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Are some developing countries caught in a hunger trap?

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Highlights

- Developing countries are not caught in an unconditional hunger trap.
- The long-term effect and relative influence of biofuel production are weak.
- Food insecurity determinants seem closer to the capability approach than to the malthusian approach.
- The key driver of food insecurity appears to be a low level of gross domestic product per capita.
- Food security policies and programs could be supported by those aimed at improving poverty and economic growth.

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Abstract

This paper aims to test the existence of an unconditional hunger trap and to determine whether biofuel production is among the key long-term determinants of food insecurity. Therefore, we consider the Markov transition matrix and ergodic distribution to test the hypothesis of an unconditional hunger trap and then the conditional inference regression tree to identify the key drivers of food insecurity. We find that developing countries are not caught in a hunger trap. The result of the transition matrix shows that all countries with high levels of food insecurity can move to a lower level. Furthermore, given the characteristics of the countries, the conditional inference regression tree results show that the most important variable is gross domestic product (GDP) per capita. However, in addition to this variable, we need to include the level of age dependency ratio, precipitation, socioeconomic conditions, and corruption index for countries with high levels of food insecurity. Considering the overall sample and sub-samples of low and high food insecure countries, biofuel production is not part of the long-term determinants. The results of the boosting model and panel data quantile regression reveal that the influence of biofuels seems very weak, meaning that they can be a way to fight climate change without penalizing food security.

Keywords: Food security · Long-run determinants · Hunger trap · Biofuels · Conditional Inference Regression tree · Transition matrix

JEL Codes: Q01 · Q16 · Q18

1 Introduction

Although more than enough food is produced to feed the global population, the level of food insecurity remains high in the world. It was estimated that 690 million people were considered as undernourished in 2019, representing 8.9 percent of the world's population, an increase of 10 million people in one year and nearly 60 million in five years. In addition, about one in 10 people worldwide were exposed to severe levels of food insecurity, and the number of stunted children was 144 million (FAO, 2020). Otherwise, around two billion people suffered from mineral and vitamin deficiencies (FAO, 2019). While there is food insecurity even in developed countries, most food insecure people come from developing countries. The majority of food insecure people in 2019 lived in Africa (20%), Asia (11%), and Latin America and the Caribbean (7%). In high-income countries, 8% of the population in North America and Europe is considered to be at moderate levels of food insecurity (FAO, 2019).

According to the World Food Summit in 1996, food security describes a situation that prevails when all people have physical and economic access to sufficient, safe and nutritious food, at all times, that meets their dietary needs and food preferences for an active and healthy life. It is a multidimensional concept including food availability, access, utilization and stability (Shaw, 2007). While food security refers to adequate access to enough food at all times, food insecurity primarily measures hunger. Therefore, hunger can be linked to one or all of the dimensions of food security. Factors that can lead to hunger include food unavailability, lack of access, misuse and instability over a given period. The hunger trap can be defined as a situation that forces people to remain in their food insecurity situation. It is so constraining that it is difficult to escape, especially for vulnerable people. In 2019 about 40% and 54% of stunted children lived in Africa and Asia, respectively, or nine out of ten children. These children were caught in the hunger trap, so-called to emphasize the intergenerational nature of the problem (Bratspies, 2014). The effects of the hunger trap not only affect the individuals involved but also impose significant economic losses due to illness, deaths, school repetitions, school dropouts and reduction in adults physical capacity. According to the Cost of Hunger in Africa (COHA) team, Malawi's economy loses nearly \$600 million every year due to the effects of child undernutrition. Some studies on the hunger trap, focus on a specific country or aspect. Chinkin and Wright (1993), by analyzing the hunger trap, examine women's role in reducing food insecurity, and McNamee (2007) assesses the hunger trap through the effects of Ganyu labor on maize output in Malawi.

Several programs and policies have been implemented worldwide by some institutions, such as the Food and Agriculture Organization (FAO, 2018) to improve the level of food security, mainly in developing

countries. Among others, these programs aim to improve their food security through rapid increases in productivity and food production on an economically and environmentally sustainable basis, the reduction of agricultural production variability from year to year by the promotion of climate-smart agriculture techniques, the improvement of food access. However, despite food programs and projects implemented in many countries and the improvement of agricultural practices, food insecurity is still high worldwide. Does this reflect the existence of an unconditional hunger trap?

According to the literature, food insecurity can be due to many factors that exacerbate the problem of food availability or food access. According to Jenkins and Scanlan (2001), inequalities, militarism, population pressure, and low economic growth are the main culprits. Smith et al. (2000) and Barrett (2008) analysis reveal that poverty is the most common cause of food insecurity. The group of countries with the greatest severity of food insecurity are those with a high poverty rate. Other authors think about high food price (Gregory and Coleman-Jensen, 2013; Grace et al., 2014; Verpoorten et al., 2013) because it leads many households to reduce both the quantity and quality of food consumption. Furthermore, climate change and extreme events (Gregory et al., 2005; Devereux and Edwards, 2004), and civil unrest (Bode, 2018) can negatively impact people's food security mainly through their effect on food production and access. Therefore, what are the key determinants of food insecurity?

Due to the significant increase in fuel production from raw materials grown on agricultural land, the debate between food and fuel has engaged many actors. since the 2000s. On average, the evidence so far has highlighted important trade-offs between biofuel production and food security (Rosegrant and Msangi, 2014). Some studies (Zilberman et al., 2013; Beckman et al., 2012; Afiff et al., 2013) revealed that biofuel production hurt food security because they contribute to reducing food availability by using food crops as feedstock and to decreasing food access by increasing food price. Therefore, given the growing interest in biofuels as an alternative energy source to fossil fuels and the literature on their negative impacts on food security, are they among the key determinants of food insecurity?

In this paper, we try to identify the conditions under which some countries could be caught in a hunger trap through a sample of 110 countries from 1992 to 2016. However, before defining the key determinants of the hunger trap, we first test the unconditional hunger trap hypothesis through the Markov transition matrix and ergodic distribution. Rejecting this hypothesis allows us to ensure that there are indeed conditions under which a country can be caught in a hunger trap and thus identify these factors. We, therefore, consider the depth of the food deficit in kilocalories per capita as our food insecurity indicator and five-year periods. Then, we classify countries into four levels of food insecurity (severe, high, moderate,

and low) based on their level at the beginning of the period. We determine through the transition matrix the probability of moving from one level of food insecurity to another. We also assess if a country from any level could end up in the low level of food insecurity with the ergodic distribution and the expected time it takes. Hence, in this paper, we consider countries to be in a hunger trap if there is more than a 50% chance that their situation will not improve, and if the transition matrix and ergodic distribution show that, on average, countries with a severe, high or moderate level of food insecurity will not move to a lower level.

To identify conditions under which a country can be caught in a hunger trap or the key determinants of food insecurity, we grouped countries with severe, high, and moderate levels of food insecurity, which we named high food insecurity, and used the conditional inference regression tree analysis. This non-parametric classification technique is robust to outliers, missing data, and allowed us to classify and find the most relevant determinants for each level of food insecurity (high and low). It does not directly determine causal effects, but it is a step toward identifying causal variables. Specifically, it is a classification exercise that looks for combinations of policy and fundamental variables that separate countries with low levels of food insecurity from those with high levels. Thus, if a variable is not considered by the regression tree method to be a predictor of food insecurity, it is unlikely to be a cause. Robustness was verified using the boosting method, other indicators of food insecurity such as the global hunger index and the prevalence of underweight (% of children under 5), additional predictors and with a panel data quantile regression method.

This paper contributes to the existing literature on five essential points. First, instead of just pointing out the unconditional transitions of a country's level of food insecurity, we examine which combinations of fundamentals and policies can distinguish countries with low levels of food insecurity from those with high levels of food insecurity. Second, we highlight an unconditional or absolute convergence, through the Markov transition matrix and ergodic distribution. Our results assume that all the countries concerned have the same steady-state, so that convergence will lead all countries to a low level of food insecurity. Third, to our knowledge, this is the first attempt to use a non-parametric classification scheme, the conditional inference regression tree, in the analysis of the determinants of food security. The technique allows for the flexible discovery of possible interaction effects between potential determinants. Forth, the regression tree technique can easily handle many potential determinants which is important in this analysis, tolerate the uneven presence of missing data across variables, countries, and time periods, and not have to make assumptions about the distribution random shocks. Five, we perform this analysis in a

set of countries instead of a specific country as many papers analyzing the determinant of food security have done (Arene and Anyaeji, 2010; Beyene and Muche, 2010; Rammohan and Pritchard, 2014).

Our results demonstrated the non-existence of an unconditional hunger trap. The only unconditional trap that may exist is food security. Furthermore, food insecurity determinants seem closer to the capability approach developed by Dreze and Sen (1990) than to the malthusian approach. The key determinants of food insecurity are related to the country economic structure. Contrary to some studies on the high negative effect of biofuel production on food security, our results revealed that biofuels are not among the long-run key determinant of food insecurity. To achieve the 13th objective of Sustainable Development Goals (Climate Action) without reducing food security, biofuel production can be a solution.

The remainder of this paper is structured as follows. The following section provides an overview of food security in developing countries and reviews its main constraints. Then, Section 3 presents our data and the methodology we use to answer the research questions posed in this study. Section 4 presents the main results of our analysis. Section 5 shows the findings of the robustness check before concluding in Section 6.

2 Background

Although governments have signed numerous treaties and made many commitments since the 1990s to eradicate hunger in the world, the numbers remain alarming. Indeed, at the World Food Summit in Rome in 1996, and then in target 3 of the first Millennium Development Goal, governments pledged to reduce hunger in the world by half by 2015. Then, the second target of the Sustainable Development Goals aims to eliminate hunger by 2030. However, the latest FAO State of Food Security and Nutrition report (FAO, 2020) indicates that the world is not on track to achieve zero hunger by 2030. One of the main indicators measuring success or failure in progress toward this goal is the depth of the food deficit (DFD). This section provides an overview of the context of food insecurity in developing countries through this indicator, followed by the main determinants of food insecurity according to the literature.

2.1 Overview of food insecurity in developing countries

The DFD in kilocalories per person per day gives an estimation of the intensity of undernourishment in the population of a country and thus, indicates the average severity of undernourishment. It is calculated by considering the difference between the average energy requirement and average caloric consumption of the undernourished population. This difference gives the food deficit multiplied by the number of

undernourished people and divided by the total population; thereby, the lower the DFD value, the better their level of food security. The prevalence of undernourishment is also considered as one of the main hunger indicators according to the UN's Food and Agriculture Organization. This indicator measures the share of the population with a dietary energy intake insufficient to meet the minimum energy requirements necessary for a given population. However, the proportion of undernourished people does not measure the average severity of undernourishment and does not tell us the extent to which people live below minimum energy requirements.

Following the DFD data, the maps below show that many developing countries reduced their level of DFD from 1992 to 2016. Indeed, we can see a reduction in the number of countries with a DFD higher than 400 kilocalories between 1992 and 2016. In addition, in 2016, many countries had a food deficit level below 200 kilocalories per person per day; however, some countries, mainly in Sub-Saharan Africa, had a deficit above 200 and between 300 and 500 kilocalories per capita per day.

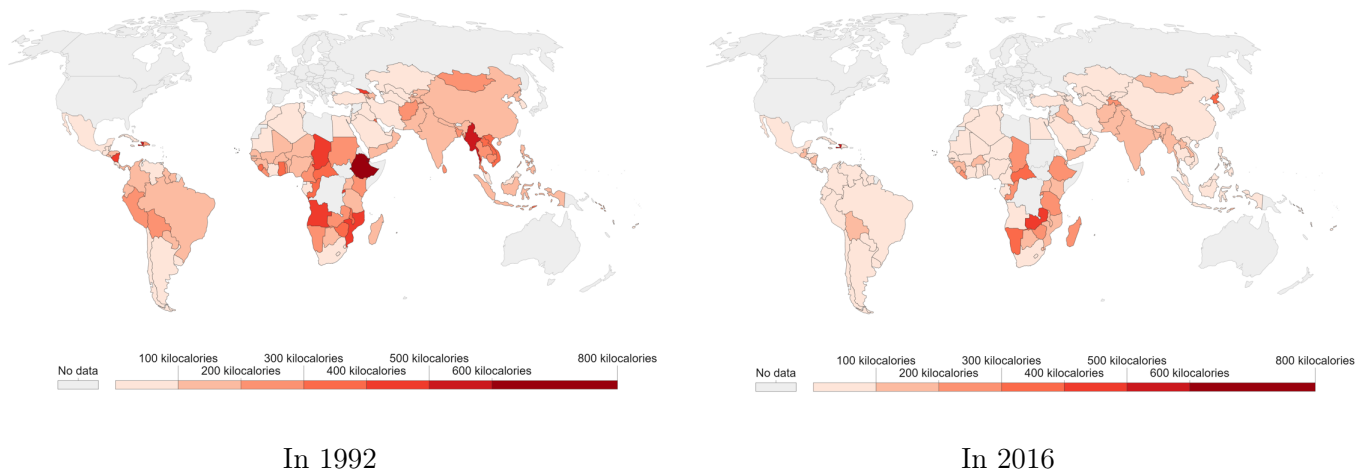


Figure 1: Depth of food deficit in kilocalories per person per day

Figure 2 shows us the food insecurity transition from 1992 to 2016 through the DFD. On average, we can see an improvement of countries level of DFD from 1992 to 2016 as most of them are under the first bisector. This means a decrease in the severity of undernourishment. However, we could notice an increase in the severity of undernourishment in countries above the first bisector, such as Haiti, Zimbabwe, Central African Republic, Cote d'Ivoire, Liberia, Tanzania. Table A.5 displays the level of DFD in 1992 and 2016 and its rate of variation from 1992 to 2016; unlike the other countries in our database, these countries had a positive growth rate indicating a deterioration in the level of food security.

Following the FAO food deprivation groups¹ and the maps above, we categorize our sample in four groups: low food insecurity when the level of DFD is lower or equal to 100 kilocalories (e.g., Tunisia and Argentina); moderate food insecurity when the level of DFD is between 100 and 300 kilocalories (e.g., Kenya and India); high food insecurity when the level of DFD is between 300 and 500 kilocalories (e.g., Rwanda and Ghana); severe food insecurity when the level of DFD is higher or equal to 500 kilocalories (e.g: Haiti and Ethiopia).

2.2 Determinants of food insecurity in developing countries

Based on the food security definition, food insecurity or hunger can be defined as a situation when people lack secure access to sufficient amounts of safe and nutritious food for normal growth and development, and active and healthy life. As it is one of the critical challenges worldwide, several studies have been done on food security concepts, definition, and determinants (Barrett, 2002, 2010; Pinstrup-Andersen, 2009), or focused on factors affecting food security for a specific country (Von Braun et al., 2003; Misselhorn, 2005; Eilerts and Vhurumuku, 1997). This subsection presents the key drivers of food insecurity in developing countries and highlights the impact of biofuel production.

Hunger is linked to poverty as people living in poverty often face food insecurity. This is due to inappropriate care practices, unsafe environments, low access to or availability of health services and education, which contribute to hunger. Moreover, Sen (1981) shows that famine is not necessarily due to food availability, but rather to the ability of people to order food through legal means available in society such as the use of production possibilities, market opportunities, entitlements to the state, etc. Hence, higher economic growth and lower wealth and income inequalities decrease food insecurity (Timmer, 2004). Specifically, based on an instrumental variables probit model, Babatunde and Qaim (2010) analysis in Nigeria revealed that economic growth and reduced wealth and income inequality contribute to improved food security by increasing food access and production, and then farmers' income from food sales. Thus, among the measures aiming to ensure food security, economic growth rate and distribution, also known as pro-poor growth, seems very important. Therefore, efficient economic growth can reduce famine, under-nourishment and favor food security, mainly in dry-land developing countries (Manap and Ismail, 2019). Likewise, countries' economic downturn negatively impact food availability and reduce people's ability to access food (Timmer, 2000b).

As seen in the previous paragraph, increasing farmers' income helps reduce food insecurity. This rise

¹According to FAO (2001), a DFD of 300 kilocalories is the threshold. A country with a level above 300 is considered highly food insecure, while a country with a level below 300 kilocalories is classified as low food insecure.

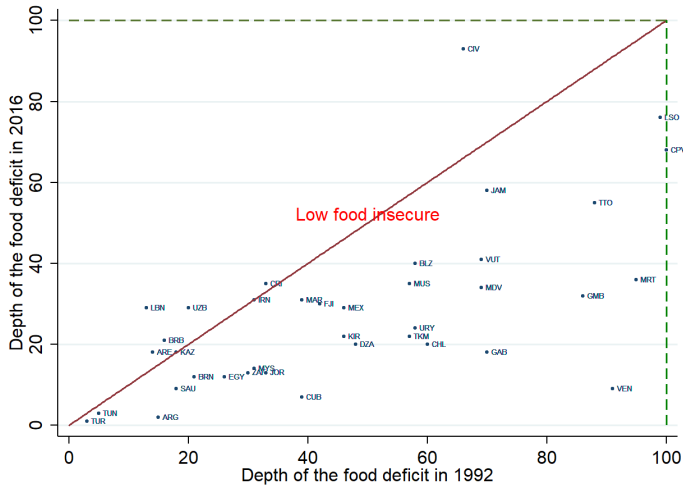


Figure 2: Food insecurity transition from 1992 to 2016

in income can be attributed to the increase in food and cash crop production, or to biofuel production (Negash and Swinnen, 2013). However, according to some studies, this renewable energy production is considered as an essential determinant of food prices variation and food insecurity. Biofuel production can rise food price volatility due to food supply variability (Beckman et al., 2012). In addition, biofuel subsidies contribute to driving up food prices, reducing net buyer's consumption and nutritional well-being

(Afiff et al., 2013). For Ewing and Msangi (2009), though, there are possibilities for biofuel production to create jobs and local energy options, to provide benefits for the poor, food security, and offset the risks to their welfare. Through a meta-analysis, Nkolo et al. (2018) also show that the promotion of biofuels leads to an improvement in income but also the level of GDP. Likewise, Boly and Sanou (2022) used a synthetic control method and showed that biodiesel production positively impacted Indonesia food security. Biodiesel export generated revenue that could be allocated to food import. In addition to biofuels, other factors can affect food security.

Food prices which are also related to food access, have a negative impact on food security, mainly for net consumers, because when they are high, they reduce their capabilities to get food (Timmer, 2000a). Since the poor spend about two-thirds of their income on food, a change in food prices implies a change in food access. Some studies used a three-level hierarchical logit model to assess the Spatio-temporal dynamics of the food price shock observed in 2007-2009 (Akter and Basher, 2014) and found a negative impact on food access, mainly for net buyers and vulnerable people.

The food security threat posed by climate change is significant in developing countries and mainly in Africa, where agricultural yields and food production per capita have been steadily declining (Masipa, 2017). High rainfall intensity and temperature harm agricultural yields and food security (Rosegrant and Cline, 2003). Wossen et al. (2018) analysis in Ethiopia and Ghana showed through an Agent-Based Modelling that climate variability reduces both food security and household income. Likewise, extreme events such as drought or flood negatively affect food production by decreasing crop yields (Wheeler and Von Braun, 2013).

Most countries with the highest number of undernourished people also have high fertility rates and population growth. The production of food depends on croplands and water supply, which are under strain as population increases. Likewise, population growth often implies the destruction of vital forest resources or overexploitation of arable land to meet the population's needs. Therefore, population pressure jeopardizes food availability and access (Jenkins and Scanlan, 2001).

Armed conflicts and events reduce food access and food availability through declining food production and supply. Conflict is also a key driver of severe food crises, including famine (Bode, 2018). Indeed, of the 144 million stunted children, 85% live in countries affected by conflict. Using a difference-in-differences approach, Martin-Shields and Stojetz (2019) displayed that children under age five born in areas affected by civil war violence have a significantly lower weight than those born in other areas. Hunger and undernutrition are worse when prolonged conflicts and institutions are weak. In addition to

civil unrest, countries' institutional quality may affect food security. Corