.

[78] South Africa, Egypt, Nigeria and Morocco are accounted for 30 percent, 12 percent, 10 percent and 8 percent of FDI inward stock to Africa respectively. The first three countries are traditionally the biggest recipients. Angola also has long been a traditional recipient of FDI.

Figure 1: Total FDI inward stock



Source: UNCTADSTAT

III - 2) Measuring Structural Economic vulnerability

Even if the assessment of vulnerability is yet to be discussed, there is no need to demonstrate the vulnerability of developing countries, in particular African countries, both economically and environmentally. Economic vulnerability can be defined as the likelihood that a country's economic development could be hindered by unforeseen exogenous shocks (Guillaumont, 2009). The concept is often measured through indices and two groups have been proposed in the literature. The first group of indicators does not disentangle the structural elements of vulnerability from other elements depending on the current policies implemented by countries (Atkins *et al*. 1998, 2000; Briguglio and Galea, 2003; Turvey, 2007). Unlike the first group of indicators, the second stresses the necessary distinction between vulnerability arising from poor economic policy choices and structural vulnerability resulting from environmental or economic factors beyond the control of policy makers of countries (UNCDP, 1999; Guillaumont, 2004, 2009a,b).

To our knowledge, the only indicator that takes into account the structural handicaps faced by developing countries is the Economic Vulnerability Index (EVI) established by the United Nations Committee for Development Policy (UN-CDP). EVI is one of the three criteria used for identifying Least Developed Countries (LDCs)[79]. Since LDCs group is largely made up of African countries, with high structural handicaps, the index should reflect truly exogenous factors. Initially established in 2000 and revised in 2005 for the 2006 triennial review of the list of LDCs, EVI remained unchanged in the 2009 review and then slightly revised in 2011 for the 2012 review, and unchanged since then[80] (Guillaumont, 2009a, 2009b, 2015, 2016a, 2016b; United Nations, 2015). Two types of vulnerabilities are considered in the EVI, hence two sub-indices namely exposure and shock. The exposure sub-index is a weighted average of 4 component indexes[81] which are smaller population (50%), remoteness from world markets (25%), export concentration (12.5%), and share of agriculture, forestry and fishery in GDP (12.5%). The shocks, sub-index is a weighted average of 3 component indexes namely the victims of natural disasters (25%), the instability in the agricultural production (25%), and the instability in exports of goods and services (50%). Components are built on different kinds of primary data such as number, percent and index, which are normalized through a min-max procedure to get component indices ranging from 0 to 100, with high scores corresponding to a high level of vulnerability. The sum of components' weights equals to 1 so that the EVI lies between 0 and 100. The retrospective series of EVI is built at Ferdi (Cariole, 2012; Feindouno and Goujon, 2016).

III - 3) Other data

Based on economic theories and previous empirical studies on the determinants of FDI, we include the Human Assets Index (HAI), a composite index of health and education, used at the UN for the identification of the LDCs. The retrospective series of HAI is built and continuously updated by Ferdi (Closset *et al*., 2014; Feindouno and Goujon, 2016). The GDP per capita, which reflects the per-person domestic resources in constant purchasing power parity in dollars captures the market size, the inflation rate as a proxy of macroeconomic uncertainty, the corporate tax (Percentage of GDP)[82] and exchange rate (USD) from the

[79] The other criteria are Human Assets Index and GNI per capita.

[80]The index was recommended by the United Nations General Assembly as a criterion for the allocation of aid as well as the two other criteria for identification Of LDCs.

[81] In the 2012 review, an environmental component namely share of population living in low elevated coastal zone was introduced in the exposure sub-index in order to address the vulnerability of Small Island developing States. This variable is less appropriate in the case of African countries which instead are suffering in general from aridity.

[82]In percentage, in order to make the corporate tax comparable across countries. Two standard ways of comparing corporate tax revenues across countries are to scale tax revenues in each country by GDP or the relative size of corporate income in total taxes of each country.

mining taxation database (Mansour, 2014), the trade openness measured by the ratio of import and export over GDP (UNCTAD, 2015), the money supply (M2 as a percentage of GDP), a proxy for financial market development (WDI, 2015), the quality of infrastructure measured by the number of telephone mainlines per 100 people[83] (WDI, 2015), the resource endowment variable highlighting the countries for which the natural and mineral resource rents are non-zero and the polity2 variable from the Polity IV dataset project as a measure for democracy and political stability. We also include a variable (actotal) reflecting the occurrence and severity of societal and intrastate conflicts from the Major Episodes of Political Violence (MEPV) and conflict regions' data by the Center for Systemic Peace (CSP).

Table 2: Potential determinants of FDI and their expected signs

Variable	Expected sign
Structural economic vulnerability	-
Human capital	+
Quality of infrastructure	+
GDP per capita	+
Openness	+
Money supply (M)	+
Inflation	-
Exchange rate	+
Resource endowment	+
Magnitude and severity of Conflicts	-
Democracy and political stability	+
Corporate tax	-

IV - Econometric specification

Our study is based on inward FDI stock since it is supposed to be more stable for regression. Nevertheless, given the temporal evolution observed in the Figure 1, we suspect the nonstationary of the variable. More generally, it is a fact that economic panel data are nonstationary either because their means or their variances are not constant over time. Most of the studies using panel data tend to ignore the issue of nonstationary. Similarly, several studies overlook spatial econometrics and therefore do not take into account the

[83] Another possibility for capturing the quality of physical infrastructure is the using of percentage of roads that are paved. We choose the variable of the number of telephone mainlines because it is more completed.

main aspects of geographical observations, namely the spatial autocorrelation, which refers to the absence of independence between geographical observations and the spatial heterogeneity which was linked to the differentiation of variables in space (Anselin, 1988). Baltagi *et al*. (2007) estimated the spatial determinants of US outward FDI stock, but they did not investigate the time-series properties of their data.

We consider a spatial panel model with the following long-run form:

$$Y_{it} = \alpha + \beta X_{it} + \rho Y_{it}^{*} + \delta X_{it}^{*} + \theta Z_{it} + u_{it} \qquad (1)$$

Where Y_{it} is the dependent variable (the logarithm of FDI stock) in the model for i=1, 2,…, N labels spatial units; $t = 1,2,3,...T$ labels time periods of the model; X_{it} the variable of interest (EVI or its main components) in country i at time t ; Z_{it} the vector of other explanatory variables (e.g., income per capita, natural resources, human capital, aid) in country i at time t; α the intercept; and u_{it} is the model's residual term. We assume that Y , X and Z are $I(1)$; therefore nonstationary in levels. The estimates of $I(1)$ variables deserve much precaution in order to avoid spurious regression. Asterisked variables refer to spatial lags defined as:

$$Y_{it}^{*} = \sum_{j \neq i}^{N} w_{ij} Y_{jt} \quad ; \; X_{it}^{*} = \sum_{j \neq i}^{N} w_{ij} X_{jt}$$

Thus, Y_{it}^{*} and X_{it}^{*} denote the FDI and EVI (or its components) in proximate countries.

w_{ij} are spatial inverse-distance, weight between any two potential host countries[84].

