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New Directions in the Capability Approach: a further view on climate change, technology and poverty

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Doctoral Thesis in Economics

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Biographical Note

Elif Göksu Öztürk was born on February 3, 1992, in Ankara, Turkey.

She concluded her undergraduate studies in Economics in 2014, at the Faculty of Economics and Administrative Sciences of the Hacettepe University, with a semester abroad at Helena Chodkowska University of Technology and Economics, Warsaw, Poland. She joined the Master in Economics at the same institution in 2014. In the last semester of her Master's degree, she attended Catholica Porto Business School in the context of the Erasmus program. In 2016, she enrolled in the Doctoral Programme in Economics (taught in English) at the School of Economics and Management, University of Porto (FEP.UP).

During her PhD, she worked as a research assistant in the Centre of Economics and Finance at the University of Porto (CEF.UP) for six months (03/2018 – 08/2018), where she dealt with large databases and literature. Afterwards, she held another research position at the Institute for Systems and Computer Engineering, Technology and Science (INESC-TEC) for three and a half years (03/2019-09/2022) on a project where she enrolled in the process of developing and testing new solution methods using evolutionary algorithms and multi-criteria decision-making methods. Moreover, she developed a web-based decision support system for optimisation. In the context of this project, she participated as a presenter and co-organiser in several international conferences and co-authored original articles, book chapters and peer review proceedings.

Besides, she participated in several academic activities during her PhD: Foundation Issues of the Capability Approach workshop organised by the Human Development and Capability Association (Leuven, BL, 2019), 13^{th} Annual Meeting of Portuguese Economic Journal (Evora, PT, 2019), 14^{th} Annual Meeting of Portuguese Economic Journal (Porto, PT, 2021) and 5^{th} International Conference on Energy and Environment (Porto, PT, 2022).

Beyond the academic life, she is passionate about music, theatre and travelling. She plays guitar and violin. She did theatre for two years between 2009 and 2011. Thereafter, she broadcasted radio programmes on a classic rock radio station for three years (2012-2015).

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Abstract

This dissertation investigates the role of human development, defined in the Capability Approach (CA) theory, to provide perspicuity on the linkages between climate change, technology and poverty from theoretical and empirical perspectives and aims to offer further insights into the literature on the area.

The first essay, called "Building a Composite Index using the Multi-objective Approach: an application to the case of human development", proposes a new and unconventional method to build a composite index (CI) to measure human development in a more robust way than the existing ones by using the Pareto optimality concept beneath multi-objective optimisation. This method consists of two steps: (i) locating each alternative on Pareto frontiers according to their performance on the selected dimensions; and (ii) obtaining the overall achievement of alternatives by predicting the index of human development using the ordered probit model, where Pareto frontiers are considered as the thresholds. In the application of the proposed CI on human development, the dimensions of the Human Development Index (HDI) are used, which allowed us to compare the two indices. Our ranking showed a significant difference from the HDI. The proposed method is novel, strong, non-compensatory, and reliable. Moreover, it provides an effective ranking of the alternatives.

The second essay, entitled "ICT and Human Development: an analysis of European Union countries", aims to understand the effect of Information and Communication Technologies (ICTs) on human development from several perspectives in EU countries. CA theory sees human capabilities and freedoms as the key to well-being. Achieving better living standards is possible only with higher capabilities. ICT emerged as a trigger to increase human capabilities due to its effect on several channels of human life. Thus, we found representing human development from a comprehensive perspective crucial. We followed a unique three-stage data-building process, starting from an inclusive micro-level survey data, the European Union Statistics on Income and Living Conditions (EU-SILC) and obtained four macro-level representative human development elements. Overall, these elements were rich in the information they included from different human development perspectives. Given that such data is not available in macroeconomic data sources, the human development variables used in this work can be considered a relevant contribution to the field. At last, four separate regression models are built where each considers one human development component as the dependent variable. Our results confirm the positive effect of ICTs on human development from all perspectives in EU countries.

Finally, the third essay is called "The Role of Reinforced Capabilities on the Triangle of Climate Change, Technology and Poverty". This work addresses an important topic that merits further attention about how human capabilities can encourage technology adoption decisions to reduce poverty associated with climate change through elaborating the following hypothesis from theoretical and empirical perspectives: "the diffusion of climate adaption technologies can reduce poverty as viewed through the lenses of the Capability Approach". This paper promises several contributions to the literature. First, it fills the gap between the role of human capabilities and technology adoption decisions by combining the CA theory and the Diffusion of Innovations theory. The evidence from existing literature helped us build an analytical framework that elaborates all the links in this complex relationship by analysing the potential impact of climate change on poverty, the importance of adaptation to climate change patterns to protect well-being through new technologies, and the significance of human capabilities to facilitate the technology adoption. Moreover, ICTs were discussed as essential tools to reinforce human development and facilitate technology diffusion. Second, we analysed the aforementioned hypothesis empirically, by observing the effect of extreme weather events on poverty and the impact of ICTs on this relationship.

JEL Classification Codes: C44, I31, I32, O15, O31, O33, O50, O52, Q16, Q54.

Keywords: Capability Approach, Technology Adoption, Climate Change, Poverty, Diffusion of Innovations, Human Development, ICT.

Resumo

Esta dissertação investiga o papel do desenvolvimento humano, definido na teoria de Abordagem das Capacidades (AC), para clarificar as ligações entre alterações climáticas, tecnologia e pobreza a partir de perspectivas teóricas e empíricas e tem como objetivo oferecer mais perceções na literatura desta área.

O primeiro ensaio, "Construção de um Índice Composto utilizando uma Abordagem Multi-objetivo: uma aplicação ao caso do desenvolvimento humano", propõe um método novo e não convencional para construir um índice composto (IC) para medir o desenvolvimento humano de uma forma mais robusta do que os métodos atualmente existentes, usando o conceito de otimalidade de Pareto no âmbito da otimização multi-objetivo. Este método consiste em dois passos: (i) localizar cada alternativa nas fronteiras de Pareto de acordo com a sua performance nas dimensões selecionadas; e (ii) obter o desempenho geral das alternativas prevendo o índice de desenvolvimento humano usando o modelo "ordered probit", onde as fronteiras de Pareto são vistas como os limites. Na aplicação do IC proposto ao desenvolvimento humano, as dimensões do Índice do Desenvolvimento Humano (IDH) são usadas, o que nos permitiu comparar os dois índices. O nosso ranking demonstrou uma diferença significativa comparativamente ao IDH. O método proposto é novo, robusto, não-compensatório e confiável. Além disso, providencia um ranking eficaz das alternativas.

O segundo ensaio, entitulado "TIC e o Desenvolvimento Humano: uma análise dos países da União Europeia", procura compreender o efeitos das Tecnologias de Informação e Comunicação (TIC) no desenvolvimento humano nos países da UE a partir de diversas perspectivas. A teoria de AC vê as capacidades humanas e liberdades como a chave para o bem-estar. Atingir melhores padrões de vida é apenas possível com maiores capacidades. As TIC emergiram como potenciadoras do aumento das capacidades humanas devido ao seu efeito em diversos canais da vida humana. Assim, nós entendemos ser crucial representar o desenvolvimento humano a partir de uma perspetiva abrangente. Nós seguimos um processo único com três etapas para a construção dos dados, partindo de um conjunto de dados inclusivo de inquéritos a um nível micro, o "European Union Statistics on Income and Living Conditions" (EU-SILC) e

obtendo quatro macro-elementos representativos do desenvolvimento humano. No geral, estes elementos são ricos na informação que incluem de diferentes perspetivas do desenvolvimento humano. Dado que tal conjunto de dados não está disponível nas fontes de dados macroeconómicos, as variáveis de desenvolvimento humano usados neste trabalho podem ser consideradas uma contribuição relevante para este campo. Por último, quatro modelos de regressão diferentes foram construídos, onde cada um considera uma componente do desenvolvimento humano como a variável dependente. Os nossos resultados confirmam o efeito positivo das TIC no desenvolvimento humano nos países da UE a partir de todas as perspectivas.

Finalmente, o terceiro ensaio é chamado "O Papel das Capacidades Reforçadas no Triângulo de Alterações Climáticas, Tecnologia e Pobreza". Este trabalho aborda um tópico importante que merece mais atenção sobre como as capacidades humanas podem encorajar as decisões de adoção tecnológica para reduzir a pobreza associada às alterações climáticas, através da elaboração da seguinte hipótese das perspectivas teórica e empírica: "a difusão das tecnologias de adaptação climática pode reduzir a pobreza vista através da lente da Abordagem das Capacidades": Este artigo promete diversas contribuições para a literatura. Primeiro, ele preenche o vazio entre o papel da capacidades humanas e as decisões de adoção tecnológica, combinando a teoria de CA e a teoria de Difusão de Inovações. As evidências da literatura existente ajudaram-nos a construir uma "framework" analítica que define todas as ligações nesta relação complexa, pela análise do potencial impacto das alterações climáticas na pobreza, da importância da adaptação aos padrões das alterações climáticas para proteger o bem-estar usando novas tecnologias, e da significância das capacidades humanas para facilitar a adoção tecnológica. Além disso, as TIC são discutidas como ferramentas essenciais para reforçar o desenvolvimento humano e facilitar a difusão tecnológica. Segundo, nós analisámos as hipóteses previamente mencionadas empiricamente, observando o efeito de eventos climáticos extremos na pobreza e o impacto das TIC nesta relação.

Códigos de Classificação JEL: C44, I31, I32, O15, O31, O33, O50, O52, Q16, Q54.

Palavras-chave: Abordagem das Capacidades, Adoção de Tecnologia, Mudança Climática, Pobreza, Difusão de Inovações, Desenvolvimento Humano, TIC.

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Chapter 1

Introduction

The Capability Approach (CA) defines a person's freedom to be or to do whatever that person values. The extent of this freedom leads to a happy life, which is the main purpose of human development. Human development, in its turn, induces the development of societies. This definition of human development is multidimensional by nature since anything can be a valuable outcome (i.e. beings or doings) for individuals. Thus, the ultimate purpose of human development is to enlarge the set of freedoms or opportunities that people have. Measuring and determining the indicators that are necessary to enlarge the set of freedoms is crucial. Several works in the literature tried to measure and define the dimensions necessary to enhance human development for this purpose. Moreover, the importance of human development to promote the mitigation of other problems such as climate change and poverty increases the importance of these efforts.

This dissertation aims at providing a further contribution to the Capability Approach from three perspectives: (i) measuring human development, (ii) enhancing human development and (iii) operating human development in practice to diminish climate change and poverty by utilising technology. Each of these perspectives is investigated in a separate essay. Thus, this thesis is comprised of five chapters. After this Introduction where we provide a general outline, three essays and the final chapter with conclusions are presented.

In Chapter 2, we proposed a new and unconventional method to build a Composite Index (CI) that measures human development. As it is explained in the Capability Approach, human development is a multidimensional concept. This definition of human development was adopted by United Nations Development Program (UNDP), and Human Development Index (HDI), which is a CI, was proposed as a measure that captures human development broader than just focusing on monetary aspects. Although HDI was revolutionary in comparison to the older methods due to its dimensional extent, it is criticised due to its computational weaknesses. CIs are powerful tools to observe the performance of various alternatives when several dimensions are in question. Normalisation, weighting, and aggregation are known as the three obligatory steps in building a CI. Particularly, the proposed method in our analysis does not require any of these steps. In this method, we suggest the use of Pareto frontiers, a concept from multi-objective optimisation, to set the solutions (e.g., countries, firms, or alternatives) in an order. Pareto frontiers help to collect similar solutions together according to their performance on several dimensions, sequentially. Each Pareto frontier represents a different achievement level. However, it is not possible to evaluate the solutions that are located in the same Pareto frontier. To identify the performance of each solution within the Pareto frontiers, we implement the ordered probit regression model by considering Pareto frontiers as the thresholds. The estimations of this model are then used to predict the latent variable that represents the unobserved index of human development. A comparison was carried out between HDI and our proposed method. According to the results, the country ranking using the proposed method shows a significant difference compared to HDI, although there is a high Spearman's correlation between them. The proposed method is strong and reliable because it does not require any vague selection of the so-called obligatory steps to build a CI. Moreover, it provides full non-compensatory results and an effective ranking of the solutions.

Chapter 3 investigates the effect of Information and Communication Technologies (ICTs) on Human Development. Human development is considered as defined in the CA theory, where the enhancement of personal opportunities and freedoms is seen as the key to achieving higher well-being. ICT has emerged as a trigger to increase human development. Given the comprehensive perspective of CA, we consider that exhaustively representing human development is critical to our analysis. Thus, departing from an inclusive micro-level survey data, the European Union Statistics on Income and Living Conditions (EU-SILC), we created the human development variables following a three-stage process. EU-SILC dataset covered a cross-section of 32 European countries from 2004 to 2017. In the first and second stages, using the selected variables from the survey data, the first 30 items and then ten dimensions, all human development-related, are created by following the Fuzzy Set Theory. These dimensions are generated by evaluating each country separately for each available year and forming an unbalanced panel of 32 countries and 14 years. Afterward, in the third stage, these ten dimensions are collected within four representative human development components, namely material well-being, financial stability, human capital, and environmental well-being, using the Principal Component Analysis. Overall, these components are rich in the information they include from different perspectives of human development. Given that such data is not available in macroeconomic data sources, the human development variables used in this work can be considered a relevant contribution to the field. At last, four separate regression models are built where each considers one human development component as the dependent variable. The effect of ICT variables (mobile phone, fixed phone, and internet usage) on each human development component is measured through the fixed-effect model by the Feasible Generalised Least Square estimator. Our results confirm the existence of positive interaction between human development and ICT variables from all perspectives.

Chapter 4 addresses an important topic that merits further attention about how human capabilities can encourage technology adoption decisions to reduce poverty associated with climate change through the following hypothesis: 'the diffusion of climate adaption technologies can reduce poverty as viewed through the lenses of the Capability Approach'. To discuss the complex relationships between the dimensions that this hypothesis encompasses, we aim to answer following research questions: (i) what is the expected impact of climate change on people living in vulnerable areas? (ii) Do human capabilities influence the adoption of climate technologies? and (iii) What is the role of reinforced capabilities in the adoption decisions of climate technologies? Thus, this paper promises several contributions to the literature. Initially, it fills the gap between the role of human capabilities and technology adoption decisions. The evidence from existing literature helped us build an analytical framework that elaborates all the links in this complex relationship by analysing the potential impact of climate change on poverty, the importance of adaptation to climate change patterns to protect well-being through new technologies, and the significance of reinforced human capabilities through ICTs to facilitate the technology adoption. To provide a systematic and critical framework for this discussion, we combine the two most relevant theories Sen's 'Capability Approach' and Rogers's 'Diffusion of Innovations'. Afterwards, this analytical framework is used to build a model, which is proper to analyse the aforementioned hypothesis empirically. Our sample covered the unbalanced data of 21 years and 168 countries. Since this model required the consideration of several interactions among the variables, we used the marginal effects to interpret the results. We found evidence of ICTs' importance in reinforcing human capabilities and diffusing climate adaption technologies for poverty reduction. The results of the empirical examination were compatible with the analytical framework.

In Chapter 5, we present the general conclusions, including limitations of our work, and some perspectives for future research.

Chapter 2

Building a Composite Index using the Multi-objective Approach: an application to the case of human development

2.1 Introduction

A composite indicator or composite index (CI) is the mathematical combination of single indicators that represent different dimensions of a concept (El Gibari et al., 2019). CIs are powerful tools for policy makers due to the summary information they provide on multiple dimensions (OECD, 2008). Typically, the construction of a CI involves several steps such as normalisation, weighting, and aggregation methods, when combining the information originating from the various measures (El Gibari et al., 2019). Normalisation is an obligatory process when the data sets have different measurement units. The effort is to convert the data into a scale between 0 and 1. The literature identifies different normalisation methods but there is no method clearly superior to the other. On the other hand, weighting has a critical effect on the final results of CIs. Although weighting each dimension equally is an option, statistical or multi-criteria decision-making approaches arise as more robust methods. Likewise, there is also a plethora of aggregation processes. It is possible to separate aggregation methods into three groups: (i) linear (additive), (ii) geometric, and (iii) multi-criteria decision-making. In the selection of the aggregation methods, compensation between the indicators should be well-considered in order to increase the reliability of the CI (El Gibari et al., 2019). Compensability, which is the likelihood of counteracting the negative effect of an indicator by a positive effect of another, might occur during the aggregation step of CIs, depending on the applied methodology (Munda, 2012). Linear methods cause full compensation, whereas geometric and multi-criteria decision-making methods either allow partial compensation or avoid it entirely.

Selection of the particular methods during these steps is acknowledged as the most disputable issue in the literature of CIs (see. Attardi et al., 2018; OECD, 2008).

In the current paper, we propose a new and unconventional non compensatory method to build a CI that does not require any of the aforementioned steps. Basically, the idea consists on using a combination of the Pareto-optimality concept borrowed from the multi-objective optimisation literature coupled with the implementation of an ordered probit model to provide a parametric structure.

Our proposed method has two phases. The first phase is based on the multi-objective optimisation concept which is a powerful method to solve several objectives simultaneously and separately. Evaluating solutions (e.g. alternatives, countries, firms, etc.) is possible using the Pareto-optimality concept associated with this method. Ultimately, all the solutions are located in Pareto frontiers sequentially, according to their performance on several dimensions. Each Pareto frontier represents a different achievement level. Since the evaluation is dimension specific, this method does not require any data manipulation, such as normalisation. However, it is not possible to evaluate the solutions that are located in the same Pareto frontier using multi-objective optimisation. In order to overcome this limitation and be able to evaluate the solutions one by one and rank them according to their overall performance, we use an 'ordered probit model' as the second phase of the proposed method. This allows ordering the frontiers for the different achievement levels. The two steps allow us to rank all the solutions according to the estimated index values for the several dimensions included in the analysis. Thus, the proposed method also does not require a weighting or aggregation methods which are mandatory in the other approaches that have been used to build a CI.

This process eliminates much of the arbitrariness that was inherent in most of the related methods of conformation clustering. Using this innovative approach we can eliminate much of the arbitrariness that was inherent in the conventional methods for the construction of CIs. There is no longer a need to manipulate of the data or to make ambiguous choices regarding the selection of the methods to follow. Hence, we believe that our proposed method may be an important methodological contribution for the construction of more robust CIs.

As an illustration, we applied our methodology to construct a new the Human Development Index (HDI). The HDI is a CI developed by the United Nations Development Programme (UNDP) in their first Human Development Report (HDR) (UNDP, 1990). The HDI captures the multidimensional nature of human development by combining social and economic indicators, namely, education, health and income.

The HDI is a quite well-known and important measure, due to its simplicity and the public awareness that it creates in society. The comparison and assessment across countries becomes possible both in the dimensional and aggregated level using the HDI (Chiappero-Martinetti and Roche, 2009). However, despite its popularity, the HDI has been criticised for both being methodologically vague and too narrow in terms of the included dimensions which are exposed as inadequate to represent the well-being (Alkire and Santos, 2010). There is a broad literature criticising the HDI (see. Ravallion, 2010; Tofallis, 2013; Sayed et al., 2018). As such, several authors have proposed improvements to the HDI that rely on either the use of different methods and/or new dimensions to be included.

This paper is structured as follows: Section 2 broadly explains our proposal for a general new method to construct a CI. Section 3 focuses on the HDI and encompasses a literature review on the concept and criticisms of this indicator. This section also reviews the efforts undertaken by several authors to address the critiques of the HDI that have been raised. Section 4 contains our empirical application. In this section we apply our method to the calculation of a new indicator for the human development. Additionally, the comparison between our proposed method and HDI is introduced in this section. Finally, Section 5 concludes the study.

2.2 Methodological Proposal based on Multi-objective optimisation

A multi-objective optimisation problem involves the simultaneous optimisation of several objective functions. This problem can be mathematically represented as follows:

$$
\begin{aligned}
\textit{Max(Min)} \qquad & \mu = (f_1(x), f_2(x), \ldots, f_k(x)) \\
\textit{s. t.} \qquad & x \in X
\end{aligned}
\tag{2.1}
$$

Here, μ stands for the objective vector, while $f_i(x)$ is the ith objective in k objectives. Moreover, x is a feasible decision vector, while X is a feasible set of decision vectors (Ishibuchi et al., 2006).

For ease of exposition, we assume a maximisation problem (all individual objectives are maximised). Solution x can dominate solution y if and only if $f_i(x) \geq f_i(y)$ for $i = 1, 2, \ldots, k$ and $f_j(x) > f_j(y)$ for at least one objective function. In other words, a solution should strongly dominate the other solution in at least one objective, while not being dominated by that solution in any other objectives (Konak et al., 2006).

This framework can be used, for example, to analyse human development. The idea is to look at the measurable dimensions of human development as individual objective functions. Countries (as solutions) can increase their level of well-being by improving any of these multiple dimensions. Thus, the particular set of values observed for the indicators that measure these dimensions represents the solution found by that country. This, in turn, means that country A can be better than country B if country A is better-off than country B in at least one dimension and not worse-off in any other dimension.

This logic of domination ultimately helps to assign all the solutions into Pareto frontiers. It is possible to see the domination concept visually in Figure 2.1 where we show hypothetical values for several solutions. Here, we assume only two dimensions, both of which are for maximisation. Under this assumption, the solution located in the point P does not dominate any solution in area B for both dimensions 1 and 2. However, point P dominates all the solutions in area A along dimension 2, but none for dimension 1. The inverse happens for solutions in area C, where the point P dominates all the solutions along dimension 1, but not for dimension 2. Finally, area D shows the full domination area of point P. Solutions located in this area are dominated in both dimensions by point P.

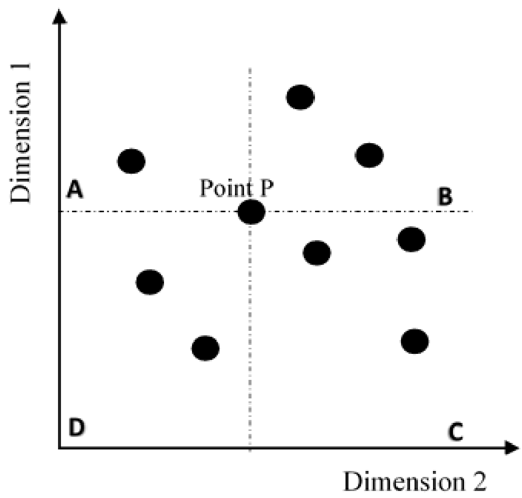


Figure 2.1. Visual representation of the domination concept (Source: Own elaboration)

The domination concept is necessary to set the different solutions on Pareto frontiers. There are two sets for each solution: the "domination count" and the "set of dominating members", which are necessary to rank the solutions on Pareto frontiers. The former shows how many other solutions dominate a given solution. For instance, if solution C is only dominated by solution A and solution B, then the domination count of solution C is equal to two ($n_C = 2$). Moreover, the latter is the set of solutions that a solution dominates. Suppose solution A dominates only solution C and solution H. In that case, the set of domination members for solution A is composed of solution C and solution H ($S_A = \{C, H\}$). These two sets have to be generated for each solution that exists in the solution space. The first Pareto frontier is composed of the solutions with the lowest domination count n. After setting the first Pareto frontier, for each solution J not in the first Pareto frontier, we have to subtract the number of solutions in the first Pareto frontier that dominate J from J's domination count. For example, if the domination count of solution J is 4 ($n_J = 4$), and two of the solutions which dominate the solution J are located in the first Pareto frontier, the domination count of solution J should be decremented one for each solution. That means the domination count of solution J has to be considered as 2 ($n_J = 2$), and solution J should be evaluated accordingly in the second round. In other words, solutions that are only dominated by the solutions located in the first frontier, constitute the second frontier. Moreover, the solutions dominated by only those solutions in the first and second frontiers are located in the third Pareto frontier. This process continues until all the solutions are ranked by their Pareto frontiers (Deb et al., 2002).

It is possible to see an example on different Pareto frontiers in Figure 2.2. Again, in this example, both dimensions are assumed for maximisation.

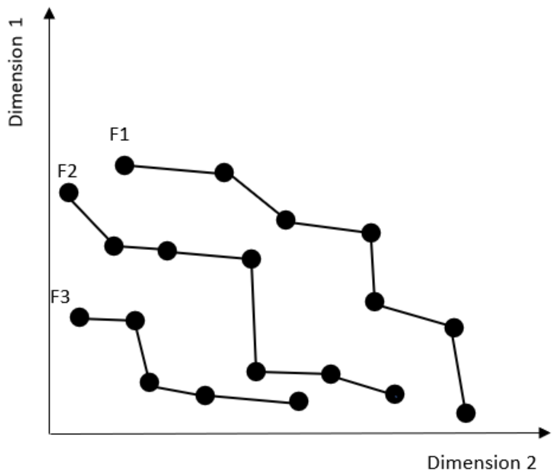


Figure 2.2. An example on Pareto Frontiers (Source: Own elaboration)

Thus, the multi-objective approach considers all the dimensions (criteria) separately. Moreover, it allows working with raw data. In other words, there is no need for any normalisation or data manipulation. The results extracted from each criterion are evaluated in the solution space and sequentially located in Pareto frontiers (Konak et al., 2006).

In the multi-objective approach the points belonging to the same Pareto frontier cannot be compared since it is not possible to say which one is superior without further information. One thing certainly known is that a solution located in a better Pareto frontier has a lower domination count in each round than a solution located in the next Pareto frontier. In a sense, Pareto frontiers are sequential thresholds constituted according to the domination counts of solutions. Likewise, Pareto frontiers provide us with an unequivocal sorting of solutions based on all dimensions that characterise the problem. Thus, after sorting the solutions into Pareto frontiers, we actually have an ordered collection of points. Hence, it is possible to give a generalised interpretation by noting that the points located in the out-most Pareto frontier are expected to be the best, and the points located in the last frontier are expected to be the worst ones.

The question that remains now is how we can explore this information to build a one-dimensional index out of it. To do this, we assume that there is a latent variable that measures the specific problem (e.g. human development). This variable is not observed but is a linear combination of all the dimensions that measure the problem. To be specific, we let

$$f^* = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \epsilon \tag{2.2}$$

where the βs are unknown parameters, the x_i are the different measurable dimensions of the problem and ϵ is an error term that includes all other factors that the model cannot account for. While we do not know f^*, the solution to the multi-objective problem provides us with ranking information that can be exploited to estimate the parameters of the model. This translates into a categorical variable f which takes the values $1, 2, 3, \ldots, J$ reflecting the ordered responses of the variable.

This is a natural setting for using ordered response models. The implicit assumption is that there are unknown cut points (thresholds) $\alpha_1 < \alpha_2 < \alpha_3 < \cdots < \alpha_{J-1}$ such that:

$$\begin{aligned} f = 1 &\text{ if } f^* \leq \alpha_1 \\ f = 2 &\text{ if } \alpha_1 < f^* \leq \alpha_2 \\ &\vdots \\ f = J &\text{ if } f^* > \alpha_{J-1} \end{aligned} \tag{2.3}$$

If we now assume that ϵ follows a known distribution, then we can use maximum likelihood to estimate the α and β parameters. As it is well known, assuming the standard normal distribution results in the ordered probit model (Wooldridge, 2010).

Once the model is created we can use it to predict the latent variable (e.g. (unobserved) index of human development). More specifically, the (estimated) latent variable for solution i can be computed as:

$$Z_i = \hat{\beta}_0 + \sum_{k=1}^{K} \hat{\beta}_k x_{ki} \tag{2.4}$$

The latent variable increases when the solution has better values for any of the dimensions. Thus, it allows us to produce a ranking of all solutions, using Z values.

It is possible to see the mechanism behind this logic in Figure 2.3, visually. The ordered probit model provides a way to obtain a linear counterpart to the Pareto frontiers. These are given by the parallel curves shaped like straight lines, which pass over the Pareto frontiers in Figure 2.3. By construction these lines are parallel to each other. Moreover, the slope of these lines is defined by the model in a way that maximizes the likelihood of the outcomes. To predict the latent variable Z, we can start by creating a new dimension, given by the direction of growth of the estimations of the model. This dimension is perpendicular to the linear curves. The upward arrow in Figure 2.3 represents this dimension. The predictions obtained for each solution are basically the projection of each solution into this new dimension.

Once the model is estimated it becomes possible to rank the solutions located in each Pareto frontier according to the scores calculated by this projection. The use of the predicted scores for the index function provides a clear ranking of all solutions. However, the researcher should be aware that the rankings provided by this method may, in some particular cases, conflict with the results obtained directly from the Pareto frontiers. To see why this may happen consider a simple two-dimension case with the occurrence of two Pareto frontiers. One of the solutions located in a better Pareto frontier may be superior in one dimension (and worse in another

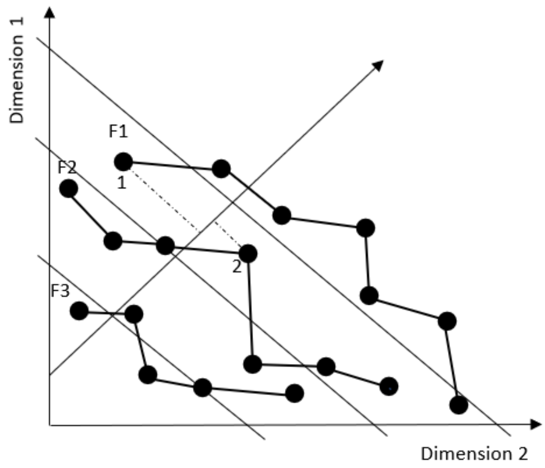


Figure 2.3. Visual representation for the estimation of Pareto frontiers (Source: Own elaboration)

dimension) than a solution appearing in a worse Pareto frontier. Although the solutions do not fully dominate each other, the one with a lower domination count appears in the better frontier. This situation can clearly be seen in Figure 2.3. Solution 1 appears in the F1 (first Pareto frontier), and Solution 2 is located in F2 (second Pareto frontier). Solution 1 is better than solution 2 in dimension 1, while the opposite is valid for dimension 2. Thus, these two solutions do not dominate each other fully. Since Solution 2 is dominated by more solutions than Solution 1, they appear on different Pareto frontiers. In these cases, when the prediction is performed following the ordered probit model, the approximation given by the projection may be better for the solution appearing in the worse Pareto frontier, as is the case in this example.

As it is seen, there is no need for data manipulation or arbitrary weight selection to rank solutions in our proposed method. We believe that this technique exploits the data without imposing many assumptions or using “ad-hoc” procedures. Thus, it provides an objective framework to better understand the contribution of each dimension on a solution for the specific problem (e.g. the level of human development in a country). Moreover, this method is non-compensatory, as all the dimensions are initially evaluated separately. In other words, there is no substitution between the dimensions. Hence, more reliable ranking of the solutions can be observed (Munda and Nardo, 2009; Greco et al., 2019).

2.3 Human Development Index: Concept, Critiques and Improvement Efforts

The CA (Capability Approach) addresses life choices within the framework of human capabilities. According to the CA, resources or commodities are perceived as means with an instrumental value. Moreover, what individuals are able to be and to do, as well as the actual 'beings' and 'doings', are noticed as the ends, which are capabilities (the potential achievements) and functionings (the achievements), with an intrinsic value. In this context, living standards are associated to the ends. In other words, well-being does not only depend on the possession of commodities but also on the ability of a person to use those commodities (Sen, 1983). This ability represents capabilities. For instance, when we consider two separate individuals with exactly the same commodity, we might expect them to have the same utility. However, achieving a higher level of well-being as a result of the potential benefit of this commodity can only be possible if those people have the same command on the same characteristics of that commodity. This command depends on the capability set or the freedom (the real opportunities) of a person. Thus, human capabilities represent the ability to achieve the better. In this example, there are two possible cases not to achieve higher well-being as a result of the possession of the commodity. First, the person may not have the capability (e.g. due to lack of information about the commodity, health constraints, lack of freedom, and so on). Second, the person may choose not to use the commodity (Sen, 1992). Therefore, having more choices in life means having more capabilities, and consequently, having freedom to obtain higher living standards.

The UNDP adopted the idea of human development with its definition under CA and presented HDI, as a comprehensive measure to capture the multidimensional nature of human development. Essentially, HDI aims at capturing the capabilities which are accessible by the individuals in a society (Zambrano, 2014). It includes three dimensions (i.e. health, knowledge and standards of living) to capture human development. These dimensions are built through the following indicators. Life expectancy at birth is used to deputise the length and health degree of life, expected and mean years of schooling are used as proxies of knowledge and GNI per capita (PPP \$) is used for measuring standards of living. These indicators are used to build three sub-indices, each corresponding to a dimension included in the HDI. The health sub-index is calculated by normalisation of the data for each year. The normalisation method used is min-max method (with references of minimum 20 and maximum 85 years of life expectancy) which rescales the data between 0 and 1 by dividing the distance of the actual value from the minimum value by the distance between maximum and minimum values. These values are referenced by UNDP according to the historical data. Income sub-index is built in two steps. First, the income data is log-transformed. Then, it is normalised using min-max method (with references of minimum $100\$$ and maximum $75,000\$$ income) and rescaled. Finally, the education sub-index is built as a composite variable given that it includes two indicators. Each indicator is first normalised by the min-max method (with references of minimum 0 for both education indicators and maximum 15 and 18 for mean years of schooling and expected years of schooling, respectively), and they are composed by arithmetic average of these normalised values.

These dimensions are referred as the essential capabilities that can be used like a tool to obtain a higher level of well-being due to their characteristics (UNDP, 1990). More precisely, all health, knowledge and income have instrumental value for living standards, since they can trigger other capabilities to develop. Furthermore, health and knowledge have also intrinsic value because they can increase human capabilities by themselves. Thus, people can ultimately increase their actual achievements through these three dimensions.

The HDI is accepted as a good measure due to its computational simplicity and its multidimensional coverage on physical quality of life besides the economic welfare. Thus, the HDI became one of the most widely used indicators to capture socio-economic development or well-being (Wu et al., 2014). Although HDI is seen as revolutionary, it is criticised from various perspectives and there have been several suggestions to improve it over the years (Bilbao-

Ubillos, 2013).

The first group of criticisms focused on the adequacy and coverage of indicators used in the HDI. Originally, the definition of human development in CA focuses on individuals with a different understanding of well-being. In such context, perception of the well-being is very rich and can cover some concepts, such as happiness, feeling satisfied, independence etc. which cannot be measured. Thus, from the point of Amartya Sen's CA, human development is not easy to formalise. This situation makes representing the human development fully by a unique number very difficult (Kaushik and Lopez-Calva, 2011). Although it was not possible to formalise all the dimensions of human development, the inclusion of just three dimensions are repeatedly criticised in the literature. The UNDP responded to these criticisms in the 1994 HDR (UNDP, 1994, 91) as follows: "The ideal would be to reflect all aspects of human experience. The lack of data imposes some limits on this, and more indicators could perhaps be added as the information becomes available. But more indicators would not necessarily be better. Some might overlap with existing indicators: infant mortality, for example, is already reflected in life expectancy. And adding more variables could confuse the picture and detract from the main trends." As can clearly be seen, the UNDP aimed to keep the dimensions as simple and clear as possible.

Besides the coverage of the dimensions, some authors criticised the fact that HDI overlooks inequality within countries due to the use of aggregated data (Anand and Sen, 1994). However, the UNDP was always aware of this problem. In fact, UNDP (1990) divulged the weakness of using the country-level average values of the indicators to calculate HDI's dimensions. They pointed out the differences in people's life expectancy, education or income levels in the different parts of the society and argued that the average values would not be representative. Nevertheless, they explained the reasons behind using the average values as follows: (i) unavailability of the more detailed education and health data and (ii) incomparability of income data among countries due to the differences in the income divisions. Thus, aggregated data was used to construct HDI, albeit the importance of inequality was always highlighted in

HDRs over years.

UNDP never altered the coverage of the dimensions in HDI. Instead, they introduced other indices that concerned inequalities. The 1995 HDR proposed the Gender Development Index (GDI) and the Gender Empowerment Index (GEM). The GDI measures the female and male-specific HDIs and proportions them to obtain the index value. On the other hand, the GEM measures the female and male participation in the economic and political life (UNDP, 1995). Furthermore, the Inequity-adjusted HDI (IHDI) and the Gender Inequality Index (GII) were proposed in the 2010 report, again, as alternative measures that emphasise the level of inequality in the societies. GII included health, empowerment, and labour market shares between females and males. IHDI, on the other hand, was a distribution-sensitive index accounting for inequalities in each HDI dimension. There is no inequality in society if IHDI and HDI values are identical (UNDP, 2010).

In addition to the self-effort of UNDP, some authors tried to contribute to the dimensional coverage of HDI. For instance, De la Vega and Urrutia (2001) suggested including the industrial carbon dioxide emission per capita by emphasising the importance of sustainability in human development. Likewise, Morse (2003) suggested adding an ecological footprint and modifying the dimensional coverage of HDI. Ranis et al. (2006) proposed a more comprehensive list of measurable dimensions, including mental health, empowerment, political and social freedom, community well-being, inequalities, work, leisure and environmental conditions, and political and economic security besides the three dimensions of HDI. Finally, it is worth mentioning the survey on HDRs by Alkire (2010) that synthesised the dimensions of HDI and the definition of human development broadly.

The second group of criticisms focused on analytical flaws such as the ambiguous normalisation method, the arbitrary equally weighting scheme and the aggregation method (Safari and Ebrahimi, 2014). Initially, the HDI was calculated as the arithmetic mean of three dimensions. However, this method was fully compensatory and misleading. In other words, perfect substitution could occur between the dimensions and this might lead to the misplacement of a country in the overall ranking (Hou et al., 2015). To avoid this situation, UNDP changed this method and started to use a geometric mean in 2010. The index was no longer fully compensatory, but partially. However, Ravallion (2010) pointed out a serious problem in this new version related to the tradeoffs between the dimensions.[1] Ravallion's findings showed that the implicit weights assigned to the dimensions are misleading. Marginal rates of substitution of educational attainment and longevity, when compared to income, are very high in some countries while being quite low in others. The importance of longevity is under-estimated in poor countries in comparison with developed ones. Thus, for example, a huge decrease in the life expectancy and a small increase in income in a less developed country, due to the implicit weighting scheme of the index, might reverberate as an increase on well-being in the overall results even though this is clearly not the case. Thus, the ranking of the countries might be biased (Ravallion, 2010).

Numerous efforts took place in the literature to eliminate these analytical problems of the HDI. For instance, Herrero et al. (2012) discussed the inconsistencies in the sub-indices that compose the HDI. They criticised the composite variable for education, the log normalisation for income and the min-max normalisation method. Although they support the HDI formula, they recreated sub-indices by following different methods. They used solely expected years of schooling instead of a combination of the two indicators for education. According to them, the definition of this single variable was more powerful for measuring capabilities. They prevented against using the logarithmic transformation for income variable to avoid undesired side effects, such as the hazy connotations on the substitution rates, and the insufficient insights on existing differences between the alternatives. Furthermore, they used just the maximum value as reference to understand how far the country is from the most desired level, instead of min-max normalisation. They rescaled the raw data by dividing them by the maximum value for each indicator. The ranking did not show any significant difference from the HDI, while the proposed method provided consistent cardinal comparisons among the countries.

[1] Tradeoffs show how much of a dimension should be decreased to have an extra unit of another dimension while keeping the index score constant.

Data Envelopment Analysis (DEA) is used by many authors both for weighting and for ranking in the context of human development. For instance, Mahlberg and Obersteiner (2001) used DEA for the first time in the human development context, to both derive weights from the original data set itself and to rank the countries. Moreover, Tofallis (2013) criticised the weighting scheme of HDI and proposed a new method for objective weighting through DEA. The author used the same indicators as in HDI. However, the proposed method is tested in both normalised and raw data form to observe the differences on new weighting scheme. The author used the geometric mean to combine the two indicators (i.e. mean and expected years of schooling) of education. According to Tofallis (2013), using the geometric mean is the equivalent to the education sub-index used by UNDP, since the minimum values are zero for both education indicators. DEA derives the weights automatically from the selected data to maximise the score of the country. It calculates the weighting scheme for each country separately. After deriving the country specific weights, the author regressed the associated scores of each country on the indicators to derive the common weights. According to their results, life expectancy took the highest weight for both normalised and raw data. Income is weighted slightly higher than education, however, both are weighted very low when compared to life expectancy. Likewise, Despotis (2005) also used DEA to measure the relative performance of countries in human development, considering the three dimensions of HDI by deriving the common weights for each indicator. Similarly, Sayed et al. (2018) calculated the weights for the dimensions using Data Envelopment Analysis/Benefit-of-the-Doubt technique (DEA-BOD). Moreover, Lozano and Gutiérrez (2008) concluded that DEA is a more efficient method than the classical method of HDI according to their findings.

It is also possible to find some statistical methods to rebuild the weighting scheme of HDI. One of the most common approaches in the literature was the principal component analysis (PCA). For example, Lai (2000) implemented PCA considering the population size of each country to improve the comparability of HDI in both time and space. Moreover, Nguefack-Tsague et al. (2011) used the PCA based on the correlation matrix of the three components included in HDI to construct weights. PCA is also used for ranking by some authors. Biswas and Caliendo (2002) used PCA technique to combine the measures of human development and create an optimal ranking. This method is evaluated as more objective than the original HDI given the statistical support.

Inconsistency in the ranking of HDI is discussed by many authors. Different methods are proposed to re-measure the HDI and erase inconsistencies. Sayed et al. (2018) proposed a new technique to re-measure the HDI based on the Goal Programming Benefit-of-the-Doubt (GP-BOD) to rank the countries adequately. Safari and Ebrahimi (2014) introduced the Modified Similarity technique, which is one of the multi criteria decision making methods, to rank the countries. They found significant differences between their approach and HDI in terms of ranking. Baliamoune-Lutz and McGillivray (2006) propounded a new method to rank countries using fuzzy set theory according to their well-being. They used the same three components of HDI. According to their results, the ranking of countries is quite different from the classical HDI. Their main claim to implement the fuzzy set theory was the vagueness on the well-being outcomes. Mazumdar (2003) proposed a new method to measure HDI based on D2-statistics. According to this measure, country scale is determined by both the distance of the country from the minimum world level and the distance to the target level of the country. These results showed that the gap between developed and less developed countries is wider than when computed by the original HDI. Moreover, Hou et al. (2015) linked the inconsistencies in the ranking of the countries to the bad choice of selected indicators. They claim that the HDI is not able to capture the flow of human development. Although income is a flow variable, health and education are stock variables which are incapable of capturing real situation of countries since they reflect the cumulative past efforts (Hou et al., 2015). Thus, the authors replaced these stock indicators by flow indicators. Under-five mortality rate is used to capture health instead of life expectancy and gross primary-school enrolment ratio to capture knowledge. Results show that using flow variables improved the ranking of the countries on average for nations with lower human development. However, the opposite is found for countries with high human development. That situation is interpreted as under-recognition of less developed countries although they have higher pace for human development in the current state.

As explained above, the effort to re-measure HDI is extensive. However, although using more advanced methods to create justifiable weighting schema for the indicators or to better rank the countries would ultimately provide superior results to capture human development, there is always subjectivity in the decisions that are made when implementing a methodology to build a CI. Building a CI requires some decision steps, such as normalisation, weighting, and aggregation. Thus, even if the researcher is using an objective method he/she still needs to make subjective decisions.

As we will see in the next section, the main advantage of the method that we propose in the current paper is that it does not require these subjective choices.

2.4 Re-measuring Human Development

As described in the previous section, the assessment of countries according to their human development levels has been the concern of many researchers. In this section, we implement our proposed method to re-measure human development and rank countries according to their performances. All the analyses are done using Python 3.7 and Stata 14.2.

We use the same three dimensions of human development, namely, education, health and income, proposed by UNDP to measure HDI. It is possible to see the dataset, which is available in the UNDP database[2], in Figure 2.4.

To execute the first step of the proposed method, we have used the raw data for income and health dimensions of human development. Moreover, we used the geometric mean of the education indicators to measure the education dimension, following the reasoning of Tofallis

[2]http://data.un.org/

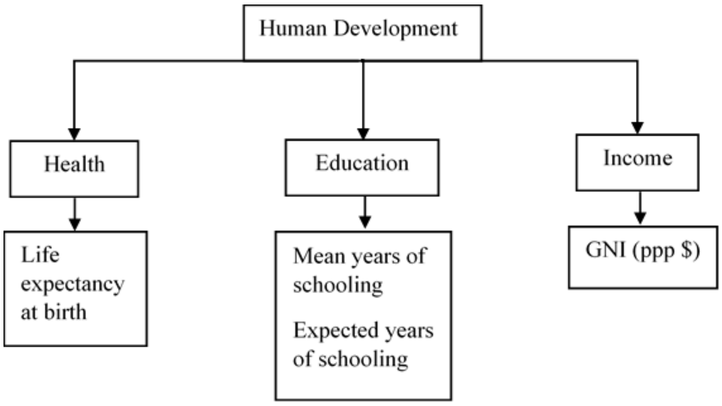


Figure 2.4. Data used to measure human development (Source: Own elaboration)

(2013), as mentioned in Section 3. The geometric mean captures the importance and effect of both indicators on the education dimension.

We have implemented the proposed method on 2018 HDI data for 188 countries. It is possible to see a sample of the data used to create the frontier set in Table 2.1. As it can be seen, no normalisation took place in our exercise.

Country	**Health**	Expected Schooling	Mean Schooling	**Education**	**Income**
Afghanistan	64.5	10.1	3.9	6.27	1746
Albania	78.5	15.2	10.1	12.39	12300
⋮	⋮	⋮	⋮	⋮	⋮
Croatia	78.3	15	11.4	13.07	23061
Cuba	78.7	14.4	11.8	13.03	7811
Cyprus	80.8	14.7	12.1	13.33	33100
⋮	⋮	⋮	⋮	⋮	⋮
Poland	78.5	16.4	12.3	14.21	27626
Portugal	81.9	16.3	9.2	12.24	27935
Qatar	80.1	12.2	9.7	10.87	110489
⋮	⋮	⋮	⋮	⋮	⋮
Turkey	77.4	16.4	7.7	11.23	24905
UK	81.2	17.4	13	15.03	39507
US	78.9	16.3	13.4	14.77	56140
⋮	⋮	⋮	⋮	⋮	⋮
Zimbabwe	61.2	10.5	8.3	9.33	2661

Table 2.1. Data used to set the countries on Pareto Frontiers (Source: Own elaboration)

Table 2.2 shows the sequence of countries allocated to the Pareto frontiers. We identified 22 frontiers for the 2018 data. Frontier 1 includes the countries that dominate all other countries for the three dimensions considered, while frontier 22 involves the countries which are dominated by others. The rest of the countries are located sequentially according to their performance on the three dimensions.[3]

Frontiers	**Countries Located in Each Frontier**
1	Australia, Singapore, Norway, Switzerland, Liechtenstein, Hong Kong, China (SAR), Ireland, Iceland, Sweden, Germany, Denmark, Qatar
2	Netherlands, Finland, Luxembourg, Belgium, Canada, Japan, United States, New Zealand, Korea (Republic of), Israel, United Arab Emirates, Brunei Darussalam
3	Austria, United Kingdom, France, Spain, Italy, Malta, Andorra, Greece, Saudi Arabia, Kuwait
4	Slovenia, Cyprus, Lithuania, Portugal, Bahrain, Oman
5	Czechia, Chile, Costa Rica
6	Estonia, Slovakia, Barbados, Cuba
7	Poland, Latvia, Bahamas, Trinidad and Tobago, Lebanon, Maldives
8	Hungary, Croatia, Argentina, Malaysia, Russian Federation, Turkey, Kazakhstan, Belarus, Palau, Albania, Georgia
9	Romania, Montenegro, Bulgaria, Panama, Uruguay, Seychelles, Iran, Antigua and Barbuda, Saint Kitts and Nevis
10	Mauritius, Serbia, Sri Lanka, Mexico, Bosnia and Herzegovina, Thailand, Colombia, Algeria, Dominica, Ukraine
11	China, Peru, Brazil, Azerbaijan, Ecuador, Armenia, Grenada, Dominican

[3]Python code and the data used to obtain the Pareto Frontiers can be found in: https://github.com/gksoztrk/Composite-Index_Pareto-Frontiers.git

11	Republic, Botswana, Turkmenistan, Fiji, Tonga, Equatorial Guinea
12	Saint Lucia, Kyrgyzstan, Tunisia, Uzbekistan, Paraguay, Marshall Islands, Saint Vincent and the Grenadines, Suriname, Mongolia, Jordan, Jamaica, Venezuela (Bolivarian Republic of), Belize, Philippines, Iraq, Gabon, Moldova, Samoa, South Africa
13	Libya, Indonesia, Viet Nam, Bolivia (Plurinational State of), Morocco, Palestine, El Salvador
14	Egypt, Guatemala, Guyana, Nicaragua, Cabo Verde, Tajikistan, Honduras
15	India, Namibia, Bhutan, Timor-Leste, Bangladesh, Kiribati, Sao Tome and Principe, Vanuatu, Ghana, Solomon Islands
16	Lao People's Democratic Republic, Micronesia (Federated States of), Eswatini, Congo, Cambodia, Nepal, Syrian Arab Republic
17	Myanmar, Pakistan, Zambia, Kenya, Angola, Zimbabwe, Senegal, Rwanda, Nigeria, Madagascar
18	Papua New Guinea, Mauritania, Cameroon, Sudan, Tanzania, Djibouti, Comoros, Uganda, Côte d'Ivoire, Yemen
19	Haiti, Benin, Lesotho, Afghanistan, Togo, Ethiopia, Malawi, Guinea, Congo (Democratic Republic of the)
20	Eritrea, Gambia, Liberia, Guinea-Bissau, Mali, Sierra Leone
21	Burkina Faso, Mozambique, South Sudan, Burundi, Chad, Niger
22	Central African Republic

Table 2.2. Frontier set and countries location (Source: Own elaboration)

Figure 2.5 shows these frontiers visually.[4] As is seen, albeit the countries located in the

[4]It is possible to observe the figure on a bigger scale in here.

higher Pareto frontiers separate more precisely, the other frontiers do not offer such clear distinction. Inspection of Figure 2.5 helps to understand why the countries should be ranked regarding their index values, not the Pareto frontiers they are assigned to.

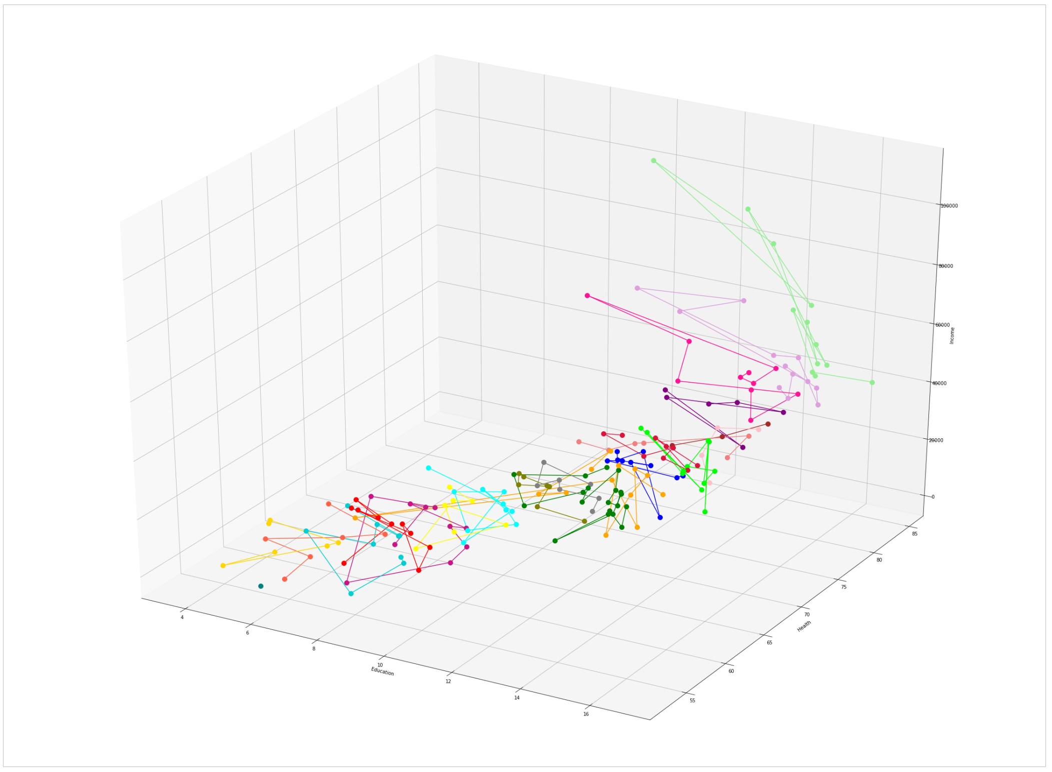


Figure 2.5. Pareto Frontiers (Source: Own elaboration)

As mentioned in Section 2, it is not possible to order two options which appear in the same frontier. Thus, the second step of our proposed method allows for an evaluation of all options located in the same frontier. We run the Ordered Probit Model using the log-transformed GNI values (due to the diminishing marginal utilities), life expectancy and education. It is possible to see the estimation results of the Ordered Probit Model in Table 2.3. Ultimately, it is possible to see that having higher income, education and health indicate better human development, as it is expected.

We next predict the latent variable, which, in our case, is the index of human development. It is possible to observe the predicted scores in Figure 2.6. The colour scale shows the performance of countries on human development. The scale from green to red represents the

Order	Coefficient (β)	Wald
Health	0.2511***	9.73
Log(GNI)	2.699***	12.65
Education	0.5963***	9.25
μ_1	34.8088	
μ_2	37.3051	
μ_3	38.7191	
μ_4	40.3997	
μ_5	41.9971	
μ_6	43.5864	
μ_7	44.6087	
μ_8	46.2914	
μ_9	47.4925	
μ_{10}	48.2885	
μ_{11}	49.7779	
μ_{12}	51.0823	
μ_{13}	52.1585	
μ_{14}	52.9323	
μ_{15}	53.7061	
μ_{16}	54.2644	
μ_{17}	54.7673	
μ_{18}	55.1898	
μ_{19}	56.0001	
μ_{20}	57.2273	
μ_{21}	58.6725	
No of obs.	188	
R^2	0.5811	
Log likelihood	-235.306	

Note: *** indicates <0.0001 significance.

Table 2.3. Ordered Probit Model Estimation Results (Source: Own elaboration)

solutions ranked from best to worst. As expected, performance is better in countries which are on higher frontiers.[5]

Furthermore, in Appendix 2.A we present the predicted score of each country and their associated rank. The latent variable (i.e. the index value) for each country can be observed under the column 'Score'. According to their scores, the overall rank of the countries is presented

[5]This figure can be seen on a larger scale on this link.

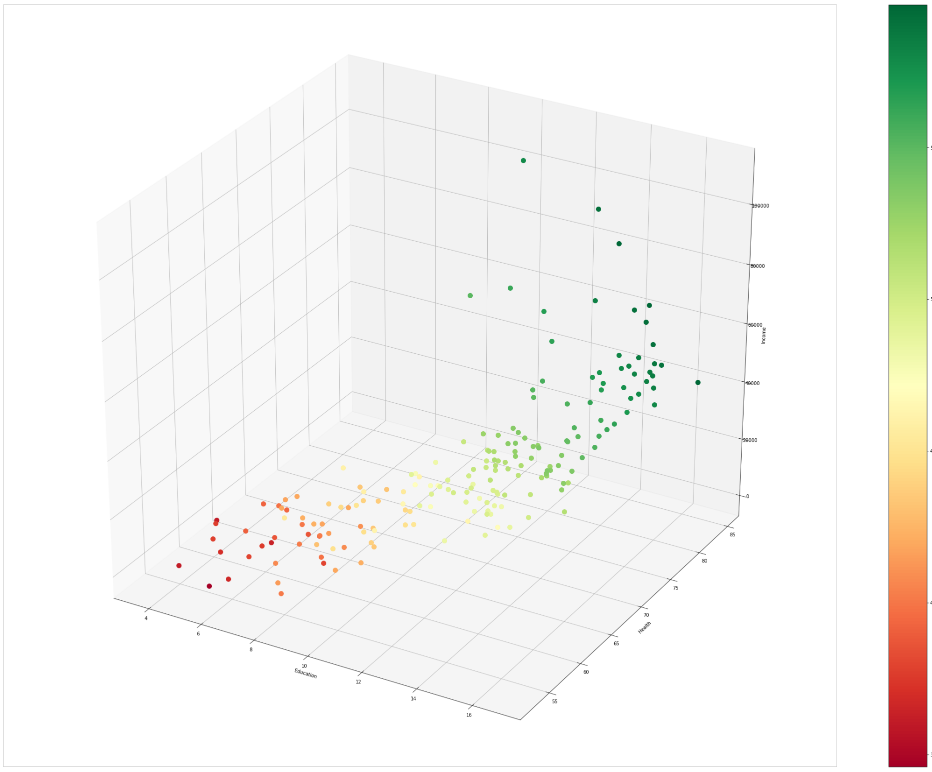


Figure 2.6. Predicted scores of each country with a colour scale (Source: Own elaboration)

in the column 'Overall Rank'. Moreover, the last two columns of the table represent the HDI 2018 ranks and the difference between the rankings of HDI and the proposed index (i.e. HDI Rank - Overall Rank). The last column 'Ranking Difference' is particularly useful since it allows us to quickly identify differences between the two measures. When a country ranks in a worse position in the HDI than the proposed index, the value in 'Ranking Difference' appears positive. The opposite happens when the country is ranked better in HDI than the proposed index. Finally, if both indices rank the country in the same position, then the difference is zero.

An overall measure to compare the the two rankings is obtained by means of a Spearman rank correlation test. According to the results, the Spearman's rank correlation is 0.996 with p-value of almost zero (i.e. $p < 0.0001$). Thus, despite the high value of the measure there is a statistically significant difference between the HDI and the proposed method.

It is possible to see the distribution of the countries comparing the proposed method and

HDI in Figure 2.7.[6] The vertical line shows the rank of the countries according to the HDI, whereas the horizontal line is the rank of the countries according to the results of the proposed model.

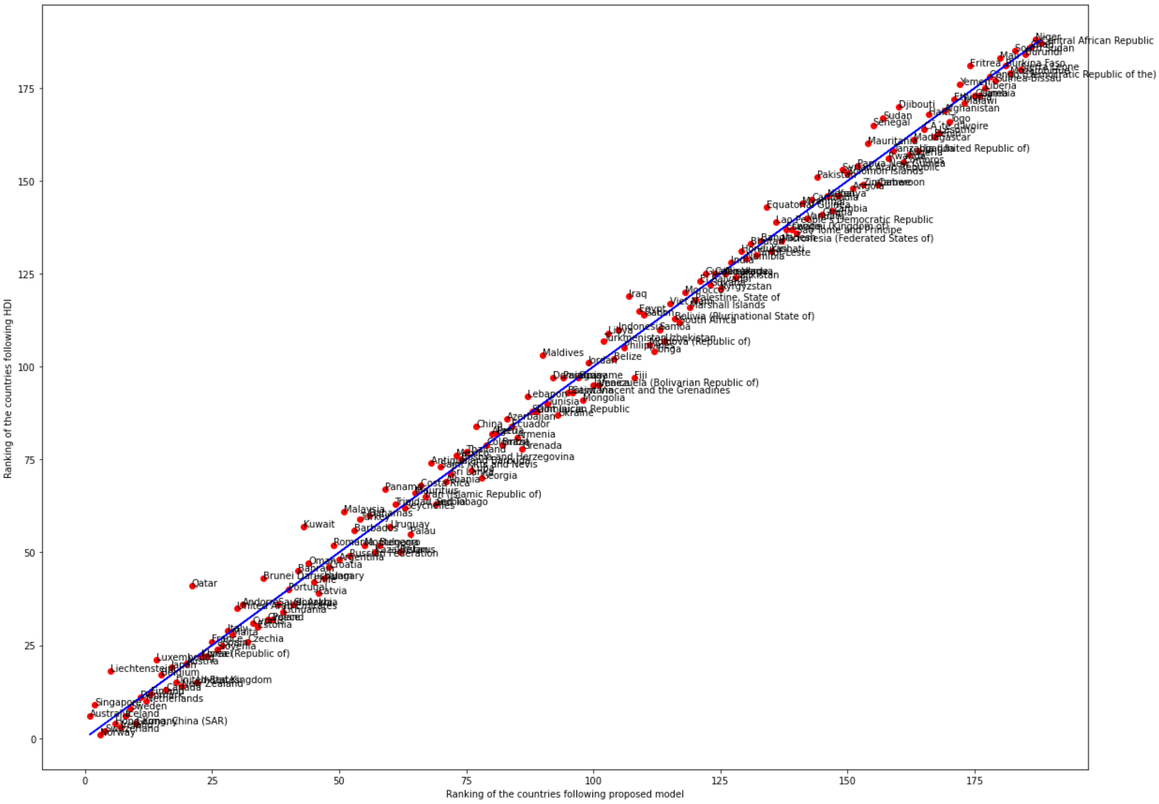


Figure 2.7. The comparison of country ranks between HDI and proposed method (Source: Own elaboration)

As can be observed, there are very few countries ranked at the same level in both the proposed method and HDI. Namely, the countries located in the diagonal are Afghanistan, Austria, Burkina Faso, Chad, Colombia, Congo (Democratic Republic of), Denmark, Ecuador, Nepal, Portugal, Saint Lucia, and Suriname among 188 countries. Moreover, although the results are quite similar for most of the countries, the ranking of some countries showed a slightly larger difference between the HDI and the proposed method, such as Maldives, Qatar, Iraq, or Liechtenstein.

To understand the reasoning behind the difference between country ranks, a closer look may be necessary. For instance, Liechtenstein is ranked as the 5^{th} best country according to

[6] Here it is possible to visualise the Figure 2.7 at a larger scale.

our proposed method, while it was ranked in the 18^{th} position by HDI. Furthermore, Denmark is ranked in the 11^{th} position in both indices. According to the statistics of both countries, Liechtenstein had a growth rate of 5 per cent in 2017 and 4.2 per cent in 2018. However, Denmark's growth rate was less than half of Liechtenstein's growth rate with about 2.4 per cent. Moreover, Liechtenstein performs better than Denmark also in the other statistics related to development, such as GDP per capita, life expectancy or percentage of school enrolment. Likewise, the United Kingdom (UK) ranked in the 22^{nd} position in the proposed method while it is ranked in the 15^{th} position by HDI. Austria ranked in the 20^{th} position in both indices. When looking at the statistics of both countries, it is possible to observe higher growth rates in Austria (with 2.6 per cent in 2018 and 2.4 per cent in 2017) than in the UK (with 1.9 per cent in 2017 and 1.5 per cent in 2018). Moreover, Austria performs better than the UK in GDP per capita and life expectancy over time, and it performs better than the UK in percentage school enrolment since 2015. There are more examples of apparent inconsistencies between the two measures.

There are two limitations of the proposed method which have to be mentioned: (i) it cannot handle missing data, and (ii) having too many dimensions may not operate well during the creation of the frontier sets. The former can be solved through the usage of one of the data imputation methods. The latter is more complicated. The concept of Pareto frontiers uses the logic of domination, as it was explained in Section 2. When there are too many dimensions to compare the solutions it is possible to have all the solutions on the same Pareto frontier. To avoid such situation, the selected indicators to build the composite index should be well considered, and only the key dimensions should be included.

2.5 Conclusion

Although CIs are strong tools to detect the performance of several units on the various dimensions or criteria, they may be controversial due to the subjectivity on the selection of the necessary associated steps, such as normalisation, weighting and aggregation. The current paper proposes a new and unconventional method to build a CI. In this two-step method, we have used the Pareto Frontiers concept of multi-objective optimisation to provide an initial ordering of the countries which is then followed by estimation of an ordered probit regression model. The first step corresponds to the composition of the solutions (e.g. countries, firms or alternatives) on Pareto frontiers according to their performance on selected dimensions, separately. Since multi-objective optimisation evaluates all selected components individually, no data manipulation is needed. Solutions can appear in the same Pareto frontier only if they do not dominate each other on any dimensions. Pareto frontiers only help us to identify the performance of the set of solutions sequentially. In other words, solutions that appear in the best Pareto frontier are supposedly superior than the solutions located in the second Pareto frontier and so on. The second step of the proposed method allows us to calculate a score for each country, and thus to unequivocally rank them. Since the Pareto frontiers are sequential, they represent an order for how the solutions performed on multiple dimensions. Thus, we estimate an ordered probit regression model using as regressors the dimensions to determine the underlying contribution of each dimension to the latent index variable. Estimation of the predicted value for the index provides us with a useful measure for our CI.

In the literature, several critiques have been made regarding the flaws of the HDI in capturing the human development level analytically. Thus, we have proposed and implemented a method that overcomes several of the problems that have been identified for measuring human development. We have used the same data as in the HDI computed by UNDP. In the first step of the analysis (i.e. construction of the Pareto frontiers), we have used the raw data for health (life expectancy at birth) and income (GNI ppp \$). Moreover, we have calculated the geometric mean of the two education indicators of HDI (i.e. mean and expected years of schooling) and included it in the analysis. In the second step (ordered probit regression model), we again have used the same data for health and education. However, we log-transformed the GNI while creating the regression model not to overestimate the impact of GNI due to the inequalities between countries. We implemented the proposed method on 2018 data.

According to the results, the country ranks in the proposed method shows a significant difference with the country ranks provided by the HDI despite the high value of Spearman's rank correlation. More specifically, only 12 countries appear in the same rank position as in HDI among 188. The rank changes for the rest of the countries. These results may be partly due to the known analytical flaws of the HDI.

The method we have proposed also has two limitations. First, missing data may create misleading results. We suggest either the omission of the observations which contain missing data or the imputation of the missing data, if possible. Second, usage of too many dimensions may create a problem due to the logic of domination behind. Given that all the dimensions are evaluated separately and simultaneously, including too many dimensions in the analysis may ultimately make impossible the formation of more than one Pareto frontier. Hence, we suggest a careful selection of the dimensions.

Nevertheless, the proposed method provides an alternative that does not require any vague selection of the so-called obligatory steps to build a CI. Moreover, it provides full non-compensatory results and effective ranking of the solutions (e.g. countries, alternatives) and can be easily applied to other contexts.

2.A The score and the ranking of the countries

Frontier (/Order)	Country	Score	Overall Rank	HDI Rank	Ranking Difference
1	Australia	59.6988	1	6	5
1	Singapore	59.6668	2	9	7
1	Norway	59.6402	3	1	-2
1	Switzerland	59.3801	4	2	-2
1	Liechtenstein	59.3033	5	18	13
1	Hong Kong, China (SAR)	59.3018	6	4	-2
1	Ireland	59.1824	7	3	-4
1	Iceland	59.0553	8	6	-2
1	Sweden	58.8945	9	8	-1
1	Germany	58.6144	10	4	-6
1	Denmark	58.6119	11	11	0
1	Qatar	57.8928	21	41	20
2	Netherlands	58.591	12	10	-2
2	Finland	58.391	13	12	-1
2	Luxembourg	58.3389	14	21	7
2	Belgium	58.3372	15	17	2
2	Canada	58.1609	16	13	-3
2	Japan	58.128	17	19	2
2	United States	58.076	18	15	-3
2	New Zealand	58.0112	19	14	-5

Frontier (/Order)	**Country**	**Score**	**Overall Rank**	**HDI Rank**	**Ranking Difference**
2	Korea (Rep.)	57.5362	23	22	-1
2	Israel	57.4622	24	22	-2
2	United Arab Emirates	56.7636	30	35	5
2	Brunei Darussalam	56.1294	35	43	8
3	Austria	57.914	20	20	0
3	United Kingdom	57.8597	22	15	-7
3	France	57.2183	25	26	1
3	Spain	57.0242	27	25	-2
3	Italy	56.8764	28	29	1
3	Malta	56.8487	29	28	-1
3	Andorra	56.561	31	36	5
3	Greece	55.915	36	32	-4
3	Saudi Arabia	55.6002	38	36	-2
3	Kuwait	55.0271	43	57	14
4	Slovenia	57.0597	26	24	-2
4	Cyprus	56.2724	33	31	-2
4	Lithuania	55.4823	39	34	-5
4	Portugal	55.4441	40	40	0
4	Bahrain	55.1099	42	45	3
4	Oman	54.9455	44	47	3
5	Czechia	56.4981	32	26	-6
5	Chile	54.8252	45	42	-3
5	Costa Rica	52.8785	66	68	2

Frontier (/Order)	Country	Score	Overall Rank	HDI Rank	Ranking Difference
6	Estonia	56.1586	34	30	-4
6	Slovakia	55.32	41	36	-5
6	Barbados	53.4876	53	56	3
6	Cuba	51.6696	76	72	-4
7	Poland	55.7205	37	32	-5
7	Latvia	54.8235	46	39	-7
7	Bahamas	53.3879	56	60	4
7	Trinidad and Tobago	53.1939	61	63	2
7	Lebanon	50.8278	87	92	5
7	Maldives	50.5745	90	103	13
8	Hungary	54.7482	47	43	-4
8	Croatia	54.5154	48	46	-2
8	Argentina	53.6809	50	48	-2
8	Malaysia	53.5909	51	61	10
8	Russian Federation	53.589	52	49	-3
8	Turkey	53.4071	54	59	5
8	Kazakhstan	53.3419	57	50	-7
8	Belarus	53.1767	62	50	-12
8	Palau	52.9859	64	55	-9
8	Albania	52.4626	71	69	-2
8	Georgia	51.533	78	70	-8
9	Romania	53.6932	49	52	3
9	Montenegro	53.3959	55	52	-3

Frontier (/Order)	Country	Score	Overall Rank	HDI Rank	Ranking Difference
9	Bulgaria	53.3115	58	52	-6
9	Panama	53.2401	59	67	8
9	Uruguay	53.2359	60	57	-3
9	Seychelles	53.0036	63	62	-1
9	Iran (Islamic Rep.)	52.8553	67	65	-2
9	Antigua and Barbuda	52.7015	68	74	6
9	Saint Kitts and Nevis	52.6113	70	73	3
10	Mauritius	52.9097	65	66	1
10	Serbia	52.6465	69	63	-6
10	Sri Lanka	51.9251	72	71	-1
10	Mexico	51.7844	73	76	3
10	Bosnia and Herzegovina	51.7593	74	75	1
10	Thailand	51.7545	75	77	2
10	Colombia	51.4197	79	79	0
10	Algeria	51.3734	80	82	2
10	Dominica	50.2163	92	97	5
10	Ukraine	50.0665	93	87	-6
11	China	51.6091	77	84	7
11	Peru	51.3002	81	82	1
11	Brazil	51.2745	82	79	-3
11	Azerbaijan	51.0546	83	86	3
11	Ecuador	51.0348	84	84	0

Frontier (/Order)	Country	Score	Overall Rank	HDI Rank	Ranking Difference
11	Armenia	50.8511	85	81	-4
11	Grenada	50.8342	86	78	-8
11	Dominican Rep.	50.7686	89	88	-1
11	Botswana	49.9524	95	93	-2
11	Turkmenistan	49.4117	102	107	5
11	Fiji	48.9228	108	97	-11
11	Tonga	48.6502	112	104	-8
11	Equatorial Guinea	45.3249	134	143	9
12	Saint Lucia	50.784	88	88	0
12	Tunisia	50.415	91	90	-1
12	Paraguay	50.0059	94	97	3
12	Saint Vincent and the Grenadines	49.8733	96	93	-3
12	Suriname	49.7269	97	97	0
12	Mongolia	49.6881	98	91	-7
12	Jordan	49.643	99	101	2
12	Jamaica	49.6214	100	95	-5
12	Venezuela (Bolivarian Rep.)	49.4958	101	95	-6
12	Belize	49.3611	104	102	-2
12	Philippines	49.0516	106	105	-1
12	Iraq	49.0467	107	119	12
12	Gabon	48.8392	110	114	4

Frontier (/Order)	Country	Score	Overall Rank	HDI Rank	Ranking Difference
12	Moldova (Rep.)	48.726	111	106	-5
12	Samoa	48.6215	113	110	-3
12	Uzbekistan	48.6124	114	107	-7
12	South Africa	48.3384	117	112	-5
12	Marshall Islands	48.2198	119	116	-3
12	Kyrgyzstan	46.9378	125	121	-4
13	Libya	49.3705	103	109	6
13	Indonesia	49.1436	105	110	5
13	Viet Nam	48.524	115	117	2
13	Bolivia (Plurinational State)	48.3594	116	113	-3
13	Morocco	48.3057	118	120	2
13	Palestine, State of	48.0961	120	118	-2
13	El Salvador	47.6251	121	123	2
14	Egypt	48.8682	109	115	6
14	Guatemala	47.555	122	125	3
14	Guyana	47.5011	123	122	-1
14	Cabo Verde	47.0634	124	125	1
14	Nicaragua	46.9181	126	125	-1
14	Tajikistan	46.3514	128	124	-4
14	Honduras	46.2658	129	131	2
15	India	46.5464	127	128	1
15	Namibia	46.2095	130	129	-1

Frontier (/Order)	Country	Score	Overall Rank	HDI Rank	Ranking Difference
15	Bhutan	46.0292	131	133	2
15	Timor-Leste	45.9118	132	130	-2
15	Bangladesh	45.4684	133	134	1
15	Kiribati	45.1429	135	131	-4
15	Sao Tome and Principe	44.5927	140	136	-4
15	Vanuatu	44.2928	142	140	-2
15	Ghana	43.8568	145	141	-4
15	Solomon Islands	43.2617	150	152	2
16	Lao People's Democratic Republic	45.0877	136	139	3
16	Micronesia (Federated States)	44.7686	137	134	-3
16	Eswatini (Kingdom)	44.7672	138	137	-1
16	Congo	44.6744	139	137	-2
16	Cambodia	43.9321	143	145	2
16	Nepal	43.6489	146	146	0
16	Syrian Arab Rep.	43.3406	149	153	4
17	Myanmar	44.4152	141	144	3
17	Pakistan	43.8694	144	151	7
17	Zambia	43.518	147	142	-5
17	Kenya	43.3682	148	146	-2
17	Angola	43.1289	151	148	-3
17	Zimbabwe	42.1781	153	149	-4

Frontier (/Order)	Country	Score	Overall Rank	HDI Rank	Ranking Difference
17	Senegal	41.952	155	165	10
17	Rwanda	41.8619	158	156	-2
17	Nigeria	41.3676	162	157	-5
17	Madagascar	41.0209	163	161	-2
18	Papua New Guinea	42.3225	152	154	2
18	Mauritania	42.1528	154	160	6
18	Cameroon	41.9427	156	149	-7
18	Sudan	41.8619	157	167	10
18	Tanzania (United Rep.)	41.8475	159	158	-1
18	Djibouti	41.8392	160	170	10
18	Comoros	41.5143	161	155	-6
18	Uganda	40.8679	164	158	-6
18	CÃ’te d'Ivoire	40.6863	165	164	-1
18	Yemen	39.3321	172	176	4
19	Haiti	40.2524	166	168	2
19	Benin	40.2273	167	162	-5
19	Lesotho	40.1634	168	163	-5
19	Afghanistan	40.0561	169	169	0
19	Togo	39.8644	170	166	-4
19	Ethiopia	39.7435	171	172	1
19	Malawi	39.2707	173	171	-2
19	Guinea	39.067	175	173	-2
19	Congo (Democ. Rep.)	38.0144	178	178	0

Frontier (/Order)	Country	Score	Overall Rank	HDI Rank	Ranking Difference
20	Eritrea	39.2457	174	181	7
20	Gambia	38.7195	176	173	-3
20	Liberia	38.7185	177	175	-2
20	Guinea-Bissau	37.9461	179	177	-2
20	Mali	37.7809	180	183	3
20	Sierra Leone	36.7347	184	180	-4
21	Burkina Faso	37.6805	181	181	0
21	Mozambique	37.5929	182	179	-3
21	South Sudan	37.016	183	185	2
21	Burundi	36.3905	185	184	-1
21	Chad	36.1686	186	186	0
21	Niger	36.0932	187	188	1
22	Central African Rep.	34.6027	188	187	-1

Chapter 3

ICT and Human Development: an analysis of European Union countries

3.1 Introduction

The Capability Approach (CA), presented by Amartya Sen, explains the scope of well-being from a more complete and comprehensive perspective by focusing on the opportunities that each individual has in order to obtain higher living standards, which they value (Robeyns, 2006). Since poverty has been conceptualised as the lacking of "some basic capabilities to function" (Van de Walle et al., 1995, p.15), freedom and human capabilities are considered as necessary conditions to decrease poverty in the CA theory. Thus, the enlargement of human capabilities is acknowledged as one of the most important remedies to defeat the low level of well-being, to capture better human development and to decrease poverty (Oosterlaken, 2013). In fact, "development" is defined by Amartya Sen in his book *Development As Freedom* as "the process of expanding the real freedoms that people enjoy" (Sen, 1999b, p.36). This definition shows how important it is to centre human achievements, freedoms and capabilities in the core of development. Hence, the enhancement of capabilities and freedoms as the goal of development constitutes, ultimately, development itself (Stewart, 2013).

Technology is an essential component to capture human development since it is often recognised as a critical factor to improve human capabilities and freedoms (see Haenssgen and Ariana, 2018). Information and Communication Technology (ICT), in particular, increases life choices through enhancing human capabilities in terms of health, education, livelihood, democracy and more (Johnstone, 2007; Zheng, 2009; Oosterlaken et al., 2012; Oosterlaken, 2013). Due to all these advantages, technology appears as a factor to consider in measuring human development. There are several theoretical works on the role of ICTs in expanding human capabilities and empirical results which prove the significant effect of ICTs on human development in the literature (Iqbal et al., 2019; Gouvea et al., 2018; Lee et al., 2017).

Besides the positive effect of ICTs on human development, these technologies have a strong potential to protect the environment and support sustainable development. Since the production and consumption patterns can be more efficient due to the transformational power of ICTs, development in the present can be achieved without compromising development in the future (Hilty and Aebischer, 2015). Thus, not only ICTs have the potential to enlarge human capabilities and freedom, but also contribute to the environment and sustainability, which are important indicators for development and well-being.

Given the above argumentation, the main goal of the present paper is to answer the following research question: Is technology an essential determinant to have a better scale of well-being or human development? We answer this question with a fixed-effect model estimated by Feasible Generalised Least Square (FGLS) using an unbalanced panel of 32 European countries over 2004 - 2017.

Since we are considering the definition of human development within the framework of CA, it is necessary to justify the effect of ICTs on many well-being related dimensions that can improve human capabilities or freedoms. For that reason, we followed a different approach to capture human development from several perspectives and built our data through a three-stage process by using an extensive survey dataset on living standards, European Union Statistics on Income and Living Conditions (EU-SILC), by Eurostat. We extracted 30 human development items in the first stage considering several personal or household level data (i.e. questions) available in the EU-SILC dataset. Then, in the second stage, these 30 items were combined to generate ten different human development dimensions at the country-level: education, health, living standards, housing conditions, labour, arrears, environmental quality and safety, desirable items, unmet health treatments, and risk of poverty. The Fuzzy-set Theory is followed during the first and second stages to build these dimensions. Although there are several methodologies for such a micro-level analysis, the fuzzy-set theory, presented by Zadeh (1965), is an adequate methodology to capture the CA since it can create a summary measure using the selected indicators to reflect the incidence of poverty and well-being (Martinetti, 2000). Moreover, it is common to use microdata (i.e. household surveys) to apply this methodology in the literature (see Pham and Mukhopadhaya, 2018; Betti et al., 2013, 2009;

Costa and De Angelis, 2008; Potsi et al., 2016; Qizilbash and Clark, 2005).

One possibility for measuring the impact of ICTs on human development was to consider each of these dimensions as a separate dependent variable. However, it is not possible to work with all ten dimensions for technical reasons. It requires a dimension reduction that we have conducted through Principle Component Analysis (PCA). The PCA is a proper method when the dimension reduction is necessary since it helps to synthesise the wider information (Nevado-Peña et al., 2019). Thus, in the third stage, we collapsed these ten human development dimensions into four components: (i) Material Well-being, (ii) Financial Stability, (iii) Human Capital, and (iv) Environmental Well-being. Each component was appropriately named for the composition of the dimensions and aimed to represent a different perspective of human development. They were formed by taking the geometric mean of the dimensions beneath each component.

In principle, human development is an individualistic concept and it is about enhancing the capabilities of people (Stewart, 2013). Thus, starting from micro-level data and obtaining aggregated components using survey specific weights allowed us to capture the country level human development proxies in a more precise way than getting them from a macroeconomic database. Moreover, another advantage of using a comprehensive micro dataset is the validity of detailed information when compared to those sources. In fact, using data from macroeconomic databases may limit the range of the analysis due to the data scarcity which is the case in most of the studies in the literature. Thus, this paper offers a relevant contribution to the literature due to the scope of the well-being components included in the analysis by following the aforementioned three-stage process.

Three indicators are selected as a proxy for ICT in the current paper to estimate their effect on the human development components. These are mobile cellular subscriptions (per 100 persons), fixed telephone subscriptions (per 100 persons), and internet usage (percentage of population). We have collected these data from the World Development Indicators (WDI) database.

Finally, four control variables (i.e. Financial Development Index, total disposable income, $CO2$ per capita and Population) are included in the analysis due to their potential effect on human development level of the countries.

To display the relationship of ICTs on human development, we used a Fixed Effect (FE) model by FGLS. We build four independent models and estimate the effect of ICTs on each human development component. The existence of heteroskedasticity and serial correlation problems in the data required using the FGLS estimator to obtain efficient estimations. As EU-SILC data includes 32 European countries, our analysis's scope is not comprehensive compared to the world scale. However, we expect to obtain an insight into the effect of ICTs on human development from several aspects.

The paper is structured as follows. Section 2 encompasses a literature review on the relationship between ICTs and human development. While focusing on the empirical literature and outcomes, we also emphasise the relationships between human development, sustainable development, financial development, growth, and ICTs. Section 3 details the data sets and the methods used in the data building process. Section 4 presents the econometric strategy. Section 5 includes the empirical results and discussion on the effect of ICTs on well-being components. Finally, Section 6 concludes.

3.2 Literature review: ICTs and Development

From the CA perspective, development is the improvement of human capabilities or freedoms. Thus, it is necessary to mitigate the reasons that block freedoms, such as low economic and social opportunities, to improve development (Sen, 1999b). Moreover, narrower concepts as growth, social modernisation, sustainability, *etc.* can contribute to improving development.

ICT emerges as a crucial dimension to advance human life from several perspectives. For example, mobile technologies like e-health, e-banking, information systems or e-government operations facilitate human life through its economic, social or environmental contributions (Malaquias et al., 2017). Thus, ICT is relevant in various dimensions of societies and is accepted as a real end due to its potential to lead the community towards a more equitable, inclusive, sustainable and competitive reality (Gouvea et al., 2018).

ICT contributes to human development both directly by improving individual freedoms and indirectly through the adjunct channels, in particular financial development, economic growth and sustainable development. All these concepts and their relationships with ICT diffusion are broadly studied in the literature. The vast majority of the empirical studies conclude for the definite contribution of ICTs on human, financial, sustainable development and economic growth (see Lipovina-Božović et al., 2019; Iqbal et al., 2019; Gouvea et al., 2018; Jin and Cho, 2015; Sassi and Goaied, 2013).

Since the beginning of the 20^{th} century, the advancement of ICT has been associated with economic growth and human development. Given that ICT applications ease access to information and increase the attraction to social initiatives, disparities regarding people's accessibility to these initiatives, both within a country and between countries, decrease (Latif et al., 2017). For instance, Gholami et al. (2010) studied the impact of ICTs on human development in 52 developed and developing countries using a panel from 1998 to 2006. Their results proved the greater positive effect of ICT in less developed countries than the highly developed countries. Hence, the mitigation of the gap between rural and urban areas in terms of development and digitisation between rich and poor countries can be possible by ICT diffusion (Lee et al., 2017; Asongu and Le Roux, 2017).

The financial development is supported by ICT through higher investment and trading activities or lower baking costs, etc., due to internet usage (Raheem et al., 2020). For instance, Chien et al. (2020) studied the relationship between ICT and financial development considering 81 countries for the period from 1990 to 2015. Not only did the authors analyse this relationship, but also they compared the differences among high and low-income countries in the nexus. The authors selected three ICT proxies: (i) internet usage, (ii) fixed phone subscriptions, and (iii) mobile cellular subscriptions. Their results showed the positive impact of ICT on financial development. Particularly, internet usage and fixed phone had a positive impact on both high and low- income countries while mobile phone had a negative effect in high-income countries.

In addition, economic growth is directly related to financial development. Sepehrdoust (2018) measured the impact of ICT and financial development on economic growth. A panel data analysis was done covering the period 2002 - 2015. The results showed that both financial development and ICT positively affect economic growth. Likewise, Sassi and Goaied (2013) examined the effect of financial development and ICTs on economic growth. Besides analysing the direct relationships, the authors checked the impact of financial development on economic growth when integrated with ICTs. The scope of their analysis covered the period 1960 – 2009 and 17 countries included in MENA (the Middle East/North Africa) region, which contains countries with distinct income levels and diverse natural resources. They have selected the percentage of internet users, fixed phone penetration, mobile phone users, and the ratio of ICT imports to the total service imports as ICT proxies. According to their results, ICTs, namely, internet usage, mobile phone and fixed phone, showed a significant positive effect on growth. Financial development initially showed a negative impact on economic growth. However, the authors demonstrated that this negative effect was positive when financial development was integrated with ICTs in high-income and low-income countries in the MENA region. This result was not surprising since the instant conversion from traditional to innovative financial sectors improves economic growth (Khan et al., 2018). Pradhan et al. (2015) studied a similar context by examining the causal relationships through panel cointegration techniques between ICT infrastructure, financial development and economic growth in 21 Asian countries. Their data covered the period between 2001 and 2012. Their results showed the bilateral integration between the three factors: ICT infrastructure - economic growth, financial development - economic growth, and ICT infrastructure - financial development in all income groups.

Furthermore, economic growth and progress in productivity through rapid technology adoption are among the most apparent consequences of ICT usage. Several authors study this first-degree positive relationship between ICT and economic growth. For instance, Dimelis and Papaioannou (2010) investigated the potential effect of ICTs on growth in 42 developed and developing countries for the period 1993 – 2001, based on growth accounting framework and generalised method of moments (GMM) panel data estimator. According to the results, economic growth is highly affected by ICT among all countries included in the analyses. Vu (2011) also employed a GMM estimator to implement a dynamic panel data analysis of the casual links between ICT indicators and economic growth. The authors used computer, mobile phones, and internet users as ICT proxies. Economic growth was measured by considering GDP and control variables as potential growth drivers, such as education, the openness of the economy, agriculture share, investments and institutional quality. Their analyses covered 102 countries and the period spanned from 1996 to 2005. Their results showed that having personal computers, mobile phones and using the internet have a significant positive effect on economic growth both in developed and in developing countries. Likewise, Niebel (2018) analysed the impact of ICT on growth considering a sample of 59 countries – developing, emerging and developed – for the period between 1995 and 2010. They used augmented Cobb-Douglas production function to observe the effect of ICT/non-ICT capital services and labour services on growth by controlling the model for time, countries and their production technology capacities. To estimate the model, the authors used four different regression models, Pooled OLS, Fixed Effect and Random Effect panel data models, as well as Panel IV regression model. Results indicated approximately equal positive impact of ICT investments on growth in developing, emerging, and developed countries. Finally, García-Muñiz and Vicente (2014) studied the connections between ICT and economic growth in sectors from European Union countries for the period 2000 – 2007, based on Input-Output tables and network analysis. According to the findings, the ICT base sectors facilitate sectors' productivity by increasing knowledge and information flows between them. This situation boosts economic productivity. As can be seen, ICT proxies (investments, access or usage) are essential drivers to obtain higher productivity growth.

Moreover, there is a nexus between economic growth, ICT and human development. Cortés and Navarro (2011) studied the influence of ICT on economic growth and human development in EU-27 countries. The authors aimed to detect the differences between selected countries by distinguishing them according to the main information society indicators. According to their findings, ICT improves both growth and human development in countries with higher productivity and social-economic transformation (i.e., countries with higher performance in information society indicators). Similarly, Iqbal et al. (2019) tested the role of ICTs and economic growth on human development in five South Asian countries by using panel data estimation techniques (with Driscoll-Kraay corrected standard errors) for the period from 1990 to 2016: Mobile phone usage and internet penetration were used as ICT indicators. Economic growth and mobile phone usage was found as the trigger to human development.

In addition to countries' innovations and technological capacity being important elements to human development, higher living standards are essential for sustainable development. Thus, it is also necessary to study the links between ICTs, sustainable development, and human development (Nevado-Peña et al., 2019). For instance, Gouvea et al. (2018) have explored the nexus between ICT, human development, and environmental sustainability. The authors implemented simple Ordinary Least Squares regression analysis on 139 countries to show the positive effect of ICTs and human development on sustainable development, both separately and together. According to their findings, enhancement on the ICT supports environmental sustainability. Given that having higher GDP per capita increase the ability to spend on more ICT products, this effect is higher in more developed countries. Likewise, better human capabilities also contribute to environmental sustainability. Finally, human development and ICTs were found as directly proportional. This situation strengths their positive effect on sustainability. The results of Lipovina-Božović et al. (2019) supported Gouvea et al. (2018). They used machine-learning techniques (a method called support vector machine), with a quite comprehensive analysis that covered 139 countries, divided as developed, countries in transition, and developing. Their results confirmed the positive effect of both ICT and human development on environmental sustainability. The more the country was developed, the higher these effects. It is important to emphasise that the effect of human development on sustainable development was found greater than the effect of ICTs. Moreover, ICTs and human development were found as reciprocally related.

These results prove the crucial role of ICT artefacts on sustainable development. Since energy consumption and waste would decrease through ICTs, and the infrastructure of the intelligent or environmentally sufficient transportation systems and buildings would increase, the ICT usage has the power to mitigate climate change and create a more environmentally sustainable economy (Khan et al., 2018). It is also possible to see the contribution of sustainable development on human development by the same reasons.

Finally, we review the direct contribution of ICTs on human development. Nevado-Peña et al. (2019) studied how ICTs (both use and capacity) can affect the quality of life in 79 European regions for the year 2015. Their analysis was quite comprehensive by considering 27 quality of life and 13 ICT indicators. They clustered the quality of life indicators within 4 groups using PCA and measured the effect of ICTs on these four clusters. The results showed that ICT use increases happiness and improves the life quality in the regions with higher ICT capacity. Moreover, Nevado Peña et al. (2020) test the relationship between ICT and human development by considering human development within the context of the CA theory. Their results show that formal education, social capacity, and openness are the most relevant factors for ICT use and ICT capacity in the study area, covering 129 European regions from 18 countries for 2014. Likewise, Oyerinde and Bankole (2019) investigated the impact of ICTs on the education dimension of HDI. According to their results, there is a strong positive relationship between the ICT infrastructure and educational attainment and adult literacy rate. They argued that ICT helps the improvement of human development within the education index. Moreover, Zelenkov and Lashkevich (2020) proposed a model, based on fuzzy linear regression, to measure the relation between ICT and living standards in 112 countries for 2019. The authors used HDI as a proxy for living standards, and network readiness index and global innovation index as proxies of ICT. The results showed the positive and balanced relationship in developed countries. In addition, Lee et al. (2017) aimed to observe the effect of ICT diffusion on human progress. Their sample covered 102 countries and 14 years from 2000 to 2013. Their results showed that ICT diffusion serves as a determinant to human development and improvement globally, although this effect is found higher in developed countries than in developing and emerging countries.

As described above, ICTs have a positive effect on human development both directly and indirectly through several channels. Appendix 3.A provides a short summary of the empirical work included in this literature review focusing on methodologies, sample period, data and data sources.

3.3 Data sources and Construction

The current section presents all the data used in empirical examination including human development, ICT and control variables.

3.3.1 Human Development Variables

As mentioned earlier, our understanding of human development is based on CA theory which requires a comprehensive perspective. EU-SILC data is a great source to capture several dimensions of human development due to its inclusive content.

The EU-SILC is an annual survey implemented on 28 EU member countries plus Iceland, Norway, Switzerland and Serbia since 2004, valid both cross-sectional and longitudinal. It has an integrated survey design to collect the data adopted by several member countries. This design includes a rotational panel that replaces part of the existing sample with new observations (Santourian and Ntakou, 2014). The data need to be comparable since the comparability allows putting different countries together and interpreting them for common standards. Data can be comparable only if the measurement methods and data collections are the same. Thus, these factors are rigidly standardised across participant countries in the EU-SILC for measurement aspects (Verma and Betti, 2006).

We use the cross-sectional version of the data in this study because of the larger number of observations. Cross-sectional data includes information from the current calendar year, provides estimates of cross-sectional levels and estimates of net annual changes (Verma and Betti, 2006).

The scope of EU-SILC is quite comprehensive. It includes variables at both household and personal levels. The questionnaire is designed to obtain information regarding the material, non-material and social attributes of the participants (Verma and Betti, 2006; Eurostat, 2017). Due to this inclusive material that EU-SILC contains, it is possible to estimate conditions on income, poverty, social exclusion, well-being or living conditions (D'Agostino et al., 2018).

Using the sample weights of the dataset is also important to capture the representativeness of the data through the population (Verma and Betti, 2006). Weights include information on i) coverage and selection probabilities, ii) characteristics and circumstances of non-responding units, and iii) structure of characteristics of the target population (Eurostat, 2017).

By starting from the EU-SILC dataset, we have created human development variables necessary to measure the impact of ICTs. These human development variables are formed at the country level, although personal and household-level survey data is used. A three-stage data building process is followed to obtain these variables through fuzzy set theory (1^{st} and 2^{nd} stages) and PCA(3^{rd} stage). The remainder of this section explains these models sequentially.

3.3.1.1 The Fuzzy Set Theory

Fuzzy set theory was first introduced under the framework of "membership in degree" by Zadeh (1965). This theory is a comprehensive and generalised version of the classical set theory (Smithson and Verkuilen, 2006). In the classical set theory, there is a crisp line between two diverse circumstances. For example, let's consider the situation of poverty. People are engaged with the value of 0 and 1 for each poverty dimension. These values show respectively the full non-membership and the full membership to the poor individual set in the classical set theory (Alkire et al., 2015). Fuzzy set theory avoids the definition of such an arbitrary cut-off between poor and non-poor (Cheli and Lemmi, 1995). Indeed, we know that people who live with 1.01$ a day are in a situation similar to people living with 0.99$ a day in terms of living standards within a certain region. However, when there is a poverty threshold set on 1$ a day, these people are treated politically different although that is not realistic. By avoiding this type of arbitrary thresholds, the fuzzy setting measures better represent the reality. Thus, using the fuzzy set allows considering the distribution of the resources in the society to create relative measures (Cheli and Lemmi, 1995). Another advantage of this approach is its ability to handle both ordinal and continuous variables, simultaneously (Chiappero-Martinetti and Roche, 2009).

Essentially, the fuzzy logic extends the set theory to identify varying degrees of membership in the sets (Alkire et al., 2015). Fuzzy set theory is adequate when there is no clear cut-off for dimensions. For example, imagine a heap of pebbles. If one pebble is reduced, the heap will still remain as a heap. Taking another pebble will also not change anything. However, if the pebbles continue to be taken, after a point, no one will call it a heap because there will not be enough pebbles (Qizilbash, 2006). Likewise, if we take 1 dollar from a rich person, the person will still be rich. If we continue taking 1 dollar from the same person, there will be a point in which this person will not be rich anymore. However, this point is vague since it varies between individuals (Smithson and Verkuilen, 2006). The fuzzy set theory is able to handle this vagueness because fuzzy set techniques are able to explore how to be "vaguely right" (Alkire et al., 2015). As Smithson and Verkuilen (2006, p.6) stated, "fuzzy set can handle a particular kind of vagueness – degree of vagueness – which results when we have a property that can be possessed by objects to varying degrees."

This conceptual motivation of the fuzzy logic seems to match with the idea presented by Sen (1992, p.48-49): "if an underlying idea has an essential ambiguity a precise formulation of that idea must try to capture that ambiguity rather than attempt to lose it. Even when precisely capturing an ambiguity proves to be a difficult exercise, that is not an argument for forgetting the complex nature of the concept and seeking a spuriously narrow exactness. In social investigation and measurement, it is undoubtedly more important to be vaguely right than to be precisely wrong."

The main point, in the fuzzy logic, is to have a function of people's achievement on a selected dimension. This achievement gives the probability of the individual to be a member of the set inspected. This function is called "membership function" and can be represented as $\mu_A : X \to [0, 1]$ where μ_A is the degree of membership for the dimension A (Martinetti, 2000). The higher degrees show the higher level of membership. Thus, the fuzzy logic grades the involvement with the set (Alkire et al., 2015). Moreover, since a gradual transition is more realistic than abrupt changes in most of the cases, this can be better captured by measuring the degree of membership with fuzzy techniques (Cerioli and Zani, 1990).

In the implementation level of the fuzzy set, there are four steps to follow: (i) choice of items, (ii) selection of membership function, (iii) grouping the items within dimensions, and (iv) aggregation of membership functions (Betti and Verma, 2008). The first step is the choice of the items which will be used to capture the degree of well-being. For the present analysis, as it was mentioned, we are using set of variables from the EU-SILC dataset that includes comparable surveys from 2004 to 2017 for all participant countries. The second step of the fuzzy set theory application is the selection of the membership function. The adequate membership function should be chosen related to the context and the indicators (Martinetti, 2000).

This step is challenging because the degree of membership changes for different membership functions.

There are three common membership functions: linear, sigmoid and trapezoidal. All of these functions require a description of the lower and upper bounds. In the case of well-being, when we consider all the selected human development dimensions, it is difficult to set these bounds. Given the difficulty to set these values for cases like human development, well-being or poverty, Cerioli and Zani (1990) propose a linear membership function to calculate membership degrees. Their method was updated by Cheli and Lemmi (1995) using distribution functions to calculate the membership degrees. This new method created a smoother transition between the degrees and did not require any bounds selection. Due to these advantages, it became one of the most commonly used membership functions in fuzzy set applications on poverty and human development (see Betti et al., 2015, 2013; Costa and De Angelis, 2008; Potsi et al., 2016). In this paper, we have also used this function, called Totally Fuzzy and Relative (TFR) which can be seen below, in Equation 3.1:

$$\mu_j(x_{ij}) = \mu_j(x_{ij}^k) = \begin{cases} 1 & \text{if } x_{ij} = min(x_{ij}) \\ \mu_j(x_{ij}^{k-1}) - \frac{F_j(x_{ij}^k) - F_j(x_{ij}^{k-1})}{1 - F_j(x_{ij}^w)} & \text{if } min(x_{ij}) < x_{ij} < max(x_{ij}) \\ 0 & \text{if } x_{ij} = max(x_{ij}) \end{cases} \tag{3.1}$$

This function shows the degree of membership of an individual for a given item. Non-monetary items can be in dichotomous or polygamous with more than two ordered categories. Dichotomous variable simply takes 0 and 1 values, while polygamous variables are scaled as represented in Equation 3.1 (Chiappero-Martinetti and Roche, 2009).

In Equation 3.1, x_{ij}^k is the category (k) that the individual i belongs to and j is the selected item (where $i = (1, \ldots, n)$ and $j = (1, \ldots, m)$). $F(\cdot)$ shows the cumulative distribution function of an individual for a specific item. Cumulative distribution functions are computed from the distance or relative frequencies between categories (Alkire et al., 2015).

For example, let's consider that the possible categories (k) which people can sign up for item j is $k = \{1, 2, 3, 4, 5\}$, where $k = 1$ represents the worst category and $k = 5$ is the best one (e.g. for the item education, an individual can sign up into one of the five categories, namely, (1) primary school, (2) elementary school, (3) tertiary education, (4) master, and (5) doctorate according to the educational achievement of that person). Thus, people who signed up to category one $(k = 1)$ for the item j, have the membership $\mu_j(x_{ij}^{(k=1)}) = 1$. Likewise, people who signed up to category five $(k = 5)$ for the item j, have the membership $\mu_j(x_{ij}^{(k=5)}) = 0$. Finally, the others who signed up the categories between two and four (i.e. $k = 2$, $k = 3$, $k = 4$) have a membership degree between 1 and 0. This degree is computed using the formula below which has already been presented in Equation 3.1.

$$\mu_j(x_{ij}^{k-1}) - \frac{F_j(x_{ij}^{k}) - F_j(x_{ij}^{k-1})}{1 - F_j(x_{ij}^{w})}$$

When $k = 2$, $\mu_j(x_{ij}^{(k-1)})$ represents the membership degree of $k = 1$, which is 1. In the numerator, $F_j(x_{ij}^{(k-1)})$ shows the cumulative distribution of $k = 1$, which is equal to relative frequency of $k = 1$, and $F_j(x_{ij}^{k})$ shows the cumulative distribution of $k = 2$, equal to the sum of the relative frequency of $k = 1$ and $k = 2$. In the denominator, $F_j(x_{ij}^{w})$ is the cumulative distribution of the worst case, which is $k = 1$ in this specific example. Moreover, the denominator is constant for each value of k. Using the deprivation score of $k = 2$, we can estimate $k = 3$ repeating the process. Likewise, $k = 4$ can be calculated using the membership degree of $k = 3$. This operation continues until $k = 5$ (which has the score of 0).

Thus, membership functions put all the selected items into the $[0, 1]$ interval for each individual and item. Equation 3.1 represents a decreasing order for membership degree of items (Alkire et al., 2015). This formulation, alternatively, can be represented and implemented with an increasing order as in Equation 3.2:

$$\mu_j(x_{ij}) = \mu_j(x_{ij}^k) = \begin{cases} 0 & \text{if } x_{ij} = min(x_{.j}) \\ \mu_j(x_{ij}^{k-1}) + \frac{F_j(x_{ij}^k) - F_j(x_{ij}^{k-1})}{1 - F_j(x_{ij}^1)} & \text{if } x_{ij} > min(x_{ij}) \end{cases} \tag{3.2}$$

The third step consists of assigning the items to distinct groups. Some statistical methods can be used for such decisions. In the current paper we used cluster methods to group the items into dimensions. However, the results obtained were inconsistent not only for each country but also for every year for the same country. Thus, although we evaluated statistical approaches, we did not adhere to this approach while forming the well-being dimensions. Instead, we took advantage of previous literature, which used the EU-SILC dataset applying the fuzzy set theory while deciding the items that represent each dimension (see Potsi et al., 2016; Betti et al., 2009, 2013).

The aggregation process composes the fourth step of the fuzzy set approach. In this step, first, the individual membership scores are created for each dimension and second, these scores are aggregated to detect the group level membership scores within dimensions (Alkire et al., 2015; Betti and Verma, 2008; Cheli and Lemmi, 1995). In this step, the estimation of the weights for the aggregation must be well-considered.

Equation 3.3 shows the individual membership scores for all items within a dimension μ_i^{jD}. This value occurs differently for each observation unit. We may call Equation 3.3 the horizontal aggregation equation. Equation 3.3 is reproduced for each selected dimension.

$$\mu_i^{jD} = \frac{\sum_{j=1}^{m} w_j \mu_j(x_{ij})}{\sum_{j=1}^{m} w_j} \tag{3.3}$$

In Equation 3.3, j $(j = 1, \ldots, m)$ indicates the items within the dimension D. Thus, Equation 3.3 shows the total membership degree of an individual for a specific dimension considering all membership degrees of all items that belong to that dimension. For example, if there are three items beneath the health dimension, Equation 3.3 aggregates those items to create the individual specific health deprivation score. $\mu_j(x_{ij})$ is the membership degree of the items obtained from Equation 3.1 and w_j is the item specific weights.

Cerioli and Zani (1990) proposed the following specification for the item specific weights.

$$w_j = ln\frac{1}{f_j}, \quad f_j > 0, \quad j = 1, ..., m \tag{3.4}$$

Here f_j shows the intensity of deprivation for the individuals in the j^{th} item, that is the inverse function of the degree of individual membership on a specific item. This specification was updated by Costa and De Angelis (2008) with a proper format for the survey data as follow:

$$w_j = ln(\frac{n}{\sum_{i=1}^{n} \mu_j(x_{ij})w_i}) \geq 0, \quad with \quad \sum_{i=1}^{n} \mu_j(x_{ij})w_i > 0 \tag{3.5}$$

In Equation 3.5, w_i shows the sample survey weights, $\mu_j(x_{ij})$ is the membership degree of the items calculated in Equation 3.1 and n is the number of observations.

Substituting Equation 3.5 into Equation 3.3 gives us the individual membership scores for each dimension. The values calculated by Equation 3.3 will be used to extract a group membership degree of all individuals for a specific dimension with another aggregation equation, which we may call the vertical aggregation equation. This can be seen in Equation 3.6.

$$\mu_i^{TD} = \frac{\sum_{i=1}^{n} \mu_i^{jD} w_i}{\sum_{i=1}^{n} w_i} \tag{3.6}$$

In Equation 3.6, μ_i^{jD} is the membership degree of an individual for a specific dimension calculated in Equation 3.3 and the w_i are the survey sampling weights of each individual. Thus, μ_i^{TD} shows the total of group membership degree of all individuals for a specific (well-being or deprivation) dimension. This score, according to the purpose, can be estimated in the country level, at the regional level, or can even be restricted for different genders and so on.

Table 3.1 shows the selected survey data (last column), which is used to construct the items (middle column) and the dimensions (first column), respectively. In total, ten well-being dimensions are obtained following the fuzzy set approach. We have extracted the country level membership degrees for each dimension separately for each available year in the EU-SILC dataset.

Dimensions	**Items**	**Data**
Education (EDU)	-Educational Achievement	-PE040: Highest ISCED level attained
	-Early school leavers	-PE010: Current education activity
	-People with low education	-PX020: Age
Health (HEALTH)	-General Health	-PH010: General Health
	-Morbidity	-PH030: Limitation in activities because of health problems
Arrears (ARREARS)	-Mortgage	-HS011: Arrears on mortgage or rental payment
	-Bills	-HS021: Arrears on utility bills
	-Loan	-HS031: Arrears on hire purchase instalments or other loan payments
Living Standards (LIV_STD)	-Warm House	-HH050: Ability to keep home adequately warm
	-Holiday	-HS040: Capacity to paying for on week holiday away from home
	-Protein	-HS050: Capacity to afford meal with protein

Dimensions	Items	Data
Living Standards (LIV_STD)	-Extra expenses	-HS060: Capacity to face unexpected expenses
	-Ability to meet the ends	-HS120: Ability to make ends meet
Housing Conditions (HOUSE)	-WC	-HH091: Indoor flushing toilet for sole use of household
	-Bath	-HH081: Bath or shower in dwelling
	-Darkness	-HS160: Problems with the dwelling, too dark, not enough light
	-Leaking roof	-HH040: Leaking roof, damp walls / floors / foundation or not in window frames or floor
Labour (LABOUR)	-Worklessness	-PL031: Self defined current economic status
	-Work intensity	-PL073: Number of months spent on at full-time work as employee
		-PL074: Number of months spent on at part-time work as employee
		-PL075: Number of months spent at full-time work as self-employed (including family worker)
		-PL076: Number of months spent at part-time work as self-employed (including family worker)

Dimensions	Items	Data
Labour (LABOUR)		-PL080: Number of months spent as unemployed -PL085: Number of months spent in retirement or early retirement -PL087: Number of months spent studying -PL090: Number of months spent in other activity
Unmet Treatment (UNMET)	-Medical needs -Dental needs	-PH040: Unmet need for medical treatment -PH060: Unmet need for dental treatment
Environmental Quality and Safety (ENV)	-Noise -Environment -Crime	-HS170: Noise from neighbours or from the street -HS180: Pollution, crime or other environmental problems -HS190: Crime, violence or vandalism in the area
Desirable Items (ITEMS)	-Phone -TV -PC -Washing Machine -Car	-HS070: Do you have Telephone? -HS080: Do you have colour TV? -HS090: Do you have computer? -HS100: Do you have washing machine? HS110: Do you have car?

Dimensions	Items	Data
Risk of Poverty (POV)	-At the risk of poverty	-HX080: Poverty Status

Table 3.1. The list of variables (Source: Own elaboration)

As can be observed in Table 3.1, the selected data are either at the personal level (*i.e.* education, health, unmet treatment and labour) or at the household level. Due to the similarity in the appearance of personal-level and household level weights[1] in EU-SILC, personal-level items are treated at the household level. However, in order not to lose all personal level information, we didn't execute the aggregation initially. First, the membership degree of each item was calculated in the level of the data (personal or household). Afterwards, the membership degrees of the items at the personal level were aggregated to the household level. That way, we got household level average membership degree for each personal-level item. Then, the horizontal aggregation (*i.e.* Equation 3.3) of the items was applied at the household level. Finally, these household-level aggregations were used to obtain country level dimensions by vertical aggregation (*i.e.* Equation 3.6).

In Table 3.1, 'Risk of Poverty' is the only dimension which was not generated by fuzzy set theory. EU-SILC data set includes a variable called 'Poverty Status'. That is a dichotomous variable that takes the value one when the household lives under the 60 per cent of the median income of their society, or zero otherwise. Thus, we took the percentage of people recorded as poor by this variable and included it in the analysis with no further modification.

Four items, namely (i) people with low education, (ii) early school leavers, (iii) worklessness, and (iv) work intensity, are constructed through specific definitions which we have adopted from Betti et al. (2009). The first two items are used as two of the proxies for the

[1] At the household level, each household has a unique weight (DB090). The personal level cross-sectional weights (RB050) are identical to DB090 for each individual. Moreover, PB040 is based on RB050 but may show some differences for the non-response individuals. In most cases and countries, these three variables are the same.

education dimension, whereas the other two are for the labour dimension. Briefly, item (i) – people with low education – shows the deprivation of people with age between 25 and retirement, and who have not more than the lower secondary degree of education. Likewise, item (ii) -early school leavers- identified people with age between 18 and 24 who are currently not into any education or training activity and have lower secondary degree of education or less. Both items are discrete.

The item (iii) -worklessness- shows the ratio between people who enrol to work-life, education or training and the ones with no adequate activity. This item is calculated using variable PL031[2]. Equation 3.7 shows the formula used to construct this item.

$$Worklessness = \frac{\sum PL031(= 1, 2, 3, 4, 9)}{\sum PL031(= 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11)} \tag{3.7}$$

The worklessness ratio is essentially calculated dividing the number of people when PL031 takes value 1, 2, 3, 4, and 9 by the sum of all possible values that this item can take. In the denominator, the value 7 and 10 are counted to the sum if the person is with age lower than retirement, and value 6 if the person is with age higher than 24.

Finally, item (iv) – work intensity – is the ratio between the number of months the person was active in a year and the maximum number of months that a person could work (i.e. 12 months). This item is calculated using the data from PL073 to PL090. It is possible to see how to construct this item in Equation 3.8.

$$\begin{matrix} Work \\ Intensity \end{matrix} = \frac{PL073 + PL074 + PL075 + PL076}{PL073 + PL074 + PL075 + PL076 + PL080 + PL085 + PL087 + PL090} \tag{3.8}$$

[2]The values that PL031 can take and their description - 1: Employee working full-time, 2:Employee working part-time, 3:Self-employed working full-time , 4:Self-employed working part-time, 5:Unemployed, 6:Pupil, student, further training, unpaid work experience, 7:In retirement or in early retirement or has given up business, 8:Permanently disabled or/and unfit to work 9:In compulsory military or community service, 10:Fulfilling domestic tasks and care responsibilities, 11:Other inactive person.

These definitions were necessary for these four items to digitise the information carried by them. Such a transformation was not required for the rest of the items since they were already categorical. Moreover, some variables of the EU-SILC were subject to a few alterations over time. It is possible to see detailed information about these variables and the changes in Appendix 3.B.

The following section explains the last stage of the data building process. A dimension reduction method took place to obtain the human development variables that reached the format used in the econometric study.

3.3.1.2 Principle Component Analysis

PCA is a dimensionality reduction method adequate when dealing with complex data which creates difficulty in the interpretation. This method minimises the information loss while facilitating the interpretability (Jolliffe and Cadima, 2016).

In this paper, PCA was used to reduce the ten human development dimensions to four. Prior to the PCA, two statistical tests, namely, the Kaiser-Meyer-Olkin (KMO) measure for Sampling Adequacy and the Bartlett's Test of Sphericity should be performed.

KMO is an index that verifies the adequacy of the sample for PCA by comparing the magnitudes of observed and partial correlation coefficients. The KMO index value of our data sample was 0.765, which is above the expected minimum value of 0.5 (Tabachnick et al., 2007; Shrestha, 2021).

Bartlett's Test of Sphericity inspects the null hypothesis "the original correlation matrix is an identity matrix". If the null hypothesis cannot be rejected, then the variables are not suitable for structure detection since they are not correlated (Bartlett, 1951; Shrestha, 2021). Our Bartlett test has a Chi-square value of 1867.249 with a p-value of 0.000. Thus, we reject the null hypothesis, and our sample is proper for PCA.

Dimension	Components			
	(1) Mat_Well	(2) Fin_Sta	(3) Hum_Cap	(4) Env_Well
HOUSE	**0.5303**	-0.11	0.0179	0.0848
UNMET	**0.4986**	-0.0629	0.117	-0.197
ITEMS	**0.4834**	-0.0747	-0.1795	0.0558
POV	**0.314**	0.1829	0.1819	0.1375
LABOUR	-0.1287	**0.7229**	-0.0388	0.1459
ARREARS	0.1084	**0.534**	0.0786	-0.273
LIV_STD	0.3137	**0.3585**	-0.1223	0.0159
EDU	0.0588	-0.0643	**0.7094**	0.1509
HEALTH	0.0878	-0.0594	**-0.6277**	0.1511
ENV	0.0049	0.033	0.0263	**0.889**

Table 3.2. Principle Component Analysis (Source: Own elaboration)

As can be seen in Table 3.2, the composition of each component shows different facets of human development. Component 1 is composed of HOUSE, UNMET, ITEMS, and POV that we call Material Well-being (Mat_Well). Here UNMET (unmet health needs) looks misplaced at first sight. However, the EU-SILC database explains that the most common reason for unmet health needs is "Too expensive or too far to travel or waiting list". This shows that the unmet health needs dimension is also related to the material power of the people. Component 2 comprises LABOUR, ARREARS, and LIV_STD that we call Financial Stability (Fin_Sta). Moreover, Component 3 consists of EDU and HEALTH, which are the essential factors of Human Capital (Hum_Cap). Thus, we named it after. Finally, Component 4 includes only the ENV dimension that we call Environmental Well-being (Env_Well).

The dimensions grouped under each component are aggregated by their geometric mean and included in the analysis.

3.3.2 Information and Communication Technology Variables

In the current paper, we have selected three ICT indicators following the empirical literature on human development and ICTs, which are (i) mobile cellular subscriptions (per 100 persons) (MP), (ii) fixed telephone subscriptions (per 100 persons) (FP) and (iii) internet usage (percentage of population) (INT) (see Asongu and Le Roux, 2017). Data is provided from the WDI database of the World Bank Group.

It is possible to see the descriptions of each data, directly taken from the WDI, in Table 3.3.

Data	Description
INT	Internet users are individuals who have used the Internet (from any location) in the last 3 months. The Internet can be used via a computer, mobile phone, personal digital assistant, games machine, digital TV etc.
MB	Mobile cellular telephone subscriptions are subscriptions to a public mobile telephone service that provide access to the PSTN using cellular technology. The indicator includes (and is split into) the number of postpaid subscriptions, and the number of active prepaid accounts (i.e. that have been used during the last three months). The indicator applies to all mobile cellular subscriptions that offer voice communications. It excludes subscriptions via data cards or USB modems, subscriptions to public mobile data services, private trunked mobile radio, telepoint, radio paging and telemetry services.
FP	Fixed telephone subscriptions refers to the sum of active number of analogue fixed telephone lines, voice-over-IP (VoIP) subscriptions, fixed wireless local loop (WLL) subscriptions, ISDN voice-channel equivalents and fixed public payphones.

Table 3.3. Description of ICT indicators (source. WDI, 2019)

The variables MP and FP are included in the analysis in the logarithmic form. Since INT is a percentage, we opted to keep it in its original form.

3.3.3 Control Variables

Four control variables are selected: Financial Development Index (FD), Carbon Dioxide Emission (metric tons per capita) ($CO2$), Total Disposable Household Income (INC), and Total Population (POP). These control variables are chosen not to overlook their potential effect on human development as proxies of Financial Development, Sustainable Development, and

Growth, respectively.

FD is a composite index developed and presented by the International Monetary Fund (IMF) that summarises the financial development in terms of debt (size and liquidity), access (ability to access financial services) and efficiency (ability to provide financial services) of financial institutions and markets. Due to its inclusive multi-dimensional content, FD is stated as a prominent option among the other financial development proxies common in the literature, such as stock market capitalisation to GDP or the ratio of private credits to GDP by Shobande and Ogbeifun (2021). Thus, we preferred to use FD to capture financial development in the present work. $CO2$ is taken from the World Development Indicators database by Worldbank and represents the carbon dioxide produced per person while consuming solid, liquid and gas fuels or gas flaring. $CO2$ is included as a control variable since, in the literature, it is the most used proxy when it comes to the environmental performance of the countries.

Household income level is often associated to the growth of the countries (Roser, 2013). Thus, we used Total Disposable Household Income data available in EU-SILC to calculate country level income variable. This variable is valid in EU-SILC at the household level with ID HY020, as the sum of all personal and household level gross income components minus the total transfers, such as insurance contractions, mortgage, taxes, etc.. Moreover, as several papers acknowledged in the literature (see Dyson et al., 2005; Zgheib et al., 2006), population is also important for human development. It is possible to obtain total population of the countries from EU-SILC using the household size (with ID HX040) variable. Thus, INC and POP data are generated from EU-SILC dataset following the formula in Equation 3.9, presented by Törmälehto et al. (2019).

$$\sum_{n=1}^{N} w_n \times X_n \tag{3.9}$$

In equation 3.9, w_n represents the sample survey weights[3] for each household n, $n =$

[3] with id DB090

$1, 2, ..., N$ and X_n is either total disposal income variable or household size.

The logarithmic transformation of INC, $CO2$ and POP are used in the econometric examination whereas FD is considered in levels since it is an index with already normalised values.

3.4 Econometric Strategy

As stated previously, we aim to evaluate the nexus between human development and ICT proxies using the data covered in 32 countries and the unbalanced panel of 14 years (2004 - 2017). It is possible to see the countries and their panel structure in Appendix 3.C.

The list of variables and their descriptive statistics are presented in Table 3.4.

Variable	Obs	Mean	Std_d	Min	Max
Mat_Well	404	0.8873961	0.0427499	0.719445	0.9488162
Fin_Sta	404	0.7815364	0.0563709	0.5826704	0.8758942
Hum_Cap	404	0.7672837	0.0169379	0.7121298	0.8116455
Env_Well	404	0.8373702	0.061816	0.5553214	0.9477338
INT	404	3.620203	0.16988	0.2142	0.9824002
ln(MP)	404	4.768824	0.1445027	4.295737	5.148202
ln(FP)	404	3.620203	0.399584	1.925496	4.206833
ln(INC)	404	24.84819	1.634806	21.68478	27.99863
ln(CO2)	404	1.946284	0.3890669	1.08678	3.245272
FD	404	0.591286	0.1963803	0.2158221	1
ln(POP)	404	15.75047	1.45847	12.54727	18.21775

Table 3.4. Descriptive Statistics (Source: Own elaboration)

The first part of the table shows the human development variables (Mat_Well, Fin_Sta, Hum_Cap and Env_Well) generated through a three-stage data building process, as is specified in Section 3. Since the human development dimensions used to construct these factors are measured using fuzzy set theory by scoring the performance of each country on each dimension between zero and one [0, 1], where 1 is the best and 0 is the worst, these factors are also in the range between zero and one. The second and third parts of Table 3.4 are the ICT and control variables, respectively, with the format that they are included in the regression models (i.e. log-transformed or level).

As mentioned before, four separate regression models are constructed. Each human development proxy is included in the models as the dependent variable to understand the effect of ICTs on human development from several perspectives. These models are described in Equations 3.10-3.13.

$$\begin{aligned} Mat\_Well_{jt} &= \beta_1 INT_{jt-1} + \beta_2 ln(MP)_{jt-1} + \beta_3 ln(FP)_{jt-1} \\ &+ \beta_4 ln(INC)_{jt-1} + \beta_5 ln(POP)_{jt-1} + \delta_t time_t + \epsilon_{jt} \end{aligned} \tag{3.10}$$

$$\begin{aligned} Fin\_Sta_{jt} &= \beta_1 INT_{jt-1} + \beta_2 ln(MP)_{jt-1} + \beta_3 ln(FP)_{jt-1} \\ &+ \beta_4 FD_{jt-1} + \beta_5 ln(POP)_{jt-1} + \delta_t time_t + \epsilon_{jt} \end{aligned} \tag{3.11}$$

$$\begin{aligned} Hum\_Cap_{jt} &= \beta_1 INT_{jt-1} + \beta_2 ln(MP)_{jt-1} + \beta_3 ln(FP)_{jt-1} \\ &+ \beta_4 ln(INC)_{jt-1} + \beta_5 ln(POP)_{jt-1} + \delta_t time_t + \epsilon_{jt} \end{aligned} \tag{3.12}$$

$$\begin{aligned} Env\_Well_{jt} &= \beta_1 INT_{jt-1} + \beta_2 ln(MP)_{jt-1} + \beta_3 ln(FP)_{jt-1} \\ &+ \beta_4 ln(CO2)_{jt-1} + \beta_5 ln(POP)_{jt-1} + \delta_t time_t + \epsilon_{jt} \end{aligned} \tag{3.13}$$

Here j is the country, and t is the time. Moreover, β and δ are the corresponding parameters to be estimated subject to independent variables and time dummies, respectively. Finally, ϵ is the error term. We included time dummies in the models to capture the trends, to account for the change over time.

We included ICT variables a year-lagged following Rogers (2010)'s diffusion and innovation theory, which suggests there is a time gap between the technological innovation emergence and its use. Thus, ICT diffusion or usage is expected to impact on people's lives after a certain time. Therefore, we observed the impact of ICT measured in time $t - 1$ on human development dimensions in time t. The control variables are also included as one year-lagged in the regression models for the same reasoning.

As it can be seen, not all control variables are used in all regression models, being considered only in the related equations. For instance, equations 3.10 and 3.12 aim to estimate the effect of ICTs on Mat_Well and Hum_Cap, respectively, and contain only INC and POP as control variables. Mat_Well is composed of four dimensions, all income-based. Thus, it is expected that INC may have an effect to be controlled on this component. Moreover, Hum_Cap includes variables related to educational achievement and health status, expected to be influenced by INC to access and benefit from these sources. Especially if the necessity to pay tuition fees to obtain higher education in most EU countries, such as Portugal, Lithuania, Netherlands, is considered. FD and $CO2$ were not thought relevant to control the relationship between Mat_Well or Hum_Cap and ICT variables. Thus, we didn't include them in Equations 3.10 and 3.12. Equation 3.11 includes FD and POP as control variables. The dependent variable Fin_Sta comprises three human development dimensions related to being financially durable. More precisely, the ability to afford a basic comfortable life without debts and a stable job and salary summarise the Fin_Sta component. When the definition of FD is considered, the potential effect of FD on the relationship between Fin_Sta and ICT variables may be relevant. For this equation, INC is also considered as control variable; however, since INC and FD are correlated (about 71 per cent), we avoided including INC. Finally, Equation 3.13 corresponds to Env_Well, which is about living in an environment with less pollution, crime or insecurity. Thus, it is adequate to control the relationship between Env_Well and ICTs by the $CO2$ and POP.

The type of estimator was selected by following several tests. Panel data structure is often characterised by problems such as heteroscedasticity, serial correlation or cross-sectional dependence (Chen et al., 2010). The presence of one or more of these problems makes most of the panel data models weak because of the difficulties in the solution procedure (Reed and Ye, 2011). Selecting a proper estimator that can handle existing problems in the data is vital to obtain efficient and reliable results.

Thus, we tested our models for these problems to decide the most convenient estimator. It is possible to see the test results in Table 3.5.

The likelihood ratio panel test was implemented to examine for heteroscedasticity. The results were significant for each model, indicating the existence of heteroscedasticity. Thus, the correct estimator must account for the variance of the perturbation term to differ across panels. Moreover, the Wooldridge panel test is used to analyse for the existence of serial correlation. The results were significant for each regression model. Thus the null hypothesis of 'no first-order autocorrelation' was rejected. Finally, according to the Pesaran test, no evidence was found for cross-sectional dependence[4].

Test	Mat_Well	Fin_Sta	Hum_Cap	Env_Well
Likelihood-Ratio Test	586.44***	146.36***	194.26***	502.99***
Wooldridge Test	122.791***	135.082***	77.704***	76.823***

Note: ***indicates significance at 0.001.

Table 3.5. Panel heteroscedasticity and serial correlation (Source: Own elaboration)

Given that we handle unbalanced panel data with heteroskedasticity and serial correlation problems, the FGLS estimator is a proper method to obtain efficient results.

Furthermore, we inspected the models for the country effects that may be overlooked. To do that, we also included country dummies in each regression model. A Wald test was used to examine whether country-specific effects enrich the estimations. It is possible to see the Wald test results in Table 3.6 being significant for all equations, which meant country-specific effects needed to be accounted for. Thus, country-specific fixed effects were included in each equation as country dummies. Accounting for country fixed effects helps understanding the static differences per country. In other words, time invariant omitted variables can be controlled by

[4]The null hypothesis of the Pesaran test inspects for cross-sectional independence. The results were insignificant in each regression model. Thus, we can conclude that there is cross-sectional independence.

including the country fixed effects in the model (i.e. country dummies).

Test	Mat_Well	Fin_Sta	Hum_Cap	Env_Well
Wald Test	1324.03***	2716.00***	1708.30***	2359.18***

Note: ***indicates significance at 0.001.

Table 3.6. Wald Test for Country-specific Fixed Effects (Source: Own elaboration)

Another problem that may appear in our models is the correlation across equations. Since we obtained the dependent variables from the same data source through several steps, the error terms of regression models may be correlated. When this occurs, the right approach is to use an estimator proper to deal with a system of equations. However, the estimators, such as the Seemingly Unrelated Regression or Three and Two-Stage Least Squares, cannot deal with the previously acknowledged problems, namely heteroskedasticity and serial correlation. Thus, we have chosen the FGLS estimator and obtained the results separately for each model.

Therefore, the fixed-effect model by FGLS was used to estimate four regression models specified in Equations 3.10 to 3.13 by including country dummies.

3.5 Results and Discussion

Tables 3.7 and 3.8 show the results of the fixed-effect model estimated by FGLS for the models specified previously (see Equations 3.10 - 3.13), that aim to measure the effect of selected ICT variables on human development from four different perspectives: (i) Mat_Well, (ii) Fin_Sta, (iii) Hum_Cap and (iv) Env_Well. Results presented in Table 3.7 correspond to the shortened models that show the impact of ICT variables on human development components without considering the control variables. Results presented in Table 3.8, on the other hand, relate to the full models where the control variables were also taken into account.

While building the models, we took into account panel specific first-order autocorrelation

(PSAR1) and panel-level heteroskedasticity of standard errors. A year and country dummies were included in both models, and standard errors were presented in the parenthesis.

According to the results of the shortened models in Table 3.7, FGLS confirmed the significant positive effect of INT on all four human development components. As it can be seen, a one percent increase in internet usage increased the likelihood of having better human development the most in the Env_Well component, followed by Mat_Well, Fin_Sta and Hum_Cap, respectively. Moreover, the positive effect of MP emerges in three human development components, namely, Mat_Well, Fin_Sta and Env_Well. However, its effect was not significant on Hum_Cap. Finally, the impact of FP was opposing on different components. More precisely, FGLS confirmed the positive effect of FP in Fin_Sta which was compatible with the previous literature (see Chien et al., 2020). On the other hand, Mat_Well was affected negatively by FP. Besides the previous literature that confirms this negative effect (see Lee et al., 2017), it is acknowledged by the International Telecommunication Union (ITU, 2015) that the fixed phone lines have had a descending trend worldwide in the last years, especially in high income countries. Thus, the negative effect of FP on Mat_Well, especially when its content is considered (i.e. mainly represents monetary-based channels of human development), was not surprising. The effect of FP was not significant for Hum_Cap and Env_Well.

The results of the full models, including the control variables, are presented in Table 3.8. Moreover, we included the estimations with the year and country dummies in Appendix 3.D.

The estimations for Equation 3.10 showed similar results to the shortened model regarding the direction of the relationship between ICT variables and Mat_Well. However, the positive impact of the INT was lower in this model. Besides, MP and FP were not significant for the level of Mat_Well. Moreover, the positive effect of INC was shown by the FGLS estimator. More precisely, a 10% increase in INC and POP affects Mat_Well by 0.17 and -0.43 percentage points in the following year, respectively.

	Mat_Well_t	Fin_Sta_t	Hum_Cap_t	Env_Well_t
INT_{t-1}	0.0433703***	0.0220672**	0.018037**	0.1124269***
	(0.0078683)	(0.0115179)	(0.0077871)	(0.0173394)
$ln(MP)_{t-1}$	0.0154025***	0.0408041***	-0.0066189	0.0272489***
	(0.0045201)	(0.007732)	(0.0042686)	(0.0112519)
$ln(FP)_{t-1}$	-0.0056635**	0.0083095**	0.0003383	-0.0090473
	(0.0024713)	(0.0044657)	(0.003074)	(0.005783)
Cons.	0.8319425***	0.5865968***	0.768963***	0.6947717***
	(0.0235307)	(0.0409987)	(0.0231474)	(0.0613234)
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
χ^2	7257.29	31704.35	2460.03	2605.64
$Obs.$	372			

$Note$:***$p \leq .01$,**$.01 < p \leq .05$,*$.05 < p \leq .1$.

Table 3.7. FGLS results without control variables (Source: Own elaboration)

The estimations for Equation 3.11 also showed similar results to the shortened model in terms of the effect of ICT variables on Fin_Sta with some differences. For instance, the INT variable was not significant. Moreover, the effect of the MP on Fin_Sta was slightly lower while FP was quite higher in comparison to the shortened model. Furthermore, the control variable FD showed a substantial positive effect on Fin_Sta while POP showed a negative impact, as expected.

According to the estimations for Equation 3.12, the positive effect of INT on the Hum_Cap component was confirmed, as was the case in the shortened model. This time, MP was significant with a negative impact on Hum_Cap. This adverse effect of MP was unexpected. The reason for that reverse relationship could be the data that has been used to generate the Hum_Cap component. Hum_Cap is composed of Education and Health dimensions. Some items used to create these dimensions were subjective, such as 'general health' based on a question that the survey participants evaluated their health status from bad to excellent. The effect of FP was again insignificant. Finally, the INC positively affected the likelihood of having a higher Hum_Cap level. The negative effect POP was not significant.

Finally, according to the estimations for Equation 3.13, INT and MP had a significant positive effect on Env_Well, with almost the same strength as in the shortened model. FP was again not significant. Moreover, both control variables $CO2$ and POP showed significant negative impacts on Env_Well, with POP having the greater effect. These results are highly predicted since environmental comfort would be unexpected in a highly polluted or populated area.

	Mat_Well_t	Fin_Sta_t	Hum_Cap_t	Env_Well_t
INT_{t-1}	0.0257039***	0.0062108	0.0133427**	0.1038268***
	(0.0082083)	(0.0115284)	(0.0071887)	(0.0168814)
$ln(MP)_{t-1}$	0.0005922	0.0283102***	-0.0128639***	0.0288734***
	(0.0046167)	(0.007653)	(0.0042984)	(0.0109028)
$ln(FP)_{t-1}$	-0.0028673	0.0104588***	0.0022575	-0.0064493
	(0.0024286)	(0.0049619)	(0.0032722)	(0.0052788)
$ln(INC)_{t-1}$	0.0173445***		0.0130308***	
	(0.0026118)		(0.0022089)	
FD_{t-1}		0.0304801***		
		(0.0151395)		
$ln(CO2)_{t-1}$				-0.030942***
				(0.0112537)
$ln(Pop)_{t-1}$	-0.042769***	-0.1400383***	-0.0106435	-0.0891132***
	(0.0126464)	(0.0249887)	(0.0100985)	(0.0326406)
Cons.	1.142382***	2.853334***	0.6326814***	2.167687***
	(0.1950952)	(0.4088789)	(0.1805777)	(0.53006)
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
χ^2	7254.52	34224.30	2510.80	3182.29
$Obs.$	372			

$Note$:***$p \leq .01$,**$.01 < p \leq .05$,*$.05 < p \leq .1$.

Table 3.8. FGLS results with control variables (Source: Own elaboration)

As it can be seen, POP affected negatively all human development components, which is compatible with the previous findings (see Gouvea et al., 2018; Lipovina-Božović et al., 2019). Moreover, the positive effect of INC and FD on human development supported the previous studies that proved the positive interactions between economic growth, financial development and human development, as mentioned in Section 2 (see Cortés and Navarro, 2011; Pradhan et al., 2015; Iqbal et al., 2019). The negative effect of $CO2$ on human development is also expected since higher pollution and environmental damage would diminish the quality of life (see Wang et al., 2019; Akbar et al., 2021). Finally, our findings support the positive effect of ICT variables on well-being from several perspectives (see Lee et al., 2017; Gouvea et al., 2018; Iqbal et al., 2019).

These results conclude that the EU countries may increase the human development level from different perspectives by investing in the access and use of ICTs.

3.6 Conclusion

Human development is associated with the opportunities and freedoms that each individual has according to Sen (1999b) in his theory 'Capability Approach'. The enhancement of freedoms is seen as the key to reaching better living standards in this theory. Technology, particularly ICT, emerged as a trigger factor for this enhancement to obtain higher human development.

The present work aims to test the relationship between ICT usage and several human development components to understand whether ICT is essential to have better well-being.

Given that we consider human development from the CA perspective, we found it critical to cover it from various perspectives in the data we used. However, the extent of data in macroeconomic databases is very deficient. Thus, we put an effort to obtain comprehensive and representative data for human development by starting from a micro-level survey dataset EU-SILC. This dataset is quite inclusive due to the information related to income, non-income, social or even more complex perspectives of people's living standards.

We followed a three-stage data building process starting from EU-SILC. We first selected 36 questions from the survey to obtain information about 30 items related to human development. In the second stage, these items were aggregated and used to create ten representative human development dimensions: education, health, living standards, housing conditions, desirable items, arrears, unmet health needs, labour, environmental quality/safety, and risk of poverty. Here we basically used individual and household level variables available in EU-SILC to calculate those human development proxies at the country level in the first two stages of the data building process. During these calculations we have implemented the fuzzy set theory. Given that fuzzy set theory can create a summary measure about the rank of an alternative among several alternatives without the necessity of any crispy threshold, it was a good option to follow to capture each country's deprivation degree on each dimension. We obtain these dimensions using the EU-SILC survey for all countries and years available in the dataset (*i.e.* 32 countries and 14 years).

Finally, in the third stage of the data building process, we used dimension reduction method PCA and grouped these ten dimensions into four components called material well-being, financial stability, human capital and environmental well-being.

These four components are used in the econometric examination, where we measured the effect of ICT on human development through the fixed effect model by the FGLS estimator.

We believe this data building process is a relevant contribution to the literature given the inclusive content of the data that we obtained. In fact, the positive effect of ICT on human development was proved theoretically and empirically by various authors through several channels, albeit the extent of the analyses was not wide due to the data scarcity. This work overcomes this problem by using a micro-level survey dataset for a macro-level level analysis.

Moreover, we selected three ICT (mobile cellular subscriptions, fixed telephone subscriptions and internet usage) and four control variables (INC, FD, $CO2$, and POP).

We built four separate models for each human development component and estimated the effect of selected ICT variables through a fixed-effect FGLS estimator. We implemented the FGLS model since our data suffered from serial correlation and heteroskedasticity problems.

According to the results, the internet showed a significant positive impact on each model. That means an increase in the percentage of internet usage reinforces human development from all four dimensions. Mobile phone subscriptions affected material well-being, financial stability and environmental well-being positively while human capital negatively, which was unexpected. Finally, fixed phone subscriptions had a negative effect on material and environmental well-being while having a significant positive impact on financial stability. Given that fixed phone subscriptions have had a descending trend in the last years, it makes sense that it negatively affects the components more income and wealth related.

The control variables also showed reliable results. The population was negatively linked to the human development components in each of the four models. INC per capita was only included in the material well-being and human capital models. The results proved a significant positive relationship between them. Likewise, FD was only included in the financial stability model. According to the findings, a unit increase in FD can enhance the likelihood of having higher financial stability. Finally, $CO2$ was included only in the model of environmental well-being. The result proved that an increase in $CO2$ decreases environmental well-being.

All these findings are compatible with the existing literature. Our analysis proved the relevance of ICT usage on human development from several perspectives. Although the scope of our panel is not very wide compared to the world scale, our results still provide meaningful insight.

3.A Literature Review summary Table

Author	Title	ICT Proxy	Data Sources	Sample Period	Sample Coverage	Methodology
Gholami et al. (2010)	Is ICT the Key to Development?	Per capita expenditure on ICT	World Development Indicators	1998 - 2006	52 developed and developing countries	Quantile Regression Analysis
Chien et al. (2020)	The non-linear Relationship between ICT Diffusion and Financial Development	Internet, Fixed Phone Subs., Mobile Cellular Subs.	World Development Indicators	1990 - 2015	81 countries	Generalised Method of Moments, Panel Smooth Transition Regression

Author	**Title**	**ICT Proxy**	**Data Sources**	**Sample Period**	**Sample Coverage**	**Methodology**
Sepehrdoust (2018)	Impact of information and communication technology and financial development on economic growth of OPEC developing economies	ICT Development Index (IDI)	International Telecommunication Union	2002 - 2015	Developing Economies of the Petroleum Exporting Countries (OPEC)	Panel Generalised Method of Moments

Author	**Title**	**ICT Proxy**	**Data Sources**	**Sample Period**	**Sample Coverage**	**Methodology**
Pradhan et al. (2015)	The dynamics of Information and Communications Technologies Infrastructure, Economic Growth, and Financial Development: Evidence from Asian Countries	Telephone Landlines, Mobile Phones, Internet Users, Internet Servers, Fixed Broadband	World Development Indicators	2001 - 2012	21 Asian countries	Panel Cointegration Techniques
Sassi and Goaied (2013)	Financial Development, ICT diffusion and Economic Growth: Lessons from MENA Region	Internet Users (%), Fixed Phone Penetration, Mobile Phone Users, Ratio of ICT Imports to the total Service Imports	World Development Indicators	1960 - 2009	17 MENA countries	Generalised Method of Moments

Author	Title	ICT Proxy	Data Sources	Sample Period	Sample Coverage	Methodology
Lee et al. (2017)	ICT diffusion as a determinant of human progress	Fixed-line Broadband, Fixed-line Telephones, and Mobile Telephones	International Telecommunication Union	2000 - 2013	102 countries	Seemingly Unrelated Regression (SUR) model
Dimelis and Papaioannou (2010)	FD and ICT Effects on Productivity Growth: A Comparative Analysis of Developing and Developed Countries	Growth rate of ICT per capita Worker	World Information Technology and Services Alliance	1993 - 2001	42 developed and developing countries	Generalised Method of Moments

Author	**Title**	**ICT Proxy**	**Data Sources**	**Sample Period**	**Sample Coverage**	**Methodology**
Lipovina-Božović et al. (2019)	A Support Vector Machine Approach for Predicting Progress toward environmental sustainability from information and communication technology and human development	Network Readiness Index	World Economic Forum	2018	139 countries	Support Vector Machine model
Nevado Peña et al. (2020)	An analysis of the key role of human and technological development in the smart Specialisation of smart European regions	13 ICT Indicators (Household and Individual Level) [see the paper]	Eurostat	2014	129 European regions (from 18 countries)	Ordinary Least Square regression model

Author	Title	ICT Proxy	Data Sources	Sample Period	Sample Coverage	Methodology
Nevado-Peña et al. (2019)	Improving quality of life perception with ICT use and technological capacity in Europe	13 ICT Indicators (Houshold and Individual Level) [see the paper]	Eurostat	2015	79 European Regions	Analysis of variance, Multivariate Regression analysis
Oyerinde and Bankole (2019)	Investigating the Efficiency of ICT Infrastructure Utilisation: A Data Envelopment Analysis Approach	Computers Infrastructure, Internet Infrastructure, Mobile Phone Infrastructure	International Telecommunication Union	2010 - 2016	Sub-Saharan and Northern Africa, Europe and Northern America	Data Envelopment Analysis
Vu (2011)	ICTs as a source of economic growth in the information age: Empirical evidence from the 1996-2005 period	Computer, Mobile Phones, Internet Users	World Development Indicators	1996 - 2005	102 countries	Dynamic Panel Data analysis using Generalised Method of Movements

Author	Title	ICT Proxy	Data Sources	Sample Period	Sample Coverage	Methodology
Iqbal et al. (2019)	Analysing the role of ICT in human development: panel data analysis	Mobile Phone Usage, Internet Penetration	World Development Indicators	1990 - 2016	5 Shout Asian countries	Driscoll-Kraay Standard Errors algorithm
Niebel (2018)	ICT and economic growth – Comparing developing, emerging and developed countries	ICT capital services, non-ICT capital services,	Conference Board Total Economy Database	1995 - 2010	59 countries	Pooled OLS, Fixed Effect, Random Effect, Panel IV regression models
García-Muñiz and Vicente (2014)	ICT technologies in Europe: A study of technological diffusion and economic growth under network theory	ICT base sectors, ICT products	Eurostat Input-Output Tables	2000, 2005, 2007	27 EU Member countries	Structural Holes in Network Analysis

Author	Title	ICT Proxy	Data Sources	Sample Period	Sample Coverage	Methodology
Cortés and Navarro (2011)	Do ICT Influence Economic Growth and Human Development in European Union Countries?	15 Information Society Indicators [see the paper]	Eurostat	not-specified	27 EU Member countries	Analysis of variance
Gouvea et al. (2018)	Assessing the nexus of sustainability and ICT	Network Readiness Index	World Economic Forum	2016	139 countries	Ordinary Least Square regression analysis
Zelenkov and Lashkevich (2020)	Fuzzy regression model of the impact of technology on living standards	Network Readiness Index, Global Innovation Index	World Economic Forum, World Intellectual Property Organisation	2019	112 countries	Fuzzy Regression Analysis

3.B Alterations in EU-SILC variable list

Variables changed in time regarding ID or values.

1) Education related variables

PE040:Highest ISCED level attained.

The values of PE040 between 2004 and 2013:

- 0 - Pre-primary education
- 1 - Primary education
- 2 - Lower secondary education
- 3 - (Upper) Secondary education
- 4 - Post-secondary non tertiary education
- 5 - First stage of tertiary education and second stage of tertiary education

The values of PE040 between 2014 and 2017:

- 000 - Less than primary education
- 100 - Primary education
- 200 - Lower secondary education
- 300 - Upper secondary education
  - 34 - General education (only for people 16-34)
    - 340 - without distinction of direct access to tertiary education
    - 342 - partial level completion and without direct access to tertiary education
    - 343 - level completion, without direct access to tertiary education
    - 344 - level completion, with direct access to tertiary education
  - 35 - Vocational education (only for people 16-34)
    - 350 - without distinction of direct access to tertiary education
    - 352 - partial level completion and without direct access to tertiary education

        - 353 - level completion, without direct access to tertiary education
        - 354 - level completion, with direct access to tertiary education
- 400 - Post-secondary non-tertiary education (not further specified)
    - 440 - General education (only for people 16-34)
    - 450 - Vocational education (only for people 16-34)
- 500 - Short cycle tertiary
- 600 - Bachelor or equivalent
- 700 - Master or equivalent
- 800 - Doctorate or equivalent

To harmonise the values PE040 before and after 2014, we grouped the altered values changed after 2014 within the 5 categorise specified in before 2014. According to this grouping, 000, 100, 200, all values started with 300, all values started with 400 were treated as they were 0, 1, 2, 3 and 4 respectively. Moreover, 500, 600, 700 and 800 were treated as they were 5 which corresponds to first and second stage of tertiary education.

2) Labour Related Variables

PL030/PL031: Self Defined Current Economic Status

The values of PL030 between 2004 and 2009

- 1-working full time
- 2-working part-time
- 3-unemployed
- 4-pupil, student, further training, unpaid work experience
- 5-in retirement or in early retirement of has given up business
- 6-permanently disables or/and unfit to work
- 7-in compulsory military community or service
- 8-fulfilling domestic tasks and care responsibilities
- 9-other inactive person

Variable PL030 is defined as PL031 after 2009

The values of PL031 after 2009

- 1-working full time
- 2-working part-time
- 3-Self-employed working full-time (including family worker)
- 4-Self-employed working part-time (including family worker)
- 5-Unemployed
- 6-Pupil, student, further training, unpaid work experience
- 7-In retirement or in early retirement or has given up business
- 8-Permanently disabled or/and unfit to work
- 9-In compulsory military or community service
- 10-Fulfilling domestic tasks and care responsibilities
- 11-Other inactive person

PL070/PL73:number of months spent at full-time work as employee

The variable PL070 changed ID to PL073 after 2009.

PL072/PL74:number of months spent at part-time work as employee

The variable PL072 changed ID to PL074 after 2009.

Two additional variables are described after 2009

- PL075:number of months spent at full time job as self-employee(including family worker)
- PL076:number of months spent at part time job as self-employee(including family worker)

The equations used to digitise the labour related items, namely, worklessness and work intensity were adjusted according to the change in the variables. More precisely, the numerator of Equation 3.7 was composed of only 1, 2 and 7, while the denominator took all the values valid in PL030 until 2009. Similarly, the variables PL075 and PL076 were not included in the numerator and denominator of Equation 3.8. Besides, the old IDs for PL073 and PL074 were used.

3) Arrears Related Variables

HS010/HS011: Arrears on mortgage or rental payment

HS020/HS021: Arrears on utility bills

HS030/HS031: Arrears on hire purchase instalments or other loan payments

The values of HS010, HS020, HS30 between 2004 and 2008

- 1-Yes
- 2-No

Variables HS010, HS020, HS30 ares defined as HS011, HS021, HS31 after 2008

The values of HS011, HS021, HS31 after 2008

- 1-Yes
- 2-Yes, twice or more
- 3-No

As it is seen, the values that arrears related variables could get, were detailed after 2008. The membership degrees were calculated according to three categories after the change in the variables (i.e. after 2008). The total group membership degree for the arrears dimension was still in line after such alteration. Thus, harmonisation between the values before and after 2008 was not necessary.

4) Housing Related Variables

HH080/HH081: Bath or shower in dwelling

HH090/HH091: Indoor flushing toilet for sole use of household

The values of HH080 and HH090 between 2004 and 2008

- 1-Yes
- 2-No

Variables HH080 and HH090 are defined as HH081 and HH091 after 2008

The values of HH081 and HH091 after 2008

- 1-Yes, for the sole use of the household
- 2-Yes, shared
- 3-No

A third value was added to the answer list of these variables after the alteration. The membership degree for each variable was calculated according to the new categories after 2008. No drastic change was observed in the total group membership degree for dimension housing conditions from 2007 to 2008. Thus, we didn't harmonise the values that the variables could take after the change.

3.C Countries and Panel Structure

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
AT	1	1	1	1	1	1	1	1	1	1	1	1	1	1
BE	1	1	1	1	1	1	1	1	1	1	1	1	1	1
BG	.	.	.	1	1	1	1	1	1	1	1	1	1	1
CH	.	.	.	1	1	1	1	1	1	1	1	1	1	.
CY	.	1	1	1	1	1	1	1	1	1	1	1	1	1
CZ	.	1	1	1	1	1	1	1	1	1	1	1	1	1
DE	.	1	1	1	1	1	1	1	1	1	1	1	1	1
DK	1	1	1	1	1	1	1	1	1	1	1	1	1	1
EE	1	1	1	1	1	1	1	1	1	1	1	1	1	1
EL	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ES	1	1	1	1	1	1	1	1	1	1	1	1	1	1
FI	1	1	1	1	1	1	1	1	1	1	1	1	1	1
FR	1	1	1	1	1	1	1	1	1	1	1	1	1	1
HR	.	.	.	.	.	.	1	1	1	1	1	1	1	1

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
HU	.	1	1	1	1	1	1	1	1	1	1	1	1	1
IE	1	1	1	1	1	1	1	1	1	1	1	1	1	.
IS	1	1	1	1	1	1	1	1	1	1	1	1	1	.
IT	1	1	1	1	1	1	1	1	1	1	1	1	1	1
LT	.	1	1	1	1	1	1	1	1	1	1	1	1	1
LU	1	1	1	1	1	1	1	1	1	1	1	1	1	1
LV	.	1	1	1	1	1	1	1	1	1	1	1	1	1
MT	.	.	.	1	1	1	1	1	1	1	1	1	1	1
NL	.	1	1	1	1	1	1	1	1	1	1	1	1	1
NO	1	1	1	1	1	1	1	1	1	1	1	1	1	.
PL	.	1	1	1	1	1	1	1	1	1	1	1	1	1
PT	1	1	1	1	1	1	1	1	1	1	1	1	1	1
RO	.	.	.	1	1	1	1	1	1	1	1	1	1	1
RS	.	.	.	.	.	.	.	.	.	1	1	1	1	.
SE	1	1	1	1	1	1	1	1	1	1	1	1	1	1
SI	.	1	1	1	1	1	1	1	1	1	1	1	1	1

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
SK	.	1	1	1	1	1	1	1	1	1	1	1	1	1
UK	.	1	1	1	1	1	1	1	1	1	1	1	1	.

3.D FGLS estimations with control variables included Year and Country dummies

	Mat_Well_t	Fin_Sta_t	Hum_Cap_t	Env_Well_t
INT_{t-1}	0.0257039***	0.0062108	0.0133427**	0.1038268***
	(.0082083)	(0.0115284)	(0.0071887)	(0.0168814)
$ln(MP)_{t-1}$	0.0005922	0.0283102***	-0.0128639***	0.0288734***
	(.0046167)	(0.007653)	(0.0042984)	(0.0109028)
$ln(FP)_{t-1}$	-0.0028673	0.0104588***	0.0022575	-0.0064493
	(.0024286)	(0.0049619)	(0.0032722)	(0.0052788)
$ln(INC)_{t-1}$	0.0173445***		0.0130308***	
	(.0026118)		(0.0022089)	
FD_{t-1}		0.0304801***		
		(0.0151395)		
$ln(CO2)_{t-1}$				-0.030942***
				(0.0112537)
$ln(Pop)_{t-1}$	-0.042769***	-0.1400383***	-0.0106435	-0.0891132***
	(0.0126464)	(0.0249887)	(0.0100985)	(0.0326406)
Cons.	1.142382***	2.853334***	0.6326814***	2.167687***
	(0.1950952)	(0.4088789)	(0.1805777)	(0.53006)
Year				
2006	-0.0001583	0.0018467	0.0011801	-0.0043925
	(0.0012438)	(0.0018918)	(0.0013521)	(0.0030873)
2007	0.002555**	0.0045154**	0.0039735***	-0.0135566***
	(0.0014769)	(0.0026251)	(0.0016252)	(0.0039199)

	Mat_Well_t	Fin_Sta_t	Hum_Cap_t	Env_Well_t
2008	0.0012544	0.0060654**	0.003901***	-0.0123125***
	(0.0017565)	(0.0032686)	(0.0018601)	(0.0047149)
2009	0.0012908	0.0006791	0.0026717	-0.0145236***
	(0.0020259)	(0.0036743)	(0.0020722)	(0.0053253)
2010	0.0040507**	-0.0054911	0.0002406	-0.0059797
	(0.0021974)	(0.0040215)	(0.0021777)	(0.0057344)
2011	0.0035203	-0.0051305	0.000313	-0.0076969
	(0.0024187)	(0.0043218)	(0.002288)	(0.0059312)
2012	0.0041502*	-0.0091279***	0.0025599	-0.0056309
	(0.0025834)	(0.0045942)	(0.0023984)	(0.0063233)
2013	0.0044875*	-0.0094947**	0.0007421	-0.0089813
	(0.0027878)	(0.0048533)	(0.0025516)	(0.006789)
2014	0.0037712	-0.0052757	0.0000323	-0.0091359
	(0.0029134)	(0.0048958)	(0.0025768)	(0.0069437)
2015	0.0028057	0.0000349	-0.0011342	-0.0081188
	(0.0030629)	(0.0053817)	(0.0027724)	(0.0072624)
2016	0.0028227	0.0059789	0.0016471	-0.006897
	(0.0031362)	(0.0057545)	(0.0029001)	(0.0072994)
2017	0.0051418	0.0165331***	-0.0006456	-0.0088996
	(0.0033469)	(0.0060185)	(0.00308)	(0.0075627)
Country				
$Belgium$	-0.0057499	0.0213224***	-0.0011444	-0.0003527
	(0.0063017)	(0.00868)	(0.0035923)	(0.0166314)

	Mat_Well_t	Fin_Sta_t	Hum_Cap_t	Env_Well_t
Bulgaria	-0.0817737***	-0.1793621***	0.0645921***	0.0051688
	(0.0105694)	(0.0111614)	(0.0059018)	(0.0153972)
Croatia	-0.0476786***	-0.2052142***	0.0174302	-0.0148669
	(0.0098963)	(0.0194183)	(0.0118114)	(0.0283812)
Cyprus	-0.0810383***	-0.4082469***	0.0353827	-0.2572267***
	(0.0291052)	(0.0594555)	(0.0262144)	(0.0818494)
Czechia	0.0311653***	0.015475**	0.0638517***	0.0058929
	(0.0063374)	(0.0092097)	(0.0041647)	(0.0164991)
Denmark	-0.0110919*	-0.0483654***	0.0151478***	-0.0359497
	(0.0068506)	(0.0121124)	(0.0065769)	(0.0229003)
Estonia	-0.1056484***	-0.2598259***	0.0275252	-0.1575132***
	(0.0234073)	(0.0475269)	(0.02139)	(0.0653494)
Finland	-0.0215517***	-0.0671945***	0.0010286	-0.0373497**
	(0.0071799)	(0.013487)	(0.006783)	(0.0206304)
France	0.0469097**	0.266273***	-0.0042922	0.1615511***
	(0.0242338)	(0.0501508)	(0.0216067)	(0.0660865)
Germany	0.0451403*	0.2977926***	0.005226	0.0796095
	(0.0276469)	(0.0582562)	(0.0265867)	(0.07621)
Greece	-0.0203886***	-0.084545	0.0261614***	-0.0284007
	(0.0058519)	(0.0821302)	(0.0081944)	(0.0264703)
Hungary	-0.009143	-0.1019***	0.0249229**	0.0143242
	(0.0063661)	(0.016569)	(0.0141035)	(0.022054)
Iceland	-0.0820161***	-0.442317***	0.0330738	-0.2971168***
	(0.0395752)	(0.0831295)	(0.0356487)	(0.1092791)

	Mat_Well_t	Fin_Sta_t	Hum_Cap_t	Env_Well_t
Ireland	-0.0339536***	-0.1379467***	0.0349181***	0.0229984
	(0.0091743)	(0.020764)	(0.0073223)	(0.0244962)
Italy	0.0262873	0.215788***	0.0025949	0.1381875***
	(0.0237146)	(0.0495404)	(0.0213321)	(0.0680416)
Latvia	-0.1480836***	-0.2751027***	0.0274491*	-0.2341936***
	(0.0180774)	(0.0388445)	(0.0170131)	(0.0529826)
Lithuania	-0.0796908***	-0.202801***	0.0340961***	-0.117301***
	(0.0191184)	(0.0283695)	(0.0129014)	(0.039314)
Luxembourg	-0.0842364***	-0.3744451***	0.0128186	-0.2870428***
	(0.0339659)	(0.0704979)	(0.0307646)	(0.0939594)
Malta	-0.0701126**	-0.467762***	0.0563614**	-0.4811259***
	(0.0362311)	(0.0783114)	(0.0334743)	(0.1018981)
Netherlands	0.0343089***	0.1126076***	0.0096641	-0.0045219
	(0.0098367)	(0.0213922)	(0.0079166)	(0.0260444)
Norway	-0.0167616***	-0.0361091***	0.0187196***	-0.0305003
	(0.0079214)	(0.01698)	(0.0063736)	(0.0225112)
Poland	0.0122166	0.1416733***	0.0412088***	0.1400903***
	(0.0192203)	(0.0380643)	(0.0154066)	(0.0525537)
Portugal	-0.0286462***	-0.0194298***	-0.0043299	-0.0284012**
	(0.0062532)	(0.0088116)	(0.0042888)	(0.0165113)
Romania	-0.0574418***	0.0535998***	0.0404949***	0.0173034
	(0.0176592)	(0.021858)	(0.0091502)	(0.0327345)
Serbia	-0.0606274***	-0.1697106***	0.0470682***	-0.0106811
	(0.0073705)	(0.0104217)	(0.0059923)	(0.0160387)

	Mat_Well_t	Fin_Sta_t	Hum_Cap_t	Env_Well_t
Slovakia	0.0073591	-0.0853877***	0.0194984***	-0.0734772***
	(0.0084054)	(0.0152782)	(0.0093318)	(0.0252344)
Slovenia	-0.0240343	-0.2257535***	0.0233821	-0.1658622***
	(0.0180065)	(0.0373058)	(0.0167757)	(0.049211)
Spain	0.0256851	0.1900155***	0.0152446	0.1473587***
	(0.0205531)	(0.0431694)	(0.0179093)	(0.0570684)
Sweden	-0.0084569**	0.0424789***	0.0208273***	0.0153116
	(0.0047906)	(0.0069918)	(0.0045447)	(0.0161705)
Switzerland	-0.017657***	0.0030093	0.0179526***	-0.0247112**
	(0.0042827)	(0.0092291)	(0.0083856)	(0.0141477)
UnitedK.	0.0341278	0.2644129***	0.0100008	0.1754425***
	(0.0243615)	(0.0510289)	(0.0222403)	(0.0665082)
χ^2	7254.52	34224.30	2510.80	3182.29
Obs.	372			

Note :***$p \leq .01$,**$.01 < p \leq .05$,*$.05 < p \leq .1$.

Chapter 4

The Role of Reinforced Capabilities on the Triangle of Climate Change, Technology and Poverty

4.1 Introduction

Being unable to meet the basic human needs in absolute terms or being worse off than the average wealth level of a country is commonly associated with being poor (Hulme and Shepherd, 2003). Climate change negatively affects people in poverty because of the alterations in their living conditions through weather variations (IPCC, 2001). The mitigation of these climatic variations is essential for the stabilisation of the living conditions of poor people and decreasing poverty (Ludwig et al., 2007).

International organisations often point out the global danger related to climate change and poverty. The United Nations Development Program (UNDP), in the report *Fighting Climate Change: Human Solidarity in a Divided World*, presented the impact of higher temperatures in poor areas. According to the UNDP, a temperature increase of 1 to 6 Celsius degrees is expected during the next century (UNDP, 2007). Masson-Delmotte et al. (2018) emphasise that the 1.5 Celsius degrees increase in the average temperature, when compared to the pre-industrial era, has been already experienced in their special report *Global Warming of 1.5ºC*, prepared for the Intergovernmental Panel on Climate Change (IPCC). Moreover, limiting this increase is mentioned as one of the major purposes of the IPCC. Also, according to the *Climate Change: Action Plan 2016-2020* report by the World Bank group, weather extremes have been affecting millions of people in terms of the risk that it creates on water and food security. According to the forecasts presented in this report, climate change has the potential to "push an additional 100 million people into poverty by 2030" (World Bank, 2016, 1)), supporting the conclusions of the 5th report of the IPCC that climate change carries social and natural risks (IPCC, 2014).

The same issue is also acknowledged in the scientific literature. For example, Webersik and Wilson (2009) state that the economic performance of countries decreases when high climate change variabilities exist. The direct effect of climate change on agricultural production is one of the reasons for this low economic performance (Lybbert and Sumner, 2012). Given that developing countries are highly dependent on agriculture, they are relatively more vulnerable. Climate change affects precisely those who are more vulnerable and may be the trigger to falling into poverty (Abraham and Kumar, 2008; McGuigan et al., 2002).

Technology emerges as an important tool for climate adaptation strategies implemented by governments. Sustained agricultural growth through technological change increases the level of human development and reduces poverty (Lipton et al., 2002). Thus, the adoption of new technologies is particularly important for vulnerable developing countries to avoid the impact of climate change (McGuigan et al., 2002). However, it is not enough just to consider the new technologies produced to decrease the impact of climate change (i.e. Climate-Smart Agriculture (CSA) technologies). Adoption decisions and conditions must also be discussed. Although the adoption of new technologies might minimise the perceived impact of climate change on poverty, not all farmers are able and willing to invest in those technologies because of their socioeconomic, institutional and environmental deterrents (Mariano et al., 2012). Moreover, some determinants such as inputs availability, risk preferences, knowledge/education, profitability, and credit conditions are necessary for the efficient adoption and correct usage of those technologies. Some of these determinants replicate personal capabilities while others reflect economic capabilities. When some of these ingredients are missing, people may hesitate to adopt new technologies because of the risk that they may need to take on their welfare combined with the idea of not being capable to use those technologies properly (Dercon and Christiaensen, 2011). Economic capabilities can be enlarged through institutional policy strategies such as providing access to the essential inputs for production, agricultural consultation, financial incentives and so on (Makate, 2019). In what concerns human capabilities, a clear argumentation based on the role of human capabilities within the climate adaptation strategies and the importance of reinforced capabilities into this relationship is needed.

The Capability Approach (CA) (see Sen, 1983, 1995, 1999a), a framework presented by the Nobel awarded economist Amartya Sen, provides a tool to conceptualise human capabilities to assess well-being and poverty (Robeyns, 2005). This approach emphasises the importance of human capabilities to determine the actions which value the life of the individual (Zheng and Stahl, 2011). Moreover, improving the living standards of an individual can only be possible with higher capabilities according to the CA framework (Robeyns, 2005). Technology, namely Information and Communication Technology (ICT), is acknowledged as one of the resources able to improve and reinforce human capabilities from many different perspectives (Haenssgen and Ariana, 2018; Oosterlaken, 2013).

Supporting this idea, the report *Making New Technologies Work for Human Development*, by the UNDP (2001) underlined the link between technology and development by focusing on the necessity of empowered people. According to this report, technology enlarges the daily life choices of people and technological change is the result of higher human capabilities achieved through technological advantages. Hence, there is a mutual self-reinforcement mechanism between technology and human capabilities.

Based on the above, this work elaborates the following proposition from both theoretical and empirical perspectives: 'the diffusion of climate adaption technologies can reduce poverty as viewed through the lenses of the CA.' We analyse this proposition by focusing on three essential links: (i) poverty related to climate change; (ii) the role of technology on human capabilities and vice-versa; and (iii) technology for climate adaptation. Based on a critical assessment of the related literature on these links, we aim answering the following research questions: (i) what is the expected impact of climate change on people living in vulnerable areas? (ii) Do human capabilities influence the adoption of CSA technologies? and (iii) What is the role of reinforced capabilities in the adoption decisions of CSA technologies? Moreover, this critical assessment was used to construct an analytical framework that allowed us to build the econometric model with several interactions to understand the range of ICTs, climate change, and agricultural production behind poverty and test our hypothesis.

Human Development Index (HDI) was used as a proxy of poverty, considered under the CA framework within a multidimensional perspective. Land surface temperature and total annual precipitation were considered elements to capture climate change. Enhanced vegetation index stood for agricultural production. The productivity of agricultural production was associated with the CSA technology adoption in the empirical analysis. Moreover, some control variables, namely, governmental effectiveness index, percentage of agricultural land and the percentage of people living in rural areas, were considered not to overlook their potential effects on poverty related to climate change. To collect all the necessary data both conventional and satellite databases were used. Our data sample covers 21 years and 168 countries. Panel-corrected standard error (PCSE) estimates were computed by Prais-Winsten regression.

The remainder of the paper is structured as follows. Section 2 presents the impact of climate variations on poverty according to the existent literature. Moreover, adaptive capacities and climate adaptation strategies are revised. Section 3 encompasses an analytical framework by introducing Rogers' Diffusion of Innovations and Sen's Capability Approach. The section is concluded with the re-analysis of Rogers' theory from the CA perspective, by articulating the importance of human capabilities for the adoption of CSA technologies and the role of reinforced human capabilities in this relationship. Section 4 presents the data and econometric strategy. Results of the econometric research are presented in Section 5. Finally, Section 6 concludes.

4.2 The Impact of Climate Variations on Poverty

Climate change can globally be affected by actions far beyond from which they originated (Gul et al., 2019). One of the most prominent consequences of climate change is global warming. Natural disasters such as floods or cyclones occur due to the rising sea levels as a result of the increasing temperatures related to global warming (McGuigan et al., 2002). Moreover, a higher probability of snow melting and intensity of other extreme weather events such as droughts and floods take place due to warmer air (Zilberman et al., 2018; Gul et al., 2019). For instance, Hisali et al. (2011) recorded that floods and livestock epidemics are becoming more common reflections of climate change, and droughts are lasting longer. These occurrences affect livelihood activities directly (Roncoli, 2006). Gul et al. (2019) showed that the impact of climate change on production affects net returns, per capita income and poverty rates. Thus, climate change has the potential to affect the economy as a whole. Regions with high economic dependency on agricultural activities are affected more due to their higher sensitivity to climatic variations (Rochdane et al., 2014; Gul et al., 2019). For example, food security is directly related to the precipitation in vulnerable regions (Roncoli, 2006). Given that most of the fertile lands and developed dwellings are closer to the coastal locations, the impact of global warming is widespread in those areas. In addition to these impacts, the adverse effect of climate change can be observed in public health as well (Begum et al., 2011). For example, a higher level of temperature might generate favourable conditions for insects and diseases (Hisali et al., 2011). In this circumstance, people might need to immigrate to other regions. These situations impact the well-being of individuals and countries.

Vulnerability is an important concept to consider in the relationship between climate change and poverty. It is interpreted under different frameworks (Roncoli, 2006). For instance, Abraham and Kumar (2008) described vulnerability as "the likelihood of a household falling into poverty, given the current status of household" (Abraham and Kumar, 2008, 77). Or, within an environmental perspective, vulnerability is defined as the probability of an individual or a household being affected by negative weather conditions and climatic stress (IPCC, 2012). Within this understanding, there are two concepts – outcome vulnerability and contextual vulnerability – which are relevant when climate change is in question. Outcome vulnerability is a direct result of climate change on outcomes. This negative impact on outcomes is more observable in climate sensitive sectors such as agriculture and fishery. Contextual vulnerability, on the other hand, is associated with being vulnerable in virtue of living within a group, a region or a country through the interactions of multiple channels, including climate variability and political, institutional, social and economic changes (O'brien et al., 2007).

High individual and national vulnerabilities may cause a severe effect of climate change on poverty at the aggregate level, especially in developing countries, due to the limited economic opportunities (McGuigan et al., 2002). Higher poverty complicates the livelihood of people (Makate, 2019).

The impact of climate change on poverty can be observed through consumption or income. Prices, assets, productivity and livelihood activities are the channels through which consumption and income get affected (Hallegatte et al., 2014). The assets channel is especially important for escaping from poverty. This channel includes both tangible and intangible assets. The former can be directly put into the actions. Human assets (driven by labour, education and skills), financial assets (credit, savings, wages and insurance) and physical assets (seeds, tools, livestock and houses) constitute tangible assets. The latter, on the other hand, refers to indirect opulence. Natural assets (timber, water resources, pastureland and farmland) and social assets (kinship and religious ties, tribal/village structure and reciprocal relations) are grouped beneath intangible assets (Penh, 2009; Makate, 2019). From all these aspects, assets reflect the "biophysical" conditions of the individual (e.g. the farmer). A shock on assets due to climate change can affect all the other channels and increase vulnerability since the climate variations discourage assets accumulation and reduce profitability and productivity (Makate, 2019).

It is important to adapt to ever-changing patterns of climate to have efficiency in agricultural production in vulnerable countries, thus reducing poverty risk by increasing income levels, improving food security, and protecting human well-being (Brooks et al., 2005; McCarthy et al., 2018; Makate, 2019). The impact of climate change can be different according to geographic locations and current climatic conditions of the countries (Gul et al., 2019). This heterogeneous and uncertain nature of different areas creates a challenge for the adaptation process (Zilberman et al., 2018). Adaptation strategies should be country-specific according to the actual and expected climatic variabilities (Hisali et al., 2011). Thus, it is essential to determine accurately the vulnerable areas for the establishment of efficient adaptation policies (Ludwig et al., 2007).

Climate Adaptation Strategies and Adaptive Capacity

Adaptation to climate change can emerge through different strategies such as decreasing consumption (to limit climate change that can ensue from high consumption levels), increasing the labour force (to increase agricultural production), borrowing required sources (to decrease economic constraints), or adoption of new technologies (Hisali et al., 2011). Among these four, the last one is the most effective and recommended adaptation strategy mentioned in the literature. For example, Gul et al. (2019) asserted the necessity of creating sustainable (or technology-based) adaptation policies. The development and adoption of new technologies are strongly motivated and supported by the authors to fight against climate change. Lybbert and Sumner (2012) highlight CSA technologies as facilitators for the adaptation to climate change, contributing to the reduction of its perceived effect.

Yet adaptation is not spontaneous. The adaptive capacity of the country should be considered an important element for adaptation (Brooks et al., 2005). According to the third assessment report of IPCC, adaptive capacity is defined as "the ability inherent in the coping range and the ability to move or expand the coping range with new or modified adaptations" (IPCC, 2001, 883). Low adaptive capacities make the countries more fragile against climate variations (Ludwig et al., 2007).

The adaptive capacity of countries can be low due to the absence of evidence, namely success stories related to the positive effects of a specific adaptation strategy on agricultural areas, lack of knowledge/education and weak institutional infrastructures (Ludwig et al., 2007; Lipton et al., 2002; Makate, 2019).

When we consider the technology-based adaptation strategies, having high or low adaptive capacity refers to the participation level of individuals in the technological change process. Although CSA practices offer a lower level of vulnerability and a higher level of productivity in climate-sensitive areas, new technologies are not easily recognised and applied due to a lack of transparency and information (Feder et al., 1985). Likewise, the *ex-ante* return of investments on CSA technologies is obscure because of uncertain forthcoming weather events. To provide a clear framework for adoption decisions of individuals, costs and benefits of the technology have to be clear (Trærup and Stephan, 2015).

Technology-based adaptation depends on some determinants which can prolong the adaptation time to the current climate variability. Several studies tried to discover the determinants of technology adoption over time. For example, Feder and Umali (1993) presented a survey where several empirical works are analysed to find the common determinants of adoption decisions for different countries. According to their findings, technology adoption determinants are related to behavioural factors such as risk expectations, the experience of the farmers, and severity of climate variability, and also to socioeconomic factors such as education, well-being, tenure status/size, available resources (credit, land, water facilities, etc.), information and distance. Similar results can be seen from more recent empirical studies which analyse the determinants of different types of technologies during the adoption decisions of individuals (see De Janvry and Sadoulet, 2000; Kammen, 2001; Dercon and Christiaensen, 2011; Hagos et al., 2012; Barrett and Bevis, 2015).

The technology adoption process is analysed by many authors in the literature. While some have focused on the micro level adoption and analysed the factors which affect individuals and households, some studies focused on macro-level adoption that corresponds to firm or population level adoption decisions (Feder and Umali, 1993). Among all models created on the technology adoption process, the contribution of Everett Rogers (2003) is commonly accepted and broadly used in the literature (Van Oorschot et al., 2018).

4.3 Analytical Framework

4.3.1 Rogers' Diffusion of Innovations Theory

Rogers' diffusion of innovations theory is built on three important concepts, which are innovation, diffusion, and adoption. These three elements are highly interrelated with each other in this theory. Rogers (2003, 12) defines innovation as "an idea, practice, or object perceived as new by an individual". Adoption emerges as a result of innovation (both in time and in logic). In other words, adoption takes place after the occurrence of the innovation. However, these two concepts cannot intersect without the role of diffusion (Adesina and Zinnah, 1993). Thus, diffusion plays an essential role in Rogers' theory.

Diffusion is the dissemination of innovation between individuals through some communication channels in society (Fisher et al., 2000). These channels transfer the messages between individuals. This transmission can occur through mass media or interpersonal networks (Rogers, 2003). However, the transfer of information and the decision on technology adoption do not occur suddenly. Thus, diffusion can only be considered by taking time into account. Time is used by Rogers to conceptualise the innovation-diffusion process, the role of early adopters and perceived pace of the adoption rate of the innovation within the society (or social system).

Rogers (2003) conceived the innovation-diffusion process under five fundamental stages: knowledge, persuasion, decision, implementation and confirmation. While knowledge refers to having perspicacity about the new technology and its functioning, persuasion means having a complete idea about the advantages and disadvantages of the innovation. A positive or negative adoption choice reflects the decision stage. If the individual chooses to adopt the technology, the implementation stage starts, and finally, positive net returns as a result of the usage of the adopted technology constitute the confirmation stage. Due to the sequence of these stages, Rogers argues that the technology diffusion and adoption have an S-shape path. This path shows the speed of technology dissemination among people (Feder and Umali, 1993; Fisher et al., 2000; Rogers, 2003).

In Rogers' discourse (2003), personal and communal heterogeneities lead to the occurrence of this S-shape path. Individuals with a higher level of education, curiosity about science, social status and a larger network, hear about the existence of the new technology primarily through mass media channels. Moreover, it is likely that these individuals also become early adopters, and they constitute the initial segment of the S-shape diffusion and adoption path. Thus, following the occurrence of the innovation, the positive effect of the mass media on technology adoption can be observed. The role of early adopters starts at this point since they act as interpersonal communication channels while the technology is becoming widespread within society. It is important to point out that the interpersonal channels are more effective overall by causing higher adoption rates because other people have a chance to observe the direct experiences of users (i.e. early adopters) and the net return of the new technologies. Thus, more individuals participate in technological change by giving adoption decisions during this wave. However, some people (i.e. late adopters and/or laggards) still refuse to adopt the technology and represent the last part of the S-shape path. Hence, innovation starts to diffuse among people at a slow pace through mass media channels. Then, the spread of innovation increases in society due to the effect of interpersonal channels. In this stage, the rate of diffusion and adoption increases. Finally, this ratio starts to decrease back over time.

Innovation creates uncertainty due to its novelty (Rogers, 2003). This uncertainty affects the pace of adoption decisions and participation (Suri, 2011). The uncertainties can be alleviated through five components identified in Rogers' theory, namely, relative advantage, compatibility, complexity, trialability and observability. These elements may increase the speed of adoption decisions. Relative advantage is the degree of how much the innovation is perceived as better than the existing one in terms of economic or sociological reasons. Moreover, compatibility shows the degree of possibility to use past experiences and knowledge. Complexity, on the other hand, is the difficulty in the usage of the innovation. Trialability is the opportunity to experience the innovation before adopting and observability entails obtaining a clear idea about the results of the practice. Especially, relative advantage and compatibility have been acknowledged by Rogers as the most effective two factors for the faster adoption of the new technologies (Rogers, 2003). In this context, the innovators of the modern agricultural systems are criticised for giving full attention to the technical part but not to the "participation or empowerment of people" (Fernández-Baldor et al., 2012, 135).

Although the participation of an individual in the technology adoption process might be achievable following the above-mentioned elements, Makate (2019) argued that lower uncertainties and heterogeneities between individuals can also increase the technology adoption pace. The reinforcement of individual and common capabilities can alleviate these dissimilarities. Thus, the adaptive capacity is enlarged by the expansion of human capabilities (Makate, 2019).

4.3.2 Sen' Capability Approach

As already mentioned, human capabilities are contextualised under the CA by Amartya Sen in his famous paper 'Poor, Relatively Speaking' (Sen, 1983). The CA, a fundamental theoretical frame to assess poverty by considering all the relevant dimensions, "is an intellectual discipline that gives a central role to the evaluation of a person's achievements and freedoms in terms of his or her actual ability to do the different things a person has reason to value doing or being" (Martinetti, 2009, 16). This definition is very comprehensive and complete since it describes essential concepts and dimensions of the CA in a single phrase.

According to the CA, there are two main terms which are "means" and "ends". "Means" refer to the resources which have instrumental importance whereas "ends" refer to capabilities (ability to achieve) and functionings (achievements) which have intrinsic value for well-being (Robeyns, 2005).

Goods and commodities are the means to achieve. What the achievement is, depends on the characteristics of each commodity. Besides, those characteristics do not change subjectively (Sen et al., 1999). For instance, imagine a bike that is produced of some material with a particular shape and colour. This bike provides faster mobility than walking due to its characteristics. Arriving faster from one place to another is the achievement of a person for this commodity. Essentially, one can enable the functionings using the characteristics of the commodities (Robeyns et al., 2000). In other words, functioning is what people achieve as a result of their command on the commodities (Clark, 2005). This command represents capabilities that are generated from commodities and their characteristics (Haenssgen and Ariana, 2018). Thus, commodities represent the means to achieve (what individual values), capabilities show the freedom to achieve (potential achievement) and functionings correspond to the achievements (valuable states and activities or "beings" and "doings") (Zheng, 2009; Egessa et al., 2018).

Well-being and living standards depend on the utility level of the person. The utility of the person is related to possessed functionings or achievements where the set of capabilities implies the ability to achieve. While the achievement of an individual corresponds to one's well-being (Sen et al., 1999), capabilities show which set of opportunities is necessary for well-being (Sumner, 2007). Thus, having a higher level of living standards (or well-being) is not only related to the commodities or their characteristics but also to the ability to use them (Sen, 1983; Sen et al., 1999).

However, the capabilities and functionings of a person are not instinctive. In the relation between commodities, capabilities and functionings, there are two transmission lines which are conversion factors and preferences. The commodities can enable the functionings depending on the individual, social and environmental conversion factors (Robeyns, 2017).

Individual or personal conversion factors are physical and mental conditions, metabolism, gender, intelligence, literacy, etc.; social conversion factors are public policies, infrastructure, gender inequalities, hierarchy, social and legal norms, etc.; and finally, environmental conversion factors are climate and geography. All these conversion factors affect how the characteristics of the commodities are converted into functionings by individuals (Robeyns, 2005).

The second transmission line (or preferences) comes after these conversion factors which show the capabilities or real opportunities and freedom to achieve the functionings (Decancq and Lugo, 2013; Oosterlaken, 2012). If we go back to the bicycle example, in the light of these transmission lines, arriving faster from one place to another is actually the achievement of a person who can ride a bike and who chooses (prefers) to ride. Riding a bike can only be in the capability set of an individual who has adequate physical conditions, suitable roads and a good climate. If a person is paralysed or living in a geographically rough location or somewhere with low infrastructure, that person has no ability or freedom to choose to ride a bike. In both cases, the individual lacks the functioning of riding a bike. Nonetheless, in the former case, not riding a bike is a personal choice while in the latter case, it is an absence. Thus, functionings are a set of achievements that a person values to do or to be while capabilities are various combinations of achievements that the person is free to choose (Sen, 1995).

Likewise, given that individuals are not the same, the characteristics of commodities are exercised differently by each of them. Achievements and the utility of people might not be equal as a result of their command of a commodity (Sen, 1995). For instance, imagine two individuals who have bikes. Everything is the same for these two persons, but one has poor eyesight. Riding a bike will be more difficult for a person with low eyesight. Thus, the achievements of these people are distinct from each other for the same commodity and characteristics. However, the person with low eyesight can get treatment, and benefit from the bike as much as the person with good eyesight. This example shows that capability deprivation or capability improvement affects achievement negatively or positively (Sen, 1999a). People who have a higher level of capabilities have a greater advantage than others. The advantage means having relatively better opportunities than other people. Well-being itself and having the freedom to achieve well-being are two perceptions of the advantage. In Sen's discourse, the latter is closer to the real concept of advantage (Sen et al., 1999). Thus, Sen sees higher capabilities as the only way to increase life quality (Clark, 2005). In other words, well-being depends on the capability set that the individual has (Sen, 1995). Education, health, employment, material resources and so on are some of the elements related to the capabilities that people would need to improve for better life quality and well-being (Decancq and Lugo, 2013).

From this taken, increasing human capabilities is one of the aims of the CA since human development depends on potential and actual achievements (Oosterlaken, 2013). Thus, the expansion of capabilities strengthens well-being and the ability of individuals to care for themselves (Oosterlaken et al., 2012).

Technology can extend human capabilities (Lawson, 2010). Although improving capabilities through technology was not explicitly presented under the capability theory, the extension took place in the literature not long after (Zheng, 2009). Technological domains were seen as a dimension to help flourish the capabilities (Johnstone, 2007). This concept can also be seen in Coeckelbergh's definition of technology "as one of the means (resources) to reach the aims (capabilities)" (Coeckelbergh, 2011, 84).

Information and Communication Technologies (ICTs) are acknowledged as important tools due to their great advantage in improving the capabilities in terms of health, education, livelihood, democracy and so on (Johnstone, 2007; Zheng, 2009; Oosterlaken et al., 2012; Oosterlaken, 2013). Essentially, ICTs are defined as "powerful tools to expand people's agency" (Oosterlaken, 2013, 51). Moreover, the internet, computers or mobile phones are approved as specific types of ICTs which benefit human capabilities directly (Wresch, 2007, 2009; Sen, 2010; Hatakka and Lagsten, 2012).

Increasing the value of life with achieved utilities and freedoms indicates the core purpose of operationalising ICTs within the CA (Egessa et al., 2018). Moreover, ICTs can change and enlarge the characteristics of other commodities (technological or not). Hence, they increase potential and actual achievements (Haenssgen and Ariana, 2018). From all these aspects, it is possible to observe the advantages of ICTs on the capability set of individuals (Haenssgen and Ariana, 2018). Possible enhancements to the living standards of people as a result of reinforced capabilities through the usage of ICTs are originated in those advantages.

Besides the positive effect of ICTs on personal capabilities, they also improve external capabilities. External capability refers to connecting with other people who have higher advantages related to their certain capabilities (Foster and Handy, 2008).

In addition to all those positive effects on human well-being, ICT goods and services are also important in terms of their characteristics. ICTs provide the potential for individuals to collect information across time and space. Moreover, the diffusion of accumulated and generated knowledge is also possible through ICTs (Zheng, 2009). Therefore, the characteristics of ICT provide information and faster diffusion of innovations. As mentioned, "access to information about innovation is the key factor determining adoption decisions" (Adesina and Zinnah, 1993, 298).

4.3.3 Re-examining the Diffusion of Innovations from Capability Perspective

Following the argumentation above, we find Rogers' "Diffusion of Innovations" and Sen's "Capability Approach" relevant to explaining climate adaptation by focusing on the role of human capabilities. Alkire (2003) acknowledged that the CA has the potential to be associated with other literature. While proceeding with the re-examination of Rogers' "Diffusion of Innovations Theory" from the capabilities perspective, we took advantage of this flexibility of the CA. The construction of the analytical framework (see. Figure 4.1) presented in this section was essential to understanding how (reinforced) human capabilities determine the adoption of the technology, especially technologies designed to reduce the impact of climate change (i.e. CSA technologies).

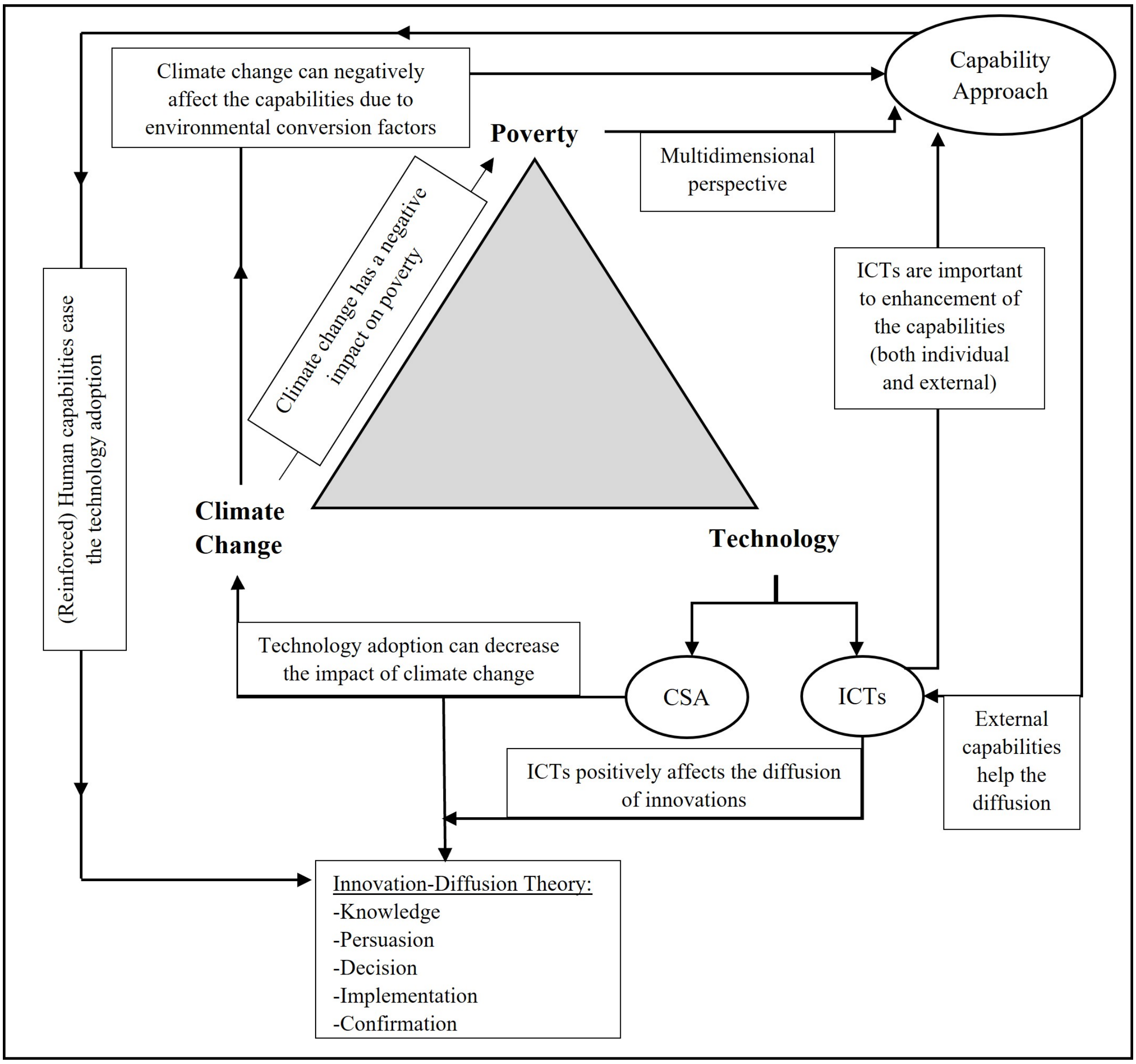


Figure 4.1. The role of human capabilities for climate adaption (Source: Own elaboration)

Climate change can have an impact on the poverty rates of countries through income and consumption channels as mentioned. Moreover, human capabilities can also be affected by climatic variations through the limitations on the capability sets because of the problems in the conversion factors (e.g. health, climate variations, landscape, etc.) (Schlosberg, 2012). Thus, alleviating the perceived climate variations is very important to sustain and increase the level of well-being.

CSA technologies can decrease the perceived impact of climate change on agricultural areas by reducing the cost of production, increasing the yields and safeguarding the food and water in vulnerable areas (Farell and Rumich, 2002). However, investments to develop new technologies can only be worthy if people participate in the process of technological change (i.e. if they adopt and use those technologies) (Fernández-Baldor et al., 2012). Although the potential positive effect of new technologies is known, not all individuals are willing to participate because of low capabilities. Thus, the CA seems like a promising tool to strengthen the link between human capabilities and technology adoption decisions.

To prevent the potential impacts of climate change on livelihood, individuals should acclimatise to the unstable climate conditions. As mentioned above, the technology-based strategy provides the most effective and fastest adaptation through technology adoption. CSA technologies are the innovations (the first of three essential steps in Rogers' theory) that are necessary to start the adoption mechanism. In the scope of CA, these technologies are the resources or the commodities (means) for people to adapt to climate variations and enlarge their well-being by improving their actual achievements (functionings). However, the participation of people in that process is related to their capabilities.

The diffusion of CSA technologies can occur due to both individual and external capabilities. In other words, people might hear about these technologies either due to their effort or due to a communal spillover in the area (Oosterlaken, 2013). This situation is mentioned in Rogers' discourse under communication mechanisms covered by mass media and interpersonal channels. The technology adoption process does not start unless one of those channels is available.

When people hear about the existence of the new technology (i.e. knowledge - the first of the five stages in Rogers' theory), human capabilities get involved in the process as a factor that influences the persuasion stage of the adoption mechanism. In other words, people who hear about the new technologies can decide their participation in the technological change process within the scope of their capabilities since they should have adequate capability set for the efficient usage of the CSA technologies. Thus, using new technologies is more likely for people with suitable capabilities. If people have suitable capabilities to use new technologies, it is expected for them to have positive adoption decisions with more probability than those who do not. Thus, people should have adequate capabilities for the efficient usage of the CSA technologies to be persuaded for the adoption. Adopting new technologies as a result of adequate human capabilities can decrease the perceived impact of climate change on poverty and well-being.

The implementation of the technology corresponds to functionings in capability theory since this stage supposedly improves the actual achievements of the people due to the positive net returns of the new technologies. If productivity and production increase through the adoption and implementation of modern technology, an increase in well-being and living standards is expected. This improvement in well-being and living standards brings along the confirmation stage. Thus, human capabilities can be considered an important factor in adopting and adequately implementing the new technology that can decrease the perceived impact of climate change on poverty and well-being.

The above argumentation leads us to the fact that people with low capabilities may hesitate to take adoption decisions. Even if they decide to adopt, the diversity in their capability sets may create certain difficulties and differences in the implementation process of the CSA technologies. Hence, the achievements of people may be diverse. To improve the level of achievement the personal and communal heterogeneities should be decreased by enlarging human capabilities. As mentioned, ICTs are one of the very effective ways to reinforce human capabilities.

ICTs are both means and ends (i.e. they have both instrumental and intrinsic value) in the capability theory due to their characteristics. Since ICTs such as the internet, telephone, computer, etc. provides an opportunity for people to increase their knowledge, educational achievement, health, recreation, and so on, they have intrinsic value for well-being (Oosterlaken, 2012). The reinforcement of human capabilities through this intrinsic value, consequently, increases the participation chance of individuals in the process of technological change. For instance, people who are eligible for ICTs might collect complete information on technical issues, advantages and disadvantages of CSA technologies. Thus, adoption decisions shall be easier given the larger capability sets.

Moreover, given their advantage to access, use and dissemination of information, ICTs also have an instrumental value for human well-being (Ahmed, 2012). This instrumental value contributes to the diffusion of information and knowledge as well as human capabilities. Hence, the instrumental value of ICTs expedites the diffusion stage of Rogers' theory. This situation can be exemplified by the following example by Oosterlaken "a farmer who can increase his income because he has an internet connection and hence access to relevant agricultural information" (Oosterlaken, 2013, 53). Furthermore, due to the usage of agricultural technology today, the well-being in the future can sustain. For instance, "a farmer might be able to pay the school fees for his children because of increased number of cattle and increased number of crop-yields today" (Oosterlaken et al., 2012, 117).

Given that technology adoption can only begin when individuals hear about the existence of the new technology, ICTs are adequate tools to fasten the essential role of the technology diffusion phase and accelerate the speed of it among people. Thus, if human capabilities expand through ICTs, we argue that the stages of the diffusion of innovations theory occur faster, with higher participation in the process of technological change. Thus, the adaptive capacity is enlarged by the expansion of human capabilities (Makate, 2019).

The discussion which took place in this section sustains that ICTs are relevant for the technology adoption process as a result of higher human capabilities and rapid diffusion. Moreover, higher technology adoption rates mitigate the perceived impact of climate change and its impact on poverty. Moreover, the analytical framework represented in Figure 4.1 is more encompassing to critically analyse how the capability theory is essential for the articulation of the links between climate change, technology, and poverty.

4.4 Material and Methods

The analytical framework described above was used to build an econometric model to estimate the effect of climate change on poverty taking into account the role of reinforced human capabilities.

This section presents the data and the econometric strategy in a structured way.

4.4.1 Data Description

Our data sample covered an unbalanced panel of 21 years and 168 countries. The list of countries included in the analysis is provided in Appendix 4.A.

Table 4.1 lists the variables used during the econometric analysis, their units and the databases. The rest of the section gives a more detailed explanation of each variable and the data collection processes.

Group	**Variable**	**Unit**	**Source**
Poverty	Human Development Index (HDI)		UNDP
Climate and Land Variables	Land Surface Temperature (LST)	Kelvin	MOD11A2.061 Terra Land Surface Temperature and Emissivity 8-Day Global 1km

Group	Variable	Unit	Source
	Precipitation (RAIN)	mm	Climate Change Knowledge Portal - WorldBank
	Enhanced Vegetation Index (EVI)		MOD13Q1.006 Terra Vegetation Indices 16-Day Global 250m
ICT Variables	Mobile Phone (MOB)	per 100 people	WorldBank
	Internet Usage (INT)	% total pop.	World Bank
Control Variables	Agricultural Area (AGRIL)	% total land	Worldbank
	Rural Population (RPOP)	% total pop.	Worldbank
	Government Effectiveness Index (GEI)		Worldbank

Table 4.1. Description of the Variables (Source: Own elaboration)

4.4.1.1 The variable poverty

Since we adopt the definition of poverty from a multidimensional perspective as articulated in the CA, selecting data that could encompass several dimensions of poverty was very important. When it comes to multidimensional poverty, there are some options: (i) the Multidimensional Poverty Index (MPI) by OPHI (Oxford Poverty and Human Development Initiative), (ii) the Human Development Index (HDI) by UNDP and (iii) the Multidimensional Poverty Measure (MPM) by the Worldbank. The MPI[1] and MPM are very similar indicators, both extracted

[1]Besides its sample size, the MPI carries more problems in terms of the household surveys used to publish current MPI values since outdated surveys were used to compute current MPI values. For instance, a survey from 2001 was used to

depending on the household surveys. Due to this dependency, they have a small and irregular sample size.

On the other hand, the HDI has a large and regular sample size in terms of countries and years. Although its multidimensionality is narrower in comparison to MPI and MPM, it is still a strong indicator to capture poverty in the context of CA. Thus, we use HDI as the proxy for poverty in this work.

HDI includes three sub-indices, namely, education, health and income. The education index includes two items: (i) mean years of schooling and (ii) expected years of schooling. The health index is measured using life expectancy at birth. Finally, the income index is measured using Gross National Income. Each index is weighted uniformly to give the equal importance to each dimension (Alkire, 2010).

4.4.1.2 Climate and Land variables

We used two proxies for climate change: precipitation (RAIN) and land surface temperature (LST). These are the most used proxies to capture climate variations in the literature (Skoufias et al., 2011; Ochieng et al., 2016). RAIN data was taken from the Climate Change Knowledge Portal (CCKP[2]) of the Worldbank Group. CCKP is a very comprehensive database that collects historical climate data globally. The data can be downloaded in the format of a map or as a time series. Moreover, users can collect the country or region level data monthly or yearly. We used annually average precipitation (in milimeters) for each country that our sample covered.

LST data is derived from MODIS (Moderate Resolution Imaging Spectroradiometer) satellite imagery from the product MOD11A2.061 (Wan and G., 2015). This product measures the 8-day average land surface temperature with a 1km spatial resolution. LST is measured by the brightness of the vegetation and bare soil temperatures. The unit of the data is in Kelvin (K).

compute the MPI value for 2011. Also, the same data is used (survey from 2009) for two MPI values (for 2013, 2014), and some countries have two different MPI values for the same year from two different surveys. It is not clear what date or value the user should consider.

[2]https://climateknowledgeportal.worldbank.org/ (accessed in 02/05/2022).

The land data used to capture vegetation as a proxy of agricultural production is the Enhanced Vegetation Index (EVI). EVI is also derived from the MODIS satellite imagery from the product MOD13Q1.006 (Didan, 2015). This data observes the earth's surface and measures 16-day average vegetation. It includes two vegetation bands for Normalised Difference Vegetation Index (NDVI) and EVI. Between them, EVI is more precise since it is a measure that minimises canopy background variations while keeping the vegetation sensitivity high. This product produces a vegetation index per pixel. Moreover, it has a very high spatial resolution with a pixel size of 250 m.

The two variables from MODIS were extracted using Google Earth Engine (GEE). GEE is an open-source platform for geospatial analyses with numerous satellite imagery and geospatial datasets. We collected average LST and EVI data for each year and country.

4.4.1.3 ICT variables

Two ICT variables are used: (i) mobile cellular subscription (per 100 people) (MOB) and (ii) individuals using the internet (% of the population) (INT), which were taken from the Worldbank. MOB covers the subscriptions to mobile telephone services. It counts for post-paid and actively prepaid telephone accounts within the last three months. INT shows the percentage of people using the internet from any location and any platform in the last three months (WDI, 2019).

4.4.1.4 Control variables

In this work, we used three control variables: (i) agricultural land (AGRIL), (ii) rural population (RPOP) and (iii) government effectiveness index (GEI). All variables were taken from the Worldbank. We selected them considering the previous literature and their potential impact on poverty related to climate change (see Shimada, 2022; Eichsteller et al., 2022).

AGRIL is the percentage of total land area used as agricultural land. RPOP is the percentage of the total population living in rural areas. Finally, GEI captures the quality of public services and infrastructure in terms of schools, hospitals, water, electricity and maintenance, political stability, and credibility of the government. We found this variable important since the dissemination of the CSA technologies or ICTs in the country could be related to the government's effectiveness (Agarwal and Maiti, 2020; Shimada, 2022).

4.4.2 Econometric Strategy

It is possible to see the descriptive statistics of the data in Table 4.2. Since the variables are collected from diverse data sources, the number of observations for each variable shows differences. The variables in the form of an index, namely, HDI, EVI and GEI, and the variables that show a percentile, namely, INT, AGRIL and RPOP, are used without a further transformation. On the other hand, the logarithmic transformation has been applied to LST, RAIN and MOB to standardize the interpretations regarding the effect of all explanatory variables on HDI.

$Variables$	$Obs.$	$Mean$	Std_d	Min	Max
HDI	3,324	0.6753914	0.162815	0.262	0.957
EVI	3,570	0.2917971	0.1261465	0.0459798	0.6187726
ln(LST)	3,556	-3.15E-10	0.0296149	-0.089225	0.060282
ln(RAIN)	3,570	-1.54E-08	0.9977228	-4.104728	1.771283
ln(MOB)	3,533	3.746221	1.533981	-4.012312	5.359596
INT	3,413	0.3205652	0.3006031	0	1
AGRIL	3,213	0.3953333	0.2179731	0.0044871	0.8548737
RPOP	3,561	44.72979	0.229041	0	0.91
GEI	3,382	-0.0815959	0.9736664	-2.475142	2.436975

Table 4.2. Descriptive Statistics (Source: Own elaboration)

As mentioned before, the analytical framework presented in Section 3, was used to construct the model presented in Equation 4.1. This model was designed to capture the complex relationships in the triangle of climate change, technology and poverty. Given that climate change can affect poverty directly through the conversion factors and indirectly through agricultural productivity, the model was designed to encompass both situations. Moreover, the effect of climate-related variables is expected to be nonlinear. Thus, these variables are included in the model as quadratic. Strong interactions between the amount of rainfall and temperature acknowledged by the literature (see. Welch et al., 2010; Ochieng et al., 2016) led us to include the interaction term between the LST and RAIN in the model as well.

We used interaction terms between agricultural productivity (EVI), climate and ICT variables. The reason for that was to understand whether there is a significant effect of agricultural productivity on poverty when combined with the climate variables and what happens to this effect when ICT variables are also interacted. Here, ICT variables were considered as the climate adaptation technology since we assume that ICT usage can increase the adoption of CSA technologies due to higher human capabilities and faster diffusion of the innovations. As mentioned, ICTs can reinforce the capability set of the people and improve the dissemination of climate-related technologies in the community. Thus, the adoption of CSA technologies is assumed through the ICT variables (i.e. mobile phone and internet use).

$$\begin{aligned}
HDI_{it} = \beta_0 + \beta_1 ln(LST)_{it} + \beta_2 ln(LST)^2_{it} + \beta_3 ln(RAIN)_{it} + \beta_4 ln(RAIN)^2_{it} + \beta_5 EVI_{it-1} \\
+\beta_6 EVI_{it-1} \times ln(LST)_{it-1} + \beta_7 EVI_{it-1} \times ln(LST)^2_{it-1} + \beta_8 EVI_{it-1} \times ln(RAIN)_{it-1} \\
+\beta_9 EVI_{it-1} \times ln(RAIN)^2_{it-1} + \beta_{10} EVI_{it-1} \times ln(RAIN)_{it-1} \times ln(LST)_{it-1} \\
\beta_{11} EVI_{it-1} \times ln(LST)^2_{it-1} \times INT_{it-1} + \beta_{12} EVI_{it-1} \times ln(LST)^2_{it-1} \times ln(MOB)_{it-1} \\
+\beta_{13} EVI_{it-1} \times ln(RAIN)^2_{it-1} \times INT_{it-1} + \beta_{14} EVI_{it-1} \times ln(RAIN)^2_{it-1} \times ln(MOB)_{it-1} \\
+\beta_{15} EVI_{it-1} \times ln(RAIN)_{it-1} \times ln(LST)_{it-1} \times INT_{it-1} \\
+\beta_{16} EVI_{it-1} \times ln(RAIN)_{it-1} \times ln(LST)_{it-1} \times ln(MOB)_{it-1} + \\
AGRIL_{it-1} + RPOP_{it-1} + GEI_{it-1} + \delta_t Country_t + \epsilon_{it}
\end{aligned} \tag{4.1}$$

where i indexes the cross sectional units and t refers to the time periods. Moreover, ϵ_{it} is the error term that was allowed to be auto correlated across t and/or contemporaneously correlated throughout i (Beck and Katz, 1995). As can be seen, the direct effect of climate variables on HDI was introduced as contemporaneous. However, their indirect effect through agricultural productivity index was inserted in the model one year lagged since the diminution in the income or consumption through the lower agricultural productivity wouldn't occur abruptly. Finally, country fixed effects were included in the model.

We estimated our model through the Prais-Winsten regression with the Panel Corrected Standard Errors (PCSE) due to the problems, namely, heteroskedasticity, serial correlation and cross-sectional dependence in our data sample.

PCSE was first introduced by Beck and Katz (1995), and is applied in a two-step procedure: (i) serial correlation is eliminated from the data and (ii) OLS estimation is applied to the serial correlation eliminated data with corrected standard errors for the cross-sectional dependence (Beck and Katz, 1995).

In the PCSE, the standard errors are solved independently of the cross-sectional dimensions to create consistent disturbance covariance matrix estimations (Khan et al., 2020). Thus, the estimations produced are robust. We used panel-specific AR1 to deal with serial correlation while controlling for panel-level heteroscedasticity of standard errors.

Since Equation 4.1 includes quadratic terms and interactions, interpretation of the results is not straightforward. For instance, the coefficients of the $ln(LST)$ and $ln(LST)^2$ cannot be interpreted individually as they appear in the model because an increase in $ln(LST)$ cannot be independent of $ln(LST)^2$ and vice-versa. Thus, we looked at the marginal effects to see the estimated absolute impact of each variable on HDI following Equation 4.2:

$$MEM_{it} = \frac{\partial y_{it}}{\partial x_{it}} \tag{4.2}$$

where MEM_{it} stands for the marginal effects at means, x_{it} represents the regressors and y_{it} stands for the dependent variable.

4.5 Results and Discussion

We started the analyses by estimating the model presented in Equation 4.1 (see Appendix 4.B). These estimations were used to calculate the marginal effects of the explanatory variables. The marginal effects helped to detect the absolute change in the HDI for a percentage change in each variable included in the model.

Initially, we measured the average marginal effects concerning all variables and observed their impact on HDI. As can be seen in Table 4.3, the marginal effects of all variables were statistically significant except for ln(RAIN) neither at time t or $t-1$. According to these results, a 10 per cent increase in LST led to a 2.33 percentage points increase in HDI at time t and 2.27 percentage points in the following year. Moreover, an increase in EVI by 10 percentage points enlarges HDI in the following year by 0.37 percentage points. Likewise, a 10 percentage point change in INT will lead to an increase of 0.08 percentage points in the HDI of the following year. A 10 per cent increase in MOB influences HDI positively at $t+1$ by 0.12 percentage points. Finally, all the control variables have the expected marginal effects and are statistically significant. These average results account for all the interactions that the model includes.

HDI		dy/dx	$Std_{err.}$
ln(LST)		0.2339***	0.0671
ln(RAIN)		0.0009	0.0010
L1.EVI		0.0377***	0.0150
L1.ln(LST)		0.227***	0.0756
L1.ln(RAIN)		-0.0008	0.0010
L1.INT		0.0084***	0.0014
L1.ln(MOB)		0.0120***	0.0004
L1.AGRIL		-0.0275***	0.0108
L1.GEI		0.0045***	0.0011
L1.RPOP		-0.5881***	0.0129
Obs.: 2,892			
dy/dx w.r.t.:	ln(LST), ln(RAIN), L1.EVI, L1.ln(LST), L1.ln(RAIN) L1.INT, L1.ln(MOB) L1.AGRIL, L1.GEI, L1.RPOP		

Note: ***indicates significance at 0.001.

Table 4.3. Average marginal effects of all variables included in the model (Source: Own elaboration)

As mentioned previously, climate change has both direct and indirect effects on poverty. The indirect effect of climate variables on poverty can be through agricultural production. If agricultural production decreases, a shock in people's living standards is expected due to instabilities in food security, welfare, income or livelihoods (Anik et al., 2021).

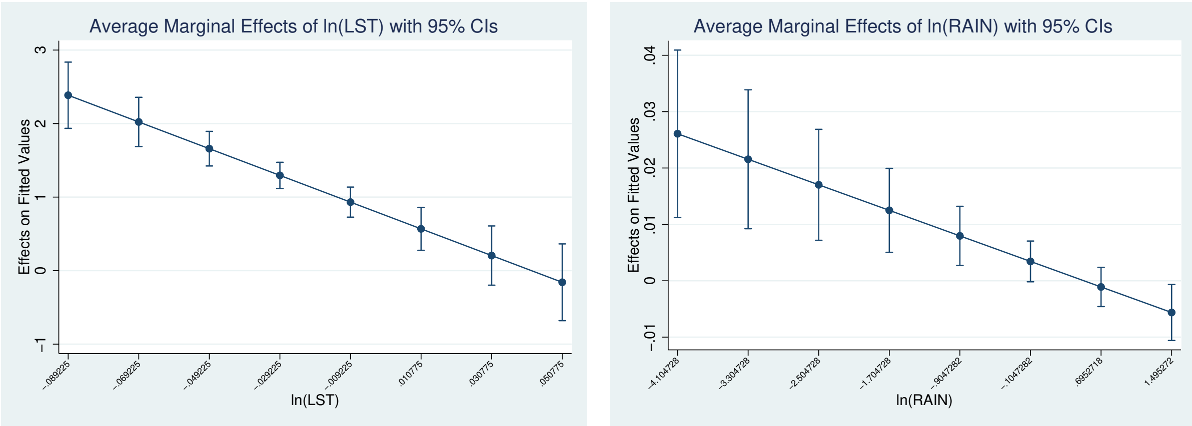
Thus, we put effort to draw a more detailed picture to analyse the direct and indirect marginal effects of climate variables on poverty. To do that, we selected specific values for the climate variables. In a way, we treated these continuous variables as discrete to have a more precise view of their effect instead of limiting ourselves to the average.

Firstly, we measured the direct and contemporaneous effect of climate variables on HDI. The marginal effects of these variables, namely LST and RAIN, are represented in Table 4.4 with the values of LST and RAIN set at different levels. As it can be seen, the effect of climate variables are not linear. The positive marginal effects showed a downward tendency when LST and RAIN increase. These results were not surprising. For instance, high temperatures can limit the ability to be outside due to the hazards to people's health (Hisali et al., 2011). Likewise, too much precipitation due to the risks, such as floods or cyclones, can impact human life negatively (Rochdane et al., 2014). Figure 4.2 depicts these marginal effects.

		dy/dx	$Std_{err.}$			dy/dx	$Std_{err.}$
ln(LST) at_	-0.09	2.386***	0.230	ln(RAIN) at_	-4.11	0.026***	0.008
	-0.07	2.022***	0.171		-3.30	0.022***	0.006
	-0.05	1.659***	0.120		-2.50	0.017***	0.005
	-0.03	1.295***	0.091		-1.70	0.012***	0.004
	-0.01	0.932***	0.104		-0.90	0.008***	0.003
	0.01	0.568***	0.149		-0.10	0.003**	0.002
	0.03	0.205	0.205		0.70	-0.001	0.002
	0.05	-0.159	0.266		1.50	-0.006***	0.003
Obs.: 2,892							
dy/dx w.r.t.	ln(LST)	and	ln(RAIN)				

Note: *** and ** indicates significance at 0.001 and 0.05, respectively.

Table 4.4. Marginal effects w.r.t ln(LST) and ln(RAIN), with ln(LST) and ln(RAIN) at different levels (Source: Own elaboration)



(a) w.r.t ln(LST), ln(LST) at different levels

(b) w.r.t ln(RAIN), ln(RAIN) at different levels

Figure 4.2. Visual representation of marginal effects w.r.t ln(LST) and ln(RAIN), with ln(LST) and ln(RAIN) at different levels (Source: Own elaboration)

Secondly, we measured the marginal effect of EVI (stands as a proxy of agricultural production) on HDI when ln(LST) and ln(RAIN) were appointed at eight equally spaced different levels within the range of minimum and the maximum values that the variables can have. This range was between -0.09 and 0.05 for the ln(LST) and -4.11 and 1.5 for the ln(RAIN), where -0.09 and -4.11 are min values of ln(LST) and ln(RAIN), respectively (see Table 4.2).

Table 4.5 and Figure 4.3 presented changes in the marginal effects of EVI when climate variables were increased gradually within their range. As is seen, initially, both LST and RAIN influenced the average marginal effects of EVI on HDI positively. However, when the level of LST or RAIN was too high, this effect started turning negative.

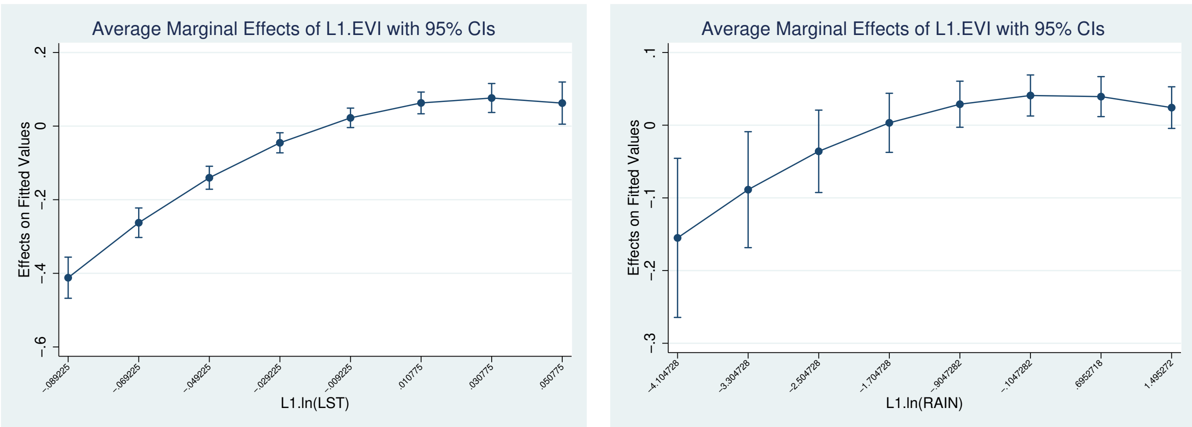
Additionally, LST appeared as a more important element to improve agricultural productivity than RAIN. As is seen, the average marginal effects of EVI on HDI were lower when LST was at the lowermost level compared to what happens for RAIN. Moreover, the marginal effects of EVI turned negative faster when it was interacted with RAIN than with LST in the upmost levels.

We carried the analysis one step further by also including the ICT variables in the relationship between EVI and HDI, already interacted with climate variables. In this examination, we set both ICT variables within four equally spaced levels in the range of minimum and max-

	level	dy/dx	$Std_{err.}$		level	dy/dx	$Std_{err.}$
L1.ln(LST) at_	-0.09	-0.412***	0.028	L1.ln(RAIN) at_	-4.11	-0.155***	0.056
	-0.07	-0.263***	0.020		-3.30	-0.089***	0.041
	-0.05	-0.140***	0.016		-2.50	-0.036	0.029
	-0.03	-0.045***	0.014		-1.70	0.003	0.021
	-0.01	0.022**	0.013		-0.90	0.029**	0.016
	0.01	0.063***	0.015		-0.10	0.041***	0.014
	0.03	0.076***	0.020		0.70	0.039***	0.014
	0.05	0.063***	0.029		1.50	0.024**	0.015
Obs.: 2,892							
dy/dx w.r.t.	L1.EVI						

Note: *** and ** indicates significance at 0.001 and 0.05, respectively.

Table 4.5. Marginal effects w.r.t L1.EVI, with ln(LST) and ln(RAIN) at different levels (Source: Own elaboration)



(a) w.r.t L1.EVI, ln(LST) at different levels

(b) w.r.t L1.EVI, ln(RAIN) at different levels

Figure 4.3. Visual representation of marginal effects w.r.t L1.EVI, with ln(LST) and ln(RAIN) at different levels (Source: Own elaboration)

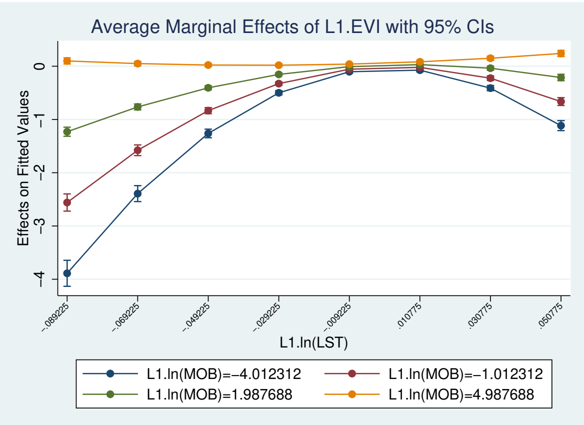
imum values that they can get. This range was between -4.012 and 4.98 for ln(MOB) and between 0 and 0.9 for INT. Afterwards, we interacted each level of ln(LST) and ln(RAIN) with each level of ln(MOB) and INT and observed the marginal effects of EVI on HDI.

The numeric results of the analyses are presented in Appendix 4.C and Appendix 4.D. These values were used to drawn the Figures 4.4 and 4.5.

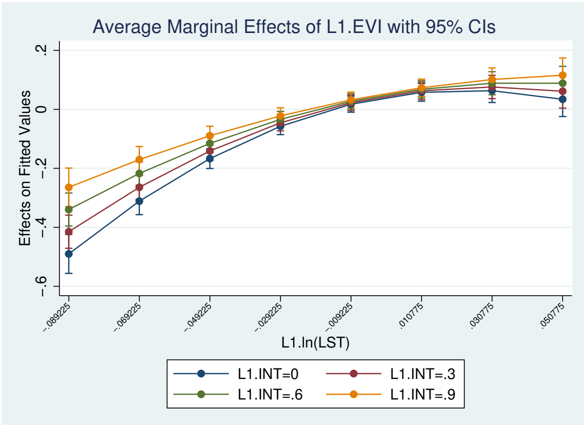
Changes in the effect of EVI for each level of ln(MOB) and INT combined with the each level of ln(LST) are represented in sub-Figures 4.4(a) and (b), respectively.

The four curves in sub-Figures 4.4(a) and (b) stood for different levels of ln(MOB) and

INT, respectively. The eight points in each curve represent the different levels of ln(LST). As is seen, with an increase in the ln(MOB) from the lower to the upper limit, the negative marginal effect of EVI diminished gradually when the temperature was appointed to the lowest level. A gradual change can also be observed for the higher levels of ln(LST). Moreover, the negative influence of too high temperatures on the marginal effects of EVI was erased by the high level of ln(MOB). Similarly, with an increase in INT from the lower to the upper level, the negative impact of ln(LST) on the average marginal effects of EVI decreased. In the comparison of the two cases, a greater influence of INT over ln(MOB) can be observed. More precisely, the highest usage of ln(MOB), represented with a straight line, didn't show much difference in the marginal effects of EVI when the higher and more dangerous temperature levels were in question. However, the increasing concave slope of the INT can be interpreted as a more eminent influence since it blocks the negative influence of high-level temperatures and even turns them into positive.



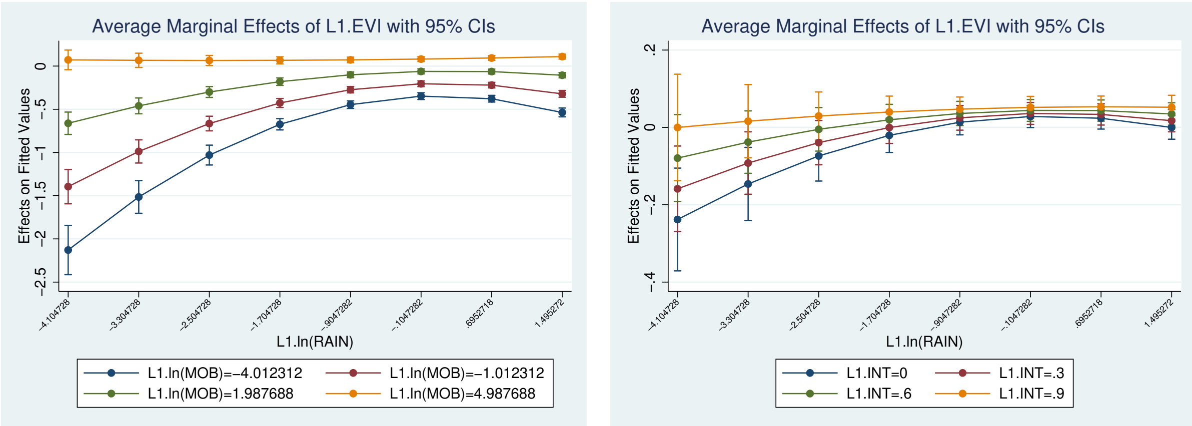
(a) w.r.t L1.EVI, ln(LST) and ln(MOB) at different levels



(b) w.r.t L1.EVI, ln(LST) and INT at different levels

Figure 4.4. Visual representation of marginal effects w.r.t. L1.EVI, with L1.ln(LST), L1.ln(MOB) and L1.INT at different levels (Source: Own elaboration)

Furthermore, the alterations in the marginal effects of EVI can be observed in sub-Figures 4.5(a) and (b) when the level of ln(RAIN) together with the level of ln(MOB) and INT usage change. Similar to the results presented in Figure 4.4, the influence of higher level of ln(MOB) and INT usage blocks the negative impact of RAIN on the marginal effects of EVI. When both ln(MOB) and INT were at the maximum level, the marginal effect of EVI wasn't affected negatively by a very little or high amount of rain.



(a) w.r.t L1.EVI, ln(RAIN) and ln(MOB) at different levels

(b) w.r.t L1.EVI, ln(RAIN) and INT at different levels

Figure 4.5. Visual representation of marginal effects w.r.t. L1.EVI, with L1.ln(RAIN), L1.ln(MOB) and L1.INT at different levels (Source: Own elaboration)

In the light of these results, we observed alterations in the average marginal effects of EVI on HDI. The negative influence of extreme climate events on these marginal effects was blocked by the high ICT levels. As articulated in Section 3, the reason for such a situation could be caused by two possibilities: (i) the enhanced capability set of people and (ii) the diffusion of the CSA technologies. As we studied the ICT variables as a factor that influences the CSA technology adoption pace through these two possibilities, we expected higher and faster participation in the technological change process. The empirical results that were presented during this section support our hypotheses.

Of course, if the CSA technologies disseminate in society faster when people have adequate capability sets and knowledge about the technologies, climate adaptation would occur more rapidly. Our results showed that ICTs are excellent tools for that to happen.

We illustrate this situation in Figure 4.6 within the discourse of Rogers' Diffusion of Innovations Theory by a shift in the S-shaped diffusion and adoption curves. This shift is expected after the interaction of ICTs.

The horizontal line shows time in years, and the vertical line shows the cumulative percentage of adopters. It is possible to observe the initial and the shifted diffusion and adoption curves with the specifications ’before ICTs’ (bold lines) and ’after ICTs’ (thin lines), respectively. As is seen, shifted curves show faster diffusion and technology adoption rates.

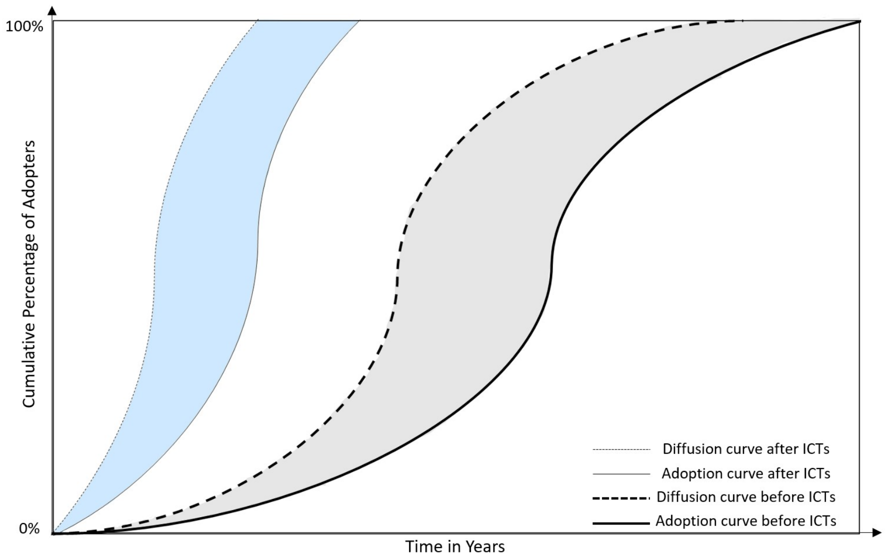


Figure 4.6. Possible effect of ICTs on the S-Shaped Technology Diffusion and Adoption Curve (adjusted from (Rogers, 2003))

As already discussed, poor people are more vulnerable to climate shocks and the economic impact of those shocks (Hallegatte et al., 2014). The positive effect of faster diffusion and a higher rate of adoption can be observed both in economic terms, namely with better production, and in individual terms with higher well-being and opportunities (Jiménez and Zheng, 2018).

The impact of climate variations might not be perceived by individuals as much as before due to the rapid diffusion and adoption curve. Faster technology adoption increases the strength of individuals against climate shocks. Thus, economic performance is positively affected by rapid adoption rates (Rogers, 2003). Besides, a higher economic performance corresponds to lower levels of vulnerability and poverty.

4.6 Conclusions

Today the world is facing two serious problems, poverty and climate change. Alleviation of these problems is crucial for both present and future generations. We aim to provide a valuable contribution to the literature on climate change and poverty with this motivation.

Climate change and poverty are interconnected problems of the world. People living in poor areas are more vulnerable to climate shocks and the economic impact of those shocks, which can be perceived through extreme weather events such as temperature and sea-level rise, drought, and floods. If no precautionary measures take place, the consequences of these events will affect the livelihoods in terms of production, income and consumption.

As clearly sustained in the literature, the impact of climate change can decrease via climate adaptation strategies. One of the most effective adaptation strategies is based on technology adoption. People can prevent the negative effects of climate variabilities if they adopt new technologies produced to decrease the impact of climate change. However, it is not easy to have adoption decisions for all individuals due to low adaptive capacities and the uncertainties associated with the new technologies.

Rogers (2003) introduced the technology adoption decision stages in his theory, where the technology adoption process starts with the diffusion of new technology among people. He presented the diffusion and adoption path with an S-shaped curve that represented the attitudes of individuals toward the new technologies over time. Individuals act differently because of the dissimilarities among them. While some people adopt the technology instantaneously, it is not an immediate decision for most.

The human capability, defined within the CA theory, is a critical element in erasing these factors that block the adoption decisions. If people have adequate capability sets to understand the usage and implementation of the new technologies as well as their advantages and disadvantages, the adoption would be expected. However, not all individuals have the same capability set. Thus, it is essential to reinforce human capabilities while decreasing the heterogeneities among people. ICTs are acknowledged in the literature as an input to enhance human capabilities.

Given the relevance of CA in the technology adoption decisions, we re-examined Rogers' Diffusion of Innovations theory from the Capability Perspective. In other words, we tried to show the relationship between the technology adoption process (as in Rogers' theory) and human capabilities (as in Sen's theory). Moreover, we articulated the importance of reinforced human capabilities in this relationship. ICTs were identified as the tools that can help to improve human capabilities. Moreover, the easy access to information and knowledge through the ICTs was also considered a factor that improves the technology diffusion pace in societies. Thus, the effect of ICTs on the technology adoption process is discussed from two different angles: (i) human capabilities and (ii) technology diffusion.

This investigation helped us build an analytical framework used to construct a model that measures the relationship between climate change, technology and poverty. The model aimed to estimate the direct and indirect effects of climate change on poverty. We used agricultural production to observe the indirect impact of climate variabilities on poverty. In this model, we also analysed the impact of ICTs on this relationship. Due to the several interactions included in the model, we calculated the average marginal effects of explanatory variables on poverty.

Our results show the direct and indirect negative impacts of climate change on poverty. Moreover, when the ICTs were interacted into the analysis, the negative influence of extreme weather events on agricultural production diminished.

Given these results, we concluded that higher participation in the technological change process occurs as a result of the positive effects of ICTs on both capabilities and diffusion. When adoption rates increase, the perceived impacts of climate change on vulnerable areas decrease. Eventually, the poverty level of countries should also reduce due to the mitigation of climate variabilities.

In this paper, therefore, we showed the relevance and importance of human capabilities in the technology adoption process and its effect on poverty. We established some relationships between these dimensions that, to the best of our knowledge, have not been discussed in the literature and that constitute our main contribution.

4.A List of Countries

Countries					
Afghanistan	Cambodia	Gabon	Kyrgyz Rep.	Niger	Spain
Albania	Cameroon	Gambia, The	Laos	Nigeria	Sri Lanka
Algeria	Central African Rep.	Georgia	Latvia	Norway	Sudan
Andorra	Chad	Germany	Lebanon	Oman	Suriname
Angola	Colombia	Ghana	Lesotho	Pakistan	Sweden
Antigua and Barbuda	Comoros	Greece	Liberia	Panama	Switzerland
Argentina	Congo (Dem. Rep. of the)	Grenada	Libya	Papua New Guinea	Tajikistan
Armenia	Congo (Rep. of the)	Guatemala	Liechtenstein	Paraguay	Tanzania, Uni. Rep
Austria	Costa Rica	Guinea	Lithuania	Peru	Thailand
Azerbaijan	Cote d'Ivoire	Guinea-Bissau	Luxembourg	Philippines	Timor Leste
Bahamas, The	Croatia	Guyana	Madagascar	Poland	Togo
Bahrain	Cyprus	Haiti	Malawi	Portugal	Tonga
Bangladesh	Czech Rep.	Honduras	Malaysia	Qatar	Trinidad and Tobago
Barbados	Denmark	Hungary	Maldives	Rep. of Serbia	Tunisia
Belarus	Djibouti	Iceland	Mali	Romania	Turkey
Belgium	Dominica	India	Malta	Rwanda	Turkmenistan
Belize	Dominican Rep.	Iran	Mauritania	Samoa	Uganda
Benin	Ecuador	Iraq	Mauritius	Sao Toma and Principe	Ukraine
Bhutan	Egypt	Ireland	Mexico	Saudi Arabia	United Arab Emirates
Bolivia	El Salvador	Italy	Moldova	Senegal	United Kingdom
Bosnia and Herzegovina	Equatorial Guinea	Jamaica	Mongolia	Seychelles	Uruguay
Botswana	Eritrea	Japan	Morocco	Sierra Leone	Uzbekistan
Brazil	Estonia	Jordan	Mozambique	Singapore	Vanuatu
Brunei	Eswatini	Kazakhstan	Namibia	Slovakia	Venezuela
Bulgaria	Ethiopia	Kenya	Nepal	Slovenia	Vietnam
Burkina Faso	Fiji	Kiribati	Netherlands	Solomon Islands	Yemen
Burundi	Finland	Korea, Rep. of	New Zealand	South Africa	Zambia
Cabo Verde	France	Kuwait	Nicaragua	South Sudan	Zimbabwe

4.B Estimations of Prais-Winsten regression with Panel Corrrected Standard Errors

HDI	Coefficients	Het-corrected Std. Errors
$ln(LST)$	0.2344596***	0.0679
$ln(LST)^2$	0.4008	0.8358
$ln(RAIN)$	0.0009	0.0010
$ln(RAIN)^2$	0.0002	0.0003
$L1.EVI$	0.0541169***	0.0134
$L1.EVI \times L1.ln(LST)$	2.127449***	0.2782
$L1.EVI \times L1.ln(LST)^2$	-250.3682***	8.2842
$L1.EVI \times L1.ln(RAIN)$	0.0134573***	0.0042
$L1.EVI \times L1.ln(RAIN)^2$	-0.0589632***	0.0044
$L1.EVI \times L1.ln(RAIN) \times L1.ln(LST)$	-4.808375***	0.3396
$L1.EVI \times L1.ln(LST)^2 \times L1.INT$	29.7855***	5.1903
$L1.EVI \times L1.ln(LST)^2 \times L1.ln(MOB)$	54.18298***	1.8420
$L1.EVI \times L1.ln(RAIN) \times L1.ln(LST) \times L1.INT$	-0.2408	0.3304
$L1.EVI \times L1.ln(RAIN) \times L1.ln(LST) \times L1.ln(MOB)$	1.083047***	0.0844
$L1.EVI \times L1.ln(RAIN)^2 \times L1.INT$	0.0141953***	0.0055
$L1.EVI \times L1.ln(RAIN)^2 \times L1.ln(MOB)$	0.0114916***	0.0010
$L1.AGRIL$	-0.0275715***	0.0108
$L1.GEI$	0.0045349***	0.0011
$L1.RPOP$	-0.5881341***	0.0129
Cons.	0.9264702***	0.0236
Country FE	Yes	
R^2 = 0.9985		
Wald χ^2 = 342700.04		
$p > \chi^2$ = 0.00		
Obs.: 2,892		
Groups: 168		
Note: ***indicates significance at 0.001.		

4.C Marginal effects with respect to L1.EVI when L1.ln(LST), L1.ln(MOB) and L1.INT are set at different levels

ln(LST) at_	ln(MOB) at_	dy/dx	$Std_{err.}$	INT at_	dy/dx	$Std_{err.}$
-0.09	-4.012	-3.888***	0.125	0	-0.490***	0.034
	-1.012	-2.559***	0.082	0.3	-0.415***	0.029
	1.987	-1.230***	0.044	0.6	-0.340***	0.029
	4.987	0.099***	0.03	0.9	-0.264***	0.033
-0.07	-4.012	-2.392***	0.076	0	-0.311***	0.023
	-1.012	-1.578***	0.051	0.3	-0.264***	0.021
	1.987	-0.764***	0.029	0.6	-0.217***	0.02
	4.987	0.049***	0.021	0.9	-0.170***	0.023
-0.05	-4.012	-1.262***	0.041	0	-0.167***	0.017
	-1.012	-0.834***	0.029	0.3	-0.141***	0.016
	1.987	-0.406***	0.019	0.6	-0.115***	0.016
	4.987	0.023	0.016	0.9	-0.090***	0.016
-0.03	-4.012	-0.499***	0.021	0	-0.057***	0.014
	-1.012	-0.326***	0.017	0.3	-0.046	0.014
	1.987	-0.154***	0.015	0.6	-0.034***	0.014
	4.987	0.019	0.014	0.9	-0.022	0.014
-0.01	-4.012	-0.103***	0.015	0	0.017	0.014
	-1.012	-0.056***	0.014	0.3	0.022**	0.013
	1.987	-0.008	0.014	0.6	0.027***	0.013
	4.987	0.040***	0.014	0.9	0.032***	0.013
0.01	-4.012	-0.074***	0.017	0	0.058***	0.015
	-1.012	-0.022	0.016	0.3	0.063***	0.015
	1.987	0.031***	0.015	0.6	0.068***	0.015
	4.987	0.083***	0.015	0.9	0.073***	0.015
0.03	-4.012	-0.411***	0.025	0	0.063***	0.02
	-1.012	-0.224***	0.022	0.3	0.076***	0.02
	1.987	-0.037**	0.02	0.6	0.088***	0.02
	4.987	-0.212***	0.031	0.9	0.089***	0.029
0.05	-4.012	-1.115***	0.048	0	0.034	0.03
	-1.012	-0.663***	0.038	0.3	0.061***	0.029
	1.987	0.150***	0.02	0.6	0.101***	0.02
	4.987	0.240***	0.03	0.9	0.116***	0.03
Obs.: 2,892						
dy/dx w.r.t.	L1.EVI					

Note: *** and ** indicates significance at 0.001 and 0.05, respectively.

4.D Marginal effects with respect to L1.EVI when L1.ln(RAIN), L1.ln(MOB) and L1.INT are set at different levels

ln(RAIN) at_	ln(MOB) at_	dy/dx	$Std_{err.}$	INT at_	dy/dx	$Std_{err.}$
-4.11	-4.012	-2.129***	0.145	0	-0.238***	0.068
	-1.012	-1.395***	0.101	0.3	-0.159***	0.056
	1.987	-0.662***	0.066	0.6	-0.079	0.057
	4.987	0.072	0.058	0.9	0	0.07
-3.3	-4.012	-1.515***	0.096	0	-0.146***	0.048
	-1.012	-0.988***	0.068	0.3	-0.092***	0.041
	1.987	-0.461***	0.047	0.6	-0.038	0.041
	4.987	0.067	0.042	0.9	0.016	0.048
-2.5	-4.012	-1.030***	0.059	0	-0.074***	0.033
	-1.012	-0.665***	0.043	0.3	-0.039	0.029
	1.987	-0.300***	0.032	0.6	-0.005	0.029
	4.987	0.065***	0.03	0.9	0.029	0.032
-1.7	-4.012	-0.674***	0.033	0	-0.02	0.023
	-1.012	-0.427***	0.027	0.3	0	0.021
	1.987	-0.180***	0.022	0.6	0.02	0.02
	4.987	0.067***	0.021	0.9	0.040**	0.021
-0.9	-4.012	-0.446***	0.022	0	0.014	0.017
	-1.012	-0.273***	0.019	0.3	0.025	0.016
	1.987	-0.101***	0.017	0.6	0.036**	0.016
	4.987	0.072***	0.016	0.9	0.047***	0.016
-0.1	-4.012	-0.348***	0.02	0	0.028**	0.015
	-1.012	-0.205***	0.017	0.3	0.036**	0.014
	1.987	-0.062***	0.015	0.6	0.044***	0.014
	4.987	0.081***	0.014	0.9	0.052***	0.014
0.7	-4.012	-0.378***	0.02	0	0.024**	0.014
	-1.012	-0.221***	0.017	0.3	0.034**	0.014
	1.987	-0.063***	0.015	0.6	0.044***	0.014
	4.987	0.094***	0.014	0.9	0.053***	0.014
1.5	-4.012	-0.537***	0.026	0	0.001	0.016
	-1.012	-0.321***	0.02	0.3	0.017	0.015
	1.987	-0.106***	0.016	0.6	0.035***	0.015
	4.987	0.110***	0.015	0.9	0.052***	0.016
Obs.: 2,892						
dy/dx w.r.t.	L1.EVI					

Note: *** and ** indicates significance at 0.001 and 0.05, respectively.

Chapter 5

Conclusion

During the previous chapters, we aimed to draw further directions in the literature on the Capability Approach (CA), which defines human development and well-being as a procedure for enhancing individuals' choices. This last chapter presents the main conclusions of the thesis and articulates the policy implications that our findings may point out. Finally, the chapter addresses a few of the research limitations and draws some lines for future research.

Chapter 2 proposed a brand-new method to build a Composite Index (CI) and re-measure human development. Traditionally, CI aims to measure a concept by a single number and requires some steps, namely, normalisation, weighting, and aggregation. There are several methods to perform each of these steps. As expected, each method can affect the final solutions directly. Thus, the decision on using any method for the required steps carries some sensitivity. The method that we proposed, on the other hand, does not require any of these steps. In this method, we used the Pareto dominance concept from multi-objective optimisation. This concept allows evaluating several alternatives (countries, firms, regions, etc.) for multiple dimensions separately and simultaneously. Such evaluation ultimately helps to allocate the alternatives on Pareto frontiers which represent different achievement levels regarding alternatives' superiority on the selected dimensions. The proposed method followed two phases, where we first allocated the alternatives on the Pareto frontiers. Then, we considered the Pareto frontiers as the ordered collection of points and used them in the ordered response model to measure the latent index of the specific problem. We used this method to re-measure human development and compared our results with the results of the Human Development Index (HDI). The country rankings by our proposed method and HDI showed a high correlation. However, when we gave a closer look, we realised significant differences in the ranking of the countries between the two indices. The high correlation showed that the proposed method was reliable. Furthermore, the difference between the country rankings (e.g. Singapore, Lichtenstein, Qatar, Belarus, Kuwait, etc.) pointed out the methodological flaws of HDI. More precisely, HDI was criticised by several authors in the literature due to its methodology. It was often disclosed as inadequate due to the vague selection of weights, the min-max normalisation, and its aggregation method. Since the proposed technique does not require any of the steps that a CI would, it is expected to obtain objective results and ranking of the countries. Thus, the ranking difference between HDI and our method showed that HDI suffers from methodological deterrents. CIs are very important tools for policy recommendations. Thus, the objectivity of the method used to build the CI makes these recommendations more trustable.

Chapter 3 introduced an econometric study where we measured the effect of Information and Communication Technologies (ICTs) on human development. Since we considered human development with its definition under the CA, we put effort into conceiving it from several perspectives. To do this, we used micro-level survey data (i.e., household, and personal) and built macro-level (i.e., country) human development elements by following a three-stage data-building process. We used EU-SILC (Statistics on Income and Living Conditions) dataset, a comprehensive survey from Eurostat, to conduct this process. In the first and the second stages, we used the Fuzzy set theory and generated the first 30 items and then ten dimensions, all human development-related, starting from the selected EU-SILC data. In the last stage, the Principal Component Analysis was used to collect these ten dimensions into four representative human development elements: (i) material well-being, (ii) financial stability, (iii) human capital, and (iv) environmental well-being. These elements were named according to the dimensions beneath. By following these stages, we aimed to emphasise the importance of analysing the CA using microdata since human development is an individualistic concept. Finally, we measure the impact of ICT variables (i.e., internet, mobile phone, and fixed phone) on these four human development elements through four separate models. Feasible Generalised Least Square using Fixed effects was used to estimate the models. The main conclusions that can be drawn from the results, all compatible with the previous literature, are the following. We found that the internet has a great potential to enhance human development from all perspectives that have been considered. To obtain higher living standards, governments should invest in the infrastructure of internet access and promote its usage in society. Mobile Phones can also contribute to human development from several perspectives, namely, material well-being, financial stability, and environmental well-being. Given the fact that mobile phones can be used as a computer on many occasions, it is important to increase the access and usage also for the mobile phone together with the internet. Fixed Phone, on the other hand, was not found as effective to improve human development. The positive effect of the fixed phone was proved only on financial stability. For the other dimensions, this variable was either negative or insignificant. That is not surprising since fixed phone usage was dominated by the mobile phone during past years.

Chapter 4 proposed a comprehensive study by exploring the linkages between climate change, technology, and poverty both theoretically and empirically through the following hypothesis: "the diffusion of climate adaption technologies can reduce poverty as viewed through the lenses of the Capability Approach". We analysed this hypothesis focusing on three essential research questions: (i) what is the expected impact of climate change on people living in vulnerable areas? (ii) Do human capabilities influence the adoption of climate technologies? and (iii) What is the role of reinforced capabilities in the adoption decisions of climate technologies? In the first part, we did a critical review by taking advantage of the previous literature and drawing an analytical framework. The two theories which are the "Diffusion of Innovations” from Everett Rogers and the “Capability Approach” from Amartya Sen were combined during this critical review. We re-interpreted Rogers’ theory from the perspective of Sen and elaborated technology diffusion and adoption stages by emphasising the role of human capabilities. According to our findings, technology adoption can reduce the perceived impact of climate change on poverty. To increase the pace of adoption decisions, the capability set of individuals should be reinforced. This reinforcement can be possible with the ICTs. Besides, ICTs could help the diffusion of climate technologies. We used this framework in the second part of the chapter to build an econometric model and prove the points we identified during the theoretical part, also empirically. In the empirical research, we measured the impact of climate change variables (i.e., temperature and precipitation) on poverty directly and through agricultural production. We also included the ICT variables (i.e., internet and mobile phone) to see their effect on this relationship. Our empirical results were along the same lines as our theoretical analysis. More precisely, climate change variables can affect poverty both directly and through agricultural production. This effect appeared positive while the amount of precipitation and the temperature were at normal levels. However, it turned negative when the climate variables reached extreme amounts. The integration of ICTs into the model resulted in the elimination of these negative effects. This finding implies that ICTs can affect the climate technology adoption decisions and also the diffusion of these technologies. This result could indicate critical policy recommendations, especially in the developing world, which is more vulnerable to climate variations. Countries shouldn’t just focus on new climate technologies, which require large amounts of resources (e.g., investments, time, and effort). Instead, they may consider shifting part of these resources to provide access to the elements necessary for the self-improvement of the people, living in a society, to reinforce the set of human capabilities. With a higher set of capabilities, people can enrol in the technology transformation process to mitigate the effects of climate change more rapidly.

There are a few research limitations that can be addressed. The topics that have been covered in this dissertation (e.g. climate change, technology, poverty, human development [dimensions and measurement]) are individually broad fields. Thus, we had to control the coverage of these topics with limited research questions to avoid the risk of over-inclusion. Moreover, the CA is a very broad and individualistic framework. The comprehensive nature of CA makes capturing human development and capabilities fully impossible since some capabilities, such as happiness or feeling satisfied, are not measurable. Thus, putting effort to represent CA numerically was challenging.

Finally, we propose some guidelines for future research in the field. Regarding the analysis conducted in Chapter 2, a dimensional extension could be insightful to capture human development more precisely. As it is studied in Chapter 3, ICT usage, for instance, could be interesting to include as the fourth human development dimension. Moreover, including a discussion about the inequalities in society would give us a chance for a broader understanding in Chapter 4.

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