In equation (1), spatial dependence may be present in the error term. The presence of spatial lags makes the spatial dependence unlikely or impossible. Spatial lagged variables must have the same order of integration as the data from which they are derived because spatially lagged variables are linear combinations of the underlying data. Thus the cointegration space is enlarged by the presence of spatial lags to find long-run specifications with a stationary residual term u_{it}. Even if some variables in the model are not integrated in

[84] We have chosen to use the distances based on the vincenty differences in kilometers between country centroids. As proposed by Poelhekke et al.(2013), the distances are normalized by the shortest distance between two host countries.

the same order of spatially lagged variables, one can model a mixture of $I(0)$ and $I(1)$ variables if there is a cointegration between the $I(1)$ variables. The residual-based panel Fully Modified OLS (FMOLS) and Dynamic OLS (DOLS) estimators allow modeling variables with different order of integration and produce asymptotically unbiased, normally distributed coefficient estimates (Phillips and Moon, 1999; Pedroni, 2000, 2001; Kao and Chiang, 2000; Mark and Sul, 2003). Dynamic OLS involves adding lags and leads of the regressors to eliminate feedback effects and endogeneity[85].

Beenstock and Felsenstein (2010) proposed a spatial Error correction model as a dynamic process, in which spatially cointegrated variables co-move over time. They argued that the equation (1) may be estimated without resorting to instrumental variables for the variables.

The resulting spatial Error Correction associated with equation (1) in its first order form can be written as:

$$\Delta Y_{it} = \gamma_0 + \gamma_1 \Delta Y_{it-1} + \gamma_2 \Delta X_{it-1} + \gamma_3 \Delta Y^*_{it-1} + \gamma_4 \Delta X^*_{it-1} + \gamma_5 \Delta Z_{it-1} + \gamma_6 u_{it-1} + \gamma_7 u^*_{it-1} + e_{it} \qquad (2)$$

Where e_{it} is the short-run residual which is assumed to be temporally uncorrelated, but might be spatially correlated such that $Cov(e_{it}e_{jt}) = \sigma_{ij}$ is non-zero. The terms u_{it-1} and u^*_{it-1} are the (spatially weighted) residuals from the long-run relationships of the systems. γ_6 and γ_7 can be interpreted as error correction coefficients. If they are significant and non-zero, then there exists a convergence towards the steady state after short-term shocks[86]. Beenstock and Felsenstein (2010) highlighted that in short-run, explanatory variables may affect the dependent variable in a different way, from how it affects it in long-run.

V - Results

As shown in Figure 1, inward FDI stock is likely to be non-stationary. The other economic variables may also appear as non-stationary. To analyze this in-depth, one can compute standard panel unit root tests proposed by Im *et al*. (2003) and Pesaran (2007). Suspecting a

[85] Kao and Chiang (2001) in multiple simulations found that the performance of the DOLS is much better than that of the FMOLS. This is consistent with simulations made by Wagner and Houskova (2010).

[86] Beenstock and Felsenstein (2010) called this case « Global error correction ». It occurs if nonstationary panel data are both cointegrated within and between cross-sections.

spatial dependence, we prefer the latter test because it is more robust to cross-sectional correlation generated by spatial dependence (Baltagui *et al.*, 2007). The Cointegrated Augmented Dickey Fuller (CADF) test eliminates cross-sectional dependence by augmenting the ADF regression with the lagged cross-sectional mean and its first differences of the individual series to capture the cross dependence by a single factor model. Table 3 suggests that all integrated variables are $I(1)$ except Inflation and the exchange rate, which are stationary in levels, thus $I(0)$.

Then, we estimate equation (1) to determine the existence of any long-run relationship between FDI and control variables. A mixture of $I(0)$ and $I(1)$ is estimated using the Dynamic spatial lag model.

Table 3: Pesaran Panel Unit Root Test

Variable	Levels		First differences	
	Without Trend	With Trend	Without Trend	With Trend
ln FDI	-0.834	0.996	-7.761***	-6.298***
EVI	2.376	1.196	-8.623***	-6.778***
HAI	1.466	2.467	-3.903***	-2.711***
ln GDP per capita (*t*-1)	2.635	1.773	-7.075***	-6.269***
Resources endowments (*t*-1)	-0.406	-0.354	-10.899***	-9.216***
Trade openness	-1.243	0.034	-10.542***	-9.203***
Money supply	-0.412	-0.275	-8.991***	-7.805***
Corporate tax	-0.881	-1.222	-9.667***	-8.368***
Inflation (t-1)	-6.879***	-3.123***	-10.978***	-8.852***
Exchange rate	-3.504***	-1.692	-9.025***	-7.514***
Political stability (5 yearly)	0.989	2.889	-2.271**	-2.222**
Conflicts' magnitude	-1.261	1.329	-7.573***	-6.196***
Infrastructures	3.616	5.190	-3.327***	-3.356***
WEVI	0.829	0.657	-8.507***	-6.633***
WLn FDI	-0.655	-1.859	-10.819***	-9.319***

Notes: *** p<0.01, ** p<0.05, *p<0.1.The variables preceded by W denote spatial lag variables.

The results of the long-run relationship are presented in Table 4. The estimated coefficients show that structural economic vulnerability measured by the EVI is statistically significant and negatively affected FDI. Similarly, corporate tax and conflict's magnitude have significant negative impact on FDI in Africa. By contrast, as expected, human capital proxied by HAI, market size proxied by per-capita GDP, trade openness, resource endowment and political stability proxied by Polity2 variable[87] have a significant and positive effect on FDI. Money supply which denotes the financial development appears not significant. Economic uncertainty proxied by the inflation rate, exchange rate and physical infrastructures are statistically significant, but their signs are inconsistent with prior expectation. The results also reveal that a high economic vulnerability of the neighbors has a positive impact on FDI.

Table 4: Dynamic estimation of the panel cointegration relationship

	Coefficient	Standard Error
EVI	-0.017***	(0.0061)
HAI	0.018**	(0.0082)
Ln GDP per capita (t-1)	1.937***	(0.0194)
Resource endowment (t-1)	0.080***	(0.0084)
Trade openness	0.012***	(0.0039)
Corpolatetax	-0.024*	(0.0124)
Inflation (t-1)	0.005**	(0.0018)
Exchange rate	-0.011***	(0.0016)
Political stability	0.107***	(0.0135)
Conflicts' magnitude	-0.024***	(0.0309)
Infrastructures	-0.144**	(0.0069)
Money supply	-0.011	(0.0085)
WEVI	0.053**	(0.0227)
WLn FDI	0.107	(0.0803)
Constant	3.358	(3.1404)
Log-likelihood	-1216	
Observations	378	
Robust LM rho=0	14.36	

Notes: Standard errors in brackets. *** p < 0.01, ** p<0.05, *p < 0.1.The variables preceded by W denote spatial lag variables.

The results presented in Table 4 seem quite weak as being unfounded. Firstly, because of missing data, the number of observations is relatively very low. This can make the results inconsistent and biased. Only a few countries (11) have a reliable data for all variables and

[87]Five-yearly averages to deal with potential endogeneity. Also some variables are lagged by one year to avoid reverse causality even if this appears unlike in dynamic spatial model.

for a significant period of time. Secondly, estimated coefficients are not those of the long-run relationships between FDI and explanatory variables. Indeed, the standard Im, Pesaran and Shin (IPS) test[88] procedure reveals that the residuals from a regression are not stationary. This implies that the null hypothesis of no cointegration cannot be rejected and suggests that there is no evidence of cointegration among the variables hitherto used in the analysis. Nonetheless, the process of testing for the long-run relationship is repeated for other combination of variables by dropping some variables in the equation (1). In the end, the presence of cointegration is detected between FDI and EVI, human capital, per-capita GDP, resource endowment and political stability.

The results in Table 5 give strong evidence that the variables are cointegrated. The IPS test is statistically significant at the 1% level. It is completed by the alternative LLC test (Levin, Lin and Chu, 2002) which has more power, but requires balanced data and assumes a homogeneous auto-regressive parameter.

Table 5: Panel cointegration tests for FDI, human capital, per-capita GDP, resource endowment and political stability

	Coint.	P-Val.
IPS	-2.29***	(0.00)
LLC	-3.89***	(0.00)

Note: *** p<0.01, ** p<0.05, *p<0.1. IPS test: H0: All panel contain unit roots
LLC test: H0: Panels contain unit roots.

The findings of Table 6 show that structural economic vulnerability, human capital, per-capita GDP, resource endowment and political stability are important determinants of FDI in Africa. Spatial lag and Dynamic spatial (without reporting the leads and lags) present almost similar results. This confirms a stable and unbiased long run relationship between the variables. All of the estimated coefficients are consistent with prior expectation and statistically significant. Furthermore, the estimated parameters relating to the spatial patterns are statistically significant and economically important. A high structural vulnerability in neighboring countries negatively affects FDI into a host country, with an

[88]This test allows for heterogeneous autoregressive parameters and is relevant in our case because of the assumption of cross sectional dependence taken into consideration by a spatially lagged dependent variable.

elasticity of -0.08. In other worlds, a 1% increase in EVI within surrounding countries decreases FDI into the country by 0.08%**.** In contrast, the spatial lag was statistically positive with a point estimate of 0.254. A 1% increase in FDI into surrounding countries spread to the host country by 0.25%.

Table 6: Dynamic estimation of the panel cointegration relationship between FDI, EVI, HAI, Per-capita GDP, Resources endowment, Political Stability

	Spatial Lag	Dynamic Spatial Lag
EVI	-0.085***	-0.086***
	(0.0039)	(0.0041)
HAI	0.010***	0.011***
	(0.0032)	(0.0033)
Ln GDP per capita (t-1)	0.365***	0.308***
	(0.0699)	(0.0753)
Resource endowment (t-1)	0.042***	0.044***
	(0.0038)	(0.0042)
Political stability	0.039***	0.044***
	(0.0087)	(0.0098)
WEVI	-0.070***	-0.080***
	(0.0247)	(0.0268)
WLn FDI	0.366***	0.254***
	(0.0611)	(0.0726)
Constant	16.147***	19.193***
	(2.1445)	(2.4494)
Observations	1147	1036
Log-likelihood	-2087	-1816
Robust LM rho=0	64.93***	32.77***

Notes: *** p<0.01. The variables preceded by W denote spatial lag variables.

Table 7 reports an estimated spatial lag error correction model. The error-correction term which is equal to the lagged residual from the model of equation (2), is statistically significant at the 1% level. This indicates that FDI is spatially cointegrated and should converge towards its equilibrium level. The speed of adjustment implied by the error correction terms u_{it-1} and u^{*}_{it-1} was about 15 % of local error within a year and 12 % of the neighboring error spill over onto a given host country. From columns A, the short-run coefficients are for the most part, statistically insignificant with the exception of per-capita GDP, Resources endowment, and FDI of neighbors. Their coefficients say about the rate at which the previous period disequilibrium of the system is being corrected. The system corrected its previous period disequilibrium at a speed of 23%, 0.4% and 26% between FDI and per-capita GDP, resource endowment, and HAI and FDI of neighbors respectively. However, the long-run coefficient of EVI appears negative and significant at the 1 % level. This implies that high EVI significantly leads to a deterioration of the FDI level in the long-run equilibrium. Similarly, a high EVI in neighboring countries has a negative impact on local FDI. Although they compete in attracting more FDI, African countries have a vested interest in having the neighbors with low structural economic vulnerability. In a deeper sense, apart from their quest of natural resources, multinational corporations in Africa are mainly marketed and efficiency seekers. Market seekers since they seek the profitability of supply on the local market and take into account the size of the host country's local market in the trade-off before exporting to an overseas economy and settling there. Efficiency seekers since they seek the efficiency of economies of scale and the diversification of risks by the choice of their location. The results also showed that human capital, political stability and neighboring countries' FDI had a significant and positive impact on host country FDI in the long-run FDI function.

The results from columns B with the clustered standard errors at the country level do not differ from those of columns A. Only minor changes in robust standard errors are observed. Columns C which include country-fixed effects present slight discrepancies mainly in the scale of the coefficients. Nevertheless, in terms of conclusion, the results do not stray too far from those of columns A and B.

Table 7: Spatial lag with Error-Correction

Long-run estimates				Short-run estimates			
	A	B	C		A	B	C
ln FDI (t-1)	-0.078***	-0.078***	-0.016***	∆ln FDI	-0.057	-0.057	-0.081
	[0.0085]	[0.0063]	[0.0123]		[0.0629]	[0.0458]	[0.0534]
HAI (t-1)	0.002**	0.002**	0.019**	∆HAI	0.007	0.007	0.009
	[0.0016]	[0.0007]	[0.0542]		[0.0064]	[0.0007]	[0.0041]
EVI (t-1)	-0.004***	-0.004***	-0.035***	∆EVI	0.0019	0.0019	0.0011
	[0.0007]	[0.0008]	[0.0018]		[0.0041]	[0.037]	[0.028]
Ln GDP per capita (t-2)	0.181*	0.181*	0.143	∆Ln GDP per capita (t-1)	0.234***	0.234***	0.163***
	[0.0148]	[0.0146]	[0.0142]		[0.0786]	[0.0773]	[0.0885]
Resources endowment (t-2)	0.002***	0.002***	0.033**	∆Resources endowment (t-1)	0.004***	0.004***	0.025**
	[0.0008]	[0.0008]	[0.0018]		[0.0014]	[0.0013]	[0.0582]
Political stability (t-1)	0.003*	0.003**	0.07**	∆Political stability	0.004	0.004	0.001
	[0.0016]	[0.0014]	[0.0204]		[0.0090]	[0.0094]	[0.0204]
WEVI (t-1)	-0.010*	-0.010*	-0.004	∆WEVI	0.026	0.026	0.034
	[0.0060]	[0.0055]	[0.011]		[0.022]	[0.0190]	[0.0512]
WLn FDI (t-1)	0.019**	0.019**	0.003	∆WLn FDI	0.261***	0.261	0.215**
	[0.0188]	[0.0139]	[0.0139]		[0.0806]	[0.2370]	[0.0056]
				u (t-1)	-0.145***	-0.145***	-0.112**
					[0.0241]	[0.0236]	[0.0162]
				Wu(t-1)	0.120***	-0.092**	-0.132***
					[0.0511]	[0.0336]	[0.0152]
Clustered standard errors		Yes				Yes	
Fixed effects			Yes				Yes
Observations	1099	1099	1099		1099	1099	1099

Robust Standard errors in parentheses. *** p<0.01, ** p<0.05, *p<0.1. The variables preceded by W denote spatialized variables.

VI - FDI in African Low-income and Middle-income countries: Disentangling structural economic vulnerability from other factors

As previously indicated in Table 1, inward FDI stock is relatively uneven across the group of African countries. Low-Income countries (LIC) account for a small part of the global FDI to Africa. The bulk of FDI into the continent goes to Middle-income countries (MIC) and High Income Counties (HIC) which are very few. We attempt to explain the difference of FDI stock between LIC and MIC by disentangling the factors due to structural economic vulnerability from other factors. For this, we applied the methodology based on the Blinder-Oaxaca decomposition originally used in labor economics to study the effect of discrimination on wages. The procedure was due to Blinder and Oaxaca (1973) and it allows decomposing mean differences in any variable based on regression models adopting a counterfactual approach. The core idea is to explain the distribution of the FDI by a set of factors that vary systematically with the components of the EVI. For instance, the variation in FDI may be explained by variations in population, remoteness, export concentration, the share of agriculture to GDP, victims of disasters, instability of agriculture and instability of exportations.

We decompose the FDI differential between African LIC and African MIC into a part that is explained by the countries' characteristics and into a residual part that is due to other factors, such as differences in the estimated coefficients associated with the previous characteristics or in unobserved variables.

If we define Y_g as the inward FDI stock of a group g $\{g = LIC, MIC\}$, then the difference of expected FDI between the two groups is written as:

$$\Delta_o^{\mu} = E(Y_{MIC} | D_{MIC} = 1) - E(Y_{LIC} | D_{MIC} = 0) \quad (3)$$

Where $D_{MIC} = 1$ if the country is MIC and $D_{MIC} = 0$ otherwise.

Let's assume that for each of the two groups of countries, there exists a linear model linking Y_g to a vector of explanatory variables $X \in R^p$, so:

$$Y_g = X'_g \beta_g + \varepsilon_g \quad (4)$$

Using the law of iterated expectations:

$$E(Y | D = j) = E(E(Y | X, D = j)) \quad (5)$$

Under the usual assumptions and rearranging, we can express the difference of expected FDI between the two groups of countries as the sum of three terms:

$$\Delta\bar{Y} = (E(X_{MIC} - X_{LIC}))'\beta_{LIC} + E(X_{LIC})'(\beta_{MIC} - \beta_{LIC}) + (E(X_{MIC} - X_{LIC}))'(\beta_{MIC} - \beta_{LIC}) \quad (6)$$

Equation (6) is the threefold Blinder-Oaxaca decomposition.

The first term E= $(E(X_{MIC} - X_{LIC}))'\beta_{LIC}$, is endowments term and represents the part of the FDI differential that is explained by the differences in EVI's components across LIC and MIC. It measures the expected change in LIC's average FDI if LIC would have the structural economic vulnerability characteristics of MIC. The second term C= $E(X_{LIC})'(\beta_{MIC} - \beta_{LIC})$ is the coefficients term, highlighting the part that is due to the two groups' differences in the coefficients. It measures the expected changes in LIC's average FDI if LIC had the same coefficients as MIC. The third term I= $(E(X_{MIC} - X_{LIC}))'(\beta_{MIC} - \beta_{LIC})$ is the interaction term and accounts for the fact that cross-group differences in EVI's components can occur at the same time.

As proposed in the literature, one can estimate a two-fold Blinder-Oaxaca decomposition by the differences in FDI between LIC and MIC which can be attributed either to differences in the structural economic vulnerability variables (explained difference) or to differences in the coefficients (unexplained difference). The latter is often used as the measure of discrimination. If LIC is considered as the reference group, the two-fold Blinder-Oaxaca decomposition can be written as:

$$\Delta\bar{Y} = (E(X_{MIC} - X_{LIC}))'\beta_{LIC} + E(X_{LIC})'(\beta_{MIC} - \beta_{LIC}) \qquad (7)$$

Results

The results for the general decomposition pertaining to the threefold Blinder-Oaxaca decomposition are presented in Table 8. We use the African LIC FDI structure as reference group. The mean value of FDI amounts to 21.28 log points for African MIC and 19.40 log points for African LIC, the FDI gap is therefore about 1.88 log points. The differences in endowment are the most important explanations for the FDI gap between the two groups. The decomposition suggests that, of the 1.9 log points difference, approximately 1.6 log points can be attributed to differences in endowments between African LIC and African MIC, -0.5 log points to differences in coefficients, and the remaining 0.8 log points is accounted for by the interaction of endowments and coefficients. If African LIC had the same characteristics as African MIC in terms of structural economic vulnerability, then, their average FDI would be raised by 1.6 log points. Similarly, if African LIC had the same coefficients as African MIC, their FDI would be reduced by 0.5 log points. The fact that the interaction term has the same sign as the endowment effect, but opposite to that of the coefficient effect makes unclear the joint effect of differences in the coefficients.

The results of twofold Blinder-Oaxaca decomposition reported in Appendix 3 show that both explained and unexplained components are positive. The variables used to measure structural economic vulnerability explained more than 87 percent of the FDI gap between African LIC and African MIC. This implies that FDI in African LIC should increase if their level in terms of structural economic vulnerability was the same as that in African MIC while their FDI should raise by 1.65 log points. The fact that the explained component was about 7 times higher than the unexplained component means that the structural economic vulnerability measured by EVI is a real handicap to develop.

Table 8: General decomposition

Average Prediction for	
African Middle-Income Countries (A)	21.279***
	(0.0904)
African Low-Income Countries (B)	19.395***
	(0.0706)
Differences (A) – (B)	1.884***
due to	(0.1147)
Endowments	1.629***
	(0.1644)
Coefficients	-0.496**
	(0.2343)
Interaction	0.751***
	(0.2637)

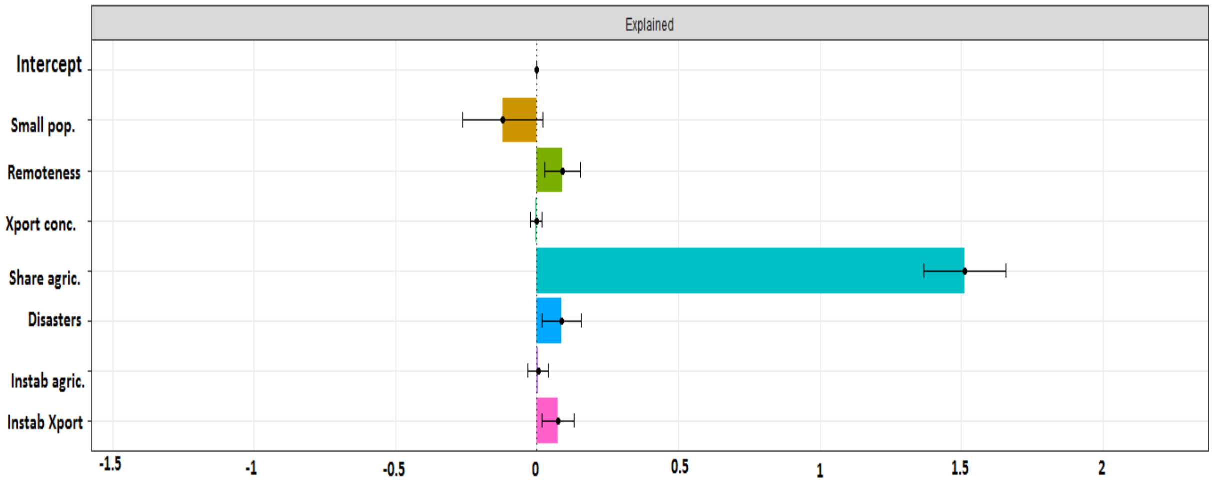
Notes: Robust Standard errors in parentheses. *** p<0.01, ** p<0.05, *p<0.1

It should be appropriate, then, to disentangle the contribution of different variables to the FDI gap. We examine the explained component of the twofold decomposition variable by variable. Figure 2 shows the estimated results for each variable, along with error bars that indicate 95 % confidence intervals. It appears that export concentration and the instability in the agricultural production are not statistically significant in the explanation of the FDI gap between African LIC and African MIC. This is in line with the raise to the observation that the agricultural sector has generally lagged behind the other sectors in attracting FDI. The agricultural sector still accounts for a very small percentage of total FDI in most developing countries. For example, Gerlach and Liu (2010) in their study on Sub-Saharan Africa suggested that less than five percent of FDI goes to agriculture. In addition, the majority of agricultural FDI flows move towards the food manufacturing sector. The low and fluctuating prices of agricultural products on the world market primarily explain the relative disinterest of foreign investors in the agricultural sector. Similarly, climate change with erratic rains can also be taken into account in the decision of foreign investors[89]. Regarding the share of agriculture, forestry and fishery in GDP, the explained component is very large and has a statistically significant influence in favour of African MIC. In this way, a significant FDI gap is driven by group differences in the share of the primary sector in the economy. In other words, African LIC need to change in structure from dominance by the agricultural sector to diversified economies. The discovery of natural resources such as oil and diamonds was fortunate for some countries that have become among the main recipients of FDI in the continent. For example, we can cite the case of Botswana and Cameroon. Diamonds for the first and oil for the latter allowed both countries to attract a lot of FDI.

Economic vulnerability arising from the smallness of the population does not in favour of African MIC. Indeed, it sounds like the size of population is more important in African LIC than African MIC. The contribution of the smallness of the population in the total FDI gap, although playing in the opposite direction appears significant at the 10 percent level. Remoteness, disasters and instability in exports of goods and services, although statistically significantly contribute minimally to explaining the difference between groups compared to the contribution of share of agriculture, forestry and fishery in GDP.

[89]In line with the conclusions made par the IPCC, the Physical Vulnerability to Climate Change Index (PVCCI), African countries are relatively vulnerable to climate change. For more details on this index, the reader will be able to refer to Guillaumont, P., Simonet, C., Closset, M and Feindouno, S. “Physical Vulnerability to Climate Change Index: Which Are the Most Vulnerable Developing Countries?” Ferdi Working Paper, 2017.

Figure 2: The explained components of a twofold Blinder-Oaxaca decomposition



VII - Conclusion

Many studies have attempted to answer the question about the reasons for which Africa is always lagging behind in attracting FDI. Besides the variables traditionally used in the literature as the determinants of FDI, we examine the link between structural economic vulnerability (measured by the EVI) and FDI. Contrary to existing studies, this study explores the short-run and long-run coefficients of the determinants of FDI, not forgetting the importance of spatial lags in the dynamic formulation of a regression model. We estimate a spatial error correction model, a slightly modified version proposed by Beenstock and Felsenstein (2010) over the period 1980 to 2010 to assess the dynamic relationships between FDI and its determinants in Africa. A more thorough cointegration analysis suggests that FDI is cointegrated with EVI, human capital, per-capita GDP, resource endowments and political stability. From the restricted model, we find a significant and negative relationship between FDI and EVI. Similarly, it appears that a high structural vulnerability in neighboring countries negatively affected FDI into a host country. But, human capital, per-capita GDP, resource endowments and political stability affect positively and significantly FDI in Africa.

Regarding the results obtained from the spatial error correction model, except for per-capita GDP, resource endowments and the FDI level in neighboring countries, no significant association is established between FDI and EVI, human capital and political stability in the short-run. However, there exists a long-run relationship between FDI and all variables in the model (at different significance levels). The structural economic vulnerability would be harmful in attracting FDI in the long-run relationship, thus demonstrating the structural character of the EVI. This finding calls on the African authorities to implement structural reforms to reduce their EVI. Of course, this is only possible within a framework of long political stability, which is not often the case in Africa.

Furthermore, our study explains the reasons for which African, Middle-Income Countries are relatively successful in attracting FDI compared to African Low-Income Countries. Using the well-known Blinder-Oaxaca decomposition, we decompose the FDI difference between the two groups into a part explained by the EVI's components and into a residual part, called unexplained part. We observed that 87% of the FDI difference is explained by EVI's components. Focusing on the contribution of each component at this difference, it appears that the share of agriculture, forestry and fishery in GDP constitutes the most important variable in the explanation of the FDI difference between African Middle-Income Countries and African Low-income Countries. The climatic hazards, and the risks associated with the volatility of agricultural commodities' prices lead foreign investors having little interest in the agricultural sector. This tells us that African leaders need to be able to diversify their economies. Through the diversification of their economies, African countries will reduce their exposure to external risks (climatic and commercial) and also invoke more interest from the foreign investments.

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Appendices

Appendix 1: List of countries used in the analysis

Algeria	Ethiopia	Namibia
Angola	Gabon	Niger
Benin	Gambia	Nigeria
Botswana	Ghana	Rwanda
Burkina Faso	Guinea	Senegal
Burundi	Guinea-Bissau	Sierra Leone
Cabo Verde	Kenya	Somalia
Cameroon	Lesotho	South Africa
Central African Republic	Liberia	Sudan
Chad	Libyan Arab Jamahiriya	Swaziland
Comoros	Madagascar	Togo
Congo	Malawi	Tunisia
Côte D'Ivoire	Mali	Uganda
Democratic Republic of the Congo	Mauritania	United Republic of Tanzania
Egypt	Mauritius	Zambia
Equatorial Guinea	Morocco	Zimbabwe
Eritrea	Mozambique	

Appendix 2: Details of the threefold decomposition

	Endowments	Coefficients	Interaction
Small population	-0.132*	0.486***	0.026
	(0.0768)	(0.1771)	(0.0181)
Remoteness	0.210***	0.022***	-0.006
	(0.0701)	(0.2845)	(0.0789)
Export concent.	-0.026***	-1.160***	0.120***
	(0.0156)	(0.1861)	(0.0451)
Share agriculture	1.179***	-2.067***	1.410***
	(0.1101)	(0.3327)	(0.2287)
Disasters	0.168***	0.863***	-0.293***
	(0.0499)	(0.1971)	(0.0714)
Agric. Instability	0.089***	-0.852***	0.211***
	(0.0290)	(0.1190)	(0.0531)
Exports Instability	0.139***	0.921***	-0.295***
	(0.0367)	(0.2106)	(0.0719)

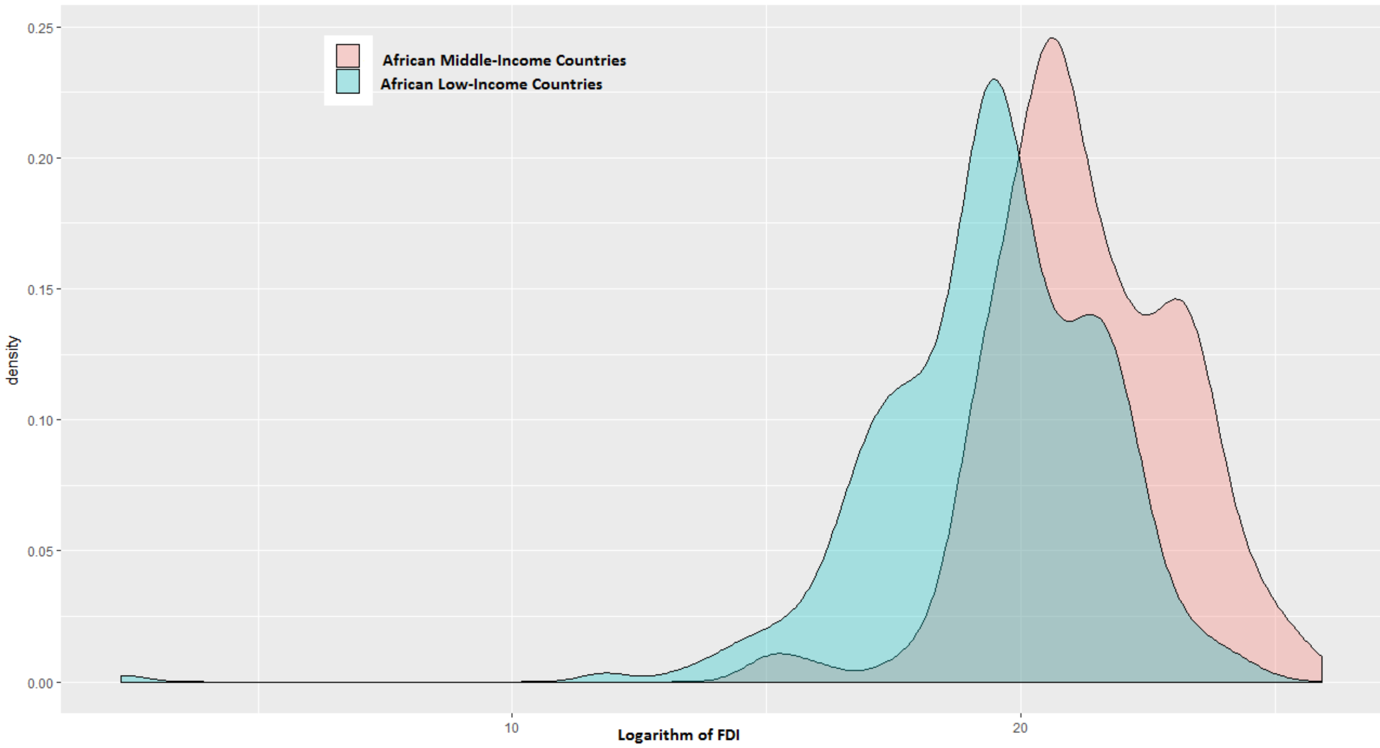
$^{*}p<0.1$ $^{**}p<0.05$ $^{***}p<0.01$. Robust standard errors in parentheses

Appendix 3: Details of the twofold decomposition

	Explained	Unexplained
Small population	-0.121^{*}	0.502^{***}
	[0.0071]	[0.1785]
Remoteness	0.090^{***}	0.136
	[0.032]	[0.2944]
Export concent.	-0.003	-1.063^{***}
	[0.095]	[0.1703]
Share agriculture	1.512^{***}	-0.989^{***}
	[0.0771]	[0.1616]
Disasters	0.088^{**}	0.650^{***}
	[0.0351]	[0.1427]
Agric. Instability	0.004	-0.978^{***}
	[0.0187]	[0.1609]
Exports Instability	0.074^{***}	0.692^{***}
	[0.0304]	[0.2079]

$^{*}p<0.1$ $^{**}p<0.05$ $^{***}p<0.01$. Robust standard errors in parentheses

Appendix 4: Distribution of the logarithm of FDI for African LIC and African MIC



Appendix 5: Descriptive statistics

Variable	Mean	SD	Min	Max
ln FDI	19.94	2.30	2.30	25.91
EVI	44.01	12.06	11.75	71.27
HAI	39.30	21.15	0.61	95.21
ln GDP per capita (*t*-1)	7.17	0.93	5.08	9.91
Resources endowment (*t*-1)	12.82	13.52	0.0067	89.001
Trade openness	70.44	40.55	12.91	315.09
Money supply	30.68	22.03	0.83	151.55
Corporate tax	1.60	1.19	0	9.06
Inflation (t-1)	69.24	970.27	-35.83	24411.03
Exchange rate	20.11	206.80	0.00017	3639.32
Political stability (5 yearly)	-1.36	5.67	-9	10
Conflicts' magnitude	0.88	1.80	0	10
Infrastructures	2.00	3.79	0.0057	30.27

Appendix 6: Oaxaca decomposition

Explained	1.645
% explained	87.3
Unexplained	0.239
% unexplained	12.7

CONCLUSION

The interest in understanding the concept of vulnerability has grown exponentially among the international community of donors in order to adapt aid policies to particularly difficult situations. Vulnerability assessment has thus become a fashionable exercise to design a special treatment in favour of vulnerable and fragile states. As a response to this interest, there has been a sharp increase in the production of various composite indicators of vulnerability, reflecting a diverse range of interests, purposes and aspirations. They are intended, among other things, to help compare relative vulnerability of one country, group of countries to another, ranking them according to levels of vulnerability. Despite the proliferation of these indices, there is no systematic, comprehensive study of such indices. This is primarily due to the elusive and blurred nature of the concept of vulnerability which is related to a large number of economic, social, environmental and political factors. This work espouses the spirit behind Guillaumont's dynamic definition of vulnerability as the "risk that economic growth of a country is markedly and extensively reduced by shocks".

The complex nature of the vulnerability makes the development of composite indicators of vulnerability highly challenging. Aside from being utterly based on a fairly methodology, vulnerability indices should support policy guidance to influence resource allocation, with greater funding going to more vulnerable countries. Within this framework, the first three chapters of this work deal with issues related to vulnerability through three composite indicators.

In the first chapter, we focus on structural economic vulnerability by looking closely at the Economic Vulnerability Index (EVI) proposed by the United Nations for identifying LDCs. The EVI lies in factors that reflect the risk for a country seeing its economy growth, and more generally its development rate, durably slowed down by exogenous shocks, independantly of its policy choices. After presenting the scope and limitations of the EVI, we show how structural economic vulnerability constitutes a trap for fragile states. By way of example, fragile African states are economically more vulnerable than non-fragile African states, and the difference between the two groups of countries seems to come from the difference in the magnitudes of shocks. Because that vulnerability assessment requires a dynamic point of view, we build retrospectives series of the EVI and its components for 145 developing countries over the 1990—2013 period. Overall, the vulnerability of LDCs, although decreasing faster than non-LDCs, still higher compared to the level of non-LDCs. With the exception of the variables of the population size and the share of population living in low elevated coastal zones (LECZ), LDCs display a high level of vulnerability at any year. The two series do not intersect anywhere. But that is not the case with the instability of agricultural production for which the two series intersect at nine points, even if the level of this variable falls rapidly since 2008 for non-LDCs and later since 2011 for LDCs.

Has the decline in structural economic vulnerability been effective in all countries? To answers this question, we employ pairwise stochastic dominance tests to analyze the evolution of the EVI over time. Our approach uses a five-year testing horizon. Our results do not show a real decline of the EVI and its main components at the first order sense but an overall decrease can be concluded at the second order sense of dominance. This suggests that the cumulative distribution function (CDF) of the following years and the one of the previous cross, meaning that the dominance is not general because the conditions are not met for some countries. However, the integrate CDF of the following years dominates that of the previous years over the time of period in most of cases. That is particularly true for shock index, suggesting a form of “learning” against external shocks.

In the second chapter, we are interesting in another form of vulnerability that is related to the lack of human capital. Indeed, human capital as well as overall level of income per capita influence the ability of countries to respond to shocks. To assess the level of human capital in developing countries, we use the Human Assets Index (HAI), a composite index of health and education outcomes. Faithful to our dynamic point of view of vulnerability assessment, we use econometric approach to generate retrospective series of the HAI and its four components for 145 developing countries over the 1990—2014 period. Preliminary analyses reveal that developing countries achieve differing patterns of HAI by dimension and component. The LDCs made big progress during the period 1990 to 2014, but with a lot of within-LDC heterogeneity. Under-five mortality and Secondary enrolment rate are the main contributors to the HAI's change over this period. But for the LDC group, the standard deviation of the HAI index score was markedly higher in 2014 than in 1990.

Moreover, given the structure of correlation ratio and nonlinearity in the HAI and its components, we derive an optimized weighting scheme in order to determine the true influence of each component. Thus, we show that the Secondary school enrolment component is redundant and suggest an alternative HAI with only three components with different weights: Undernourishment rate (1/2), Literacy rate (1/3), and Under-five mortality (1/6). As a result, this weight-optimized HAI implies significant ranking changes for some countries.

In the third chapter, we focus on the environmental dimension of vulnerability linked to the issue of climate change. We begin by introducing a Physical Vulnerability to Climate Change Index (PVCCI) which captures the only physical vulnerability to climate change through its various manifestations. The index is built for a large sample of countries (191), including developed countries because all countries are concerned by climate change. Early analysis indicates a higher average level of the PVCCI for developing countries, in particular for LDCs, SIDS and African countries. However, based on standard deviations' analysis, we observe a wide disparity in PVCCI's scores within these groups of countries. The analysis seems to be fairly robust in view of various options that are discussed in the chapter.

The relationship between climate change and conflict is not left out. We attempt to explore the link between the PVCCI and civil conflict. We show that the PVCCI has a positive and significant effect on civil conflict. We test the sensitivity of our results to a set of options, among others, the use of other measures of conflict and the introduction of region and time effects. Overall, our baseline model is not affected. Specially, the effect of the PVCCI on civil conflict is unambiguous when we use conflict incidence as dependent variable, but the significance of the link is weak when we consider conflict onset as dependent variable. We also find that conflict risk is generally higher in countries with large populations, in mountainous countries, in ethnically fractionalized countries. By contrast, a relatively high per capita GDP contributes to the decrease of the likelihood of conflict.

On the whole, these first three chapters are intended to provide a general framework for assessing structural vulnerability, highlighting the vulnerability of developing countries through its three main dimensions: economic, social and environmental. The indices that are used to this end are based on the underlying rationale of development actors to take into account the vulnerability for resource allocation. A consensus seems to emerge in the assessment of the three dimensions of vulnerability: LDCs are the most vulnerable countries on earth. Aside from their socio-political environment marked by violence, and the weakness of legitimacy, authority and capacity of state institutions, they face major structural handicaps that hinder their development. Their situation requires special attention from the international community.

In the fourth chapter, we examine the link between structural economic vulnerability (measured by the EVI) and Foreign Direct Investment (FDI). The idea here is to investigate whether the structural handicaps of African countries are responsible for the low inflow of foreign capital compared to other parts of the world. We estimate a spatial error correction model over the period 1980 to 2010 to assess the dynamic relationships between FDI and its determinants in Africa. A more thorough cointegration analysis suggests that FDI is cointegrated with EVI, human capital, per-capita GDP, resource endowments and political stability. From the restricted model, we find a significant and negative relationship between FDI and EVI. Similarly, it appears that a high structural vulnerability in neighboring countries negatively affected FDI into a host country. But, human capital, per-capita GDP, resource endowments and political stability affected positively and significantly FDI in Africa. Regarding the results obtained from the spatial error correction model, except for per-capita GDP, resource endowments and the FDI level in neighboring countries, no significant association is established between FDI and EVI, human capital and political stability in the short-run. However, there exists a long-run relationship between FDI and all variables in the model (at different significance levels). The structural economic vulnerability would be harmful in attracting FDI in the long-run relationship, thus demonstrating the structural character of the EVI.

Moreover, the chapter attempts to explain the reasons for which African Middle-Income Countries are relatively successful in attracting FDI compared to African Low-Income Countries. We observe that 87 percent of the FDI difference is explained by EVI's components. In particular, the share of agriculture, forestry and fishery in GDP constitutes the most important variable in the explanation of the FDI difference between African Middle-Income Countries and African Low-income Countries.

Two lessons emerge from the fourth chapter. Firstly, structural economic vulnerability constitutes a real barrier to foreign investment. Consequently, African authorities should implement structural reforms to reduce their economic vulnerability. But many of the African countries experience violent conflict and other countries suffer from political instability. Good governance, rule of law, sustainable economic development and the reduction of social inequalities are powerful tools to reduce the risks of social instability spilling over into social violence and conflict. Secondly, the lack of diversification does not foster foreign investments. Specifically, countries with a high share of agriculture, forestry and fishery in GDP are not appealing to FDI. In fact, the climatic hazards, and the risks associated with the volatility of agricultural commodities' prices lead foreign investors having little interest in the agricultural sector. This tells us that African authorities need to be able to diversify their economies.

As I am writing the final words of this thesis, I would like to emphasize the fact that no index is perfect. As uncertainty is unavoidable, important efforts have been undertaken to minimize it in this work. Nonetheless, the degree of uncertainty of composite indices should not be neglected, even if this uncertainty must not lead to discard them. In that respect, there is certainly room for methodological improvements of the indices presented here to assess the vulnerability of countries in various dimensions. This would be an obvious subject for future research. Special attention will be given to issues related to the aggregation methods and the use of better data that is already available in many places, but it is not published and collected. This is crucial for monitoring progress and advancing the study of vulnerability.

I should also like to draw attention to the fact that vulnerability indices should never be used as the sole source of information for guiding policies. Policy makers need to combine them with quantified results or external support policies that extend beyond the simple dimension captured by indicator. In this sense, future research could take place along two axes.

Firstly, as is shown in this thesis, there is a certain degree of heterogeneity even within the same group of countries, suggesting that each country is different. Future research would focus to tailored approach, obviously with great care, to the vulnerability assessment of each individual country on its own. This should not be done for comparison purposes, but it should make it possible to understand the characteristics inherent to the vulnerability of each country so as to bring more appropriate political solutions. This type of study must be done by targeting the most fragile states coupled with countries that have serious structural handicaps to their development.

Secondly, in our work on structural vulnerability, we have treated each dimension separately. But, the concept of structural vulnerability is holistic. It would be interesting to aggregate the various dimensions of vulnerability into a single index. Such broad and comprehensive index is often inspired by requests from development actors to represent phenomena in their whole complexity. This constitutes an even bigger challenge.

Summary: Vulnerability and fragility are at the heart of the global debate arising from the definition and implementation of the sustainable development goals. This PhD dissertation offers enhanced tools to assess structural vulnerability and fragility from various aspects: economic, social, and environmental. The proposed approach for apprehending these concepts is based on the construction and refinement of composite indicators. It is divided into four chapters.

In Chapter 1, we build the retrospective series of the economic vulnerability index (EVI), proposed by the United Nations' Committee for Development Policy (CDP). Some choices and measures are discussed, such as the methodology used to calculate the instabilities of exports and agricultural production. From our analyses, it appears that the structural economic vulnerability of LDCs is still higher compared to non-LDCs. As well, focusing on the African context, we show that fragile African states are economically more vulnerable than non-fragile African states, and the difference between the two groups of countries seems to come from the difference in the magnitude of shocks. Finally, employing a stochastic dominance approach and using a five-year testing horizon to assess the evolution of the EVI and its main components over time, we observe that there is no real decline of the EVI and its main components at the first order sense. But, an overall decrease can be concluded at the second order sense of dominance.

The second chapter focuses on the issue of structural resilience through the Human Assets Index (HAI), another index designed by the UN-CDP for identification of LDCs. We start with a presentation of retrospective series of the HAI and its components, for which, to a limited extend, we have used econometric tools to consistently impute missing data. Secondly, we analyze the HAI's dynamics by assessing the contributions of each component to this. Finally, we debate about the choice of equal weighting for the four components in the HAI. Taking into account the fact that the correlation between indicators is closely linked to the issue, we propose a new scheme pattern based on the correlation ratio and linearity (or nonlinearity) dependence between components.

The third chapter is devoted to the climate change vulnerability. We design a composite indicator called "Physical Vulnerability to Climate Change (PVCCI)". This indicator based only on the physical characteristics of climate change is independent of present and future country policy, and aims to be used for international allocation of resources. After explaining the specific methodology used to build the PVCCI and presenting the results for developing countries, we investigate the relationship between civil conflict and vulnerability to climate change measured here by the PVCCI. We show that, the PVCCI has a positive and significant effect on civil conflict. This effect is particularly relevant when the conflict is proxied by incidence. But once the conflict is measured by onset, we notice a weakness in the relationship between the PVCCI and civil conflict.

The starting point of the fourth chapter is that African countries are still lagging behind when it comes to attracting Foreign Direct Investments (FDI). We suspect the structural economic vulnerability, measured by the Economic Vulnerability Index (EVI), in part, responsible for the relative lack of interest of foreign investors towards Africa. We estimate a spatial error correction model during the time period from 1980 to 2010 to assess the dynamic relationships between FDI and its determinants including EVI in Africa. Our finding reveals that in the long run, there is a significant negative relationship between FDI and EVI. The results also suggest that a high EVI in neighboring countries negatively affects the amount of FDI into a host country. Later on, we also observe that structural economic vulnerability plays an important role in explaining the FDI gap between African Low-Income Countries and African Middle-Income Countries. The share of agriculture, forestry and fishery in Gross domestic products (GDP) appears as the strongest contributing factor to this difference.

Keywords: Vulnerability; Fragility; Human capital; Sustainable development; Historical series; Imputation; Composite; Hypothesis testing; Comparative studies of countries; Climate change; Civil conflict; Foreign direct investment; Spatial Error Correction Model; Cointegration.

JEL codes: C21; C43; C82; F21; I15; I25; O15; O15; O57; Q01; Q34; Q54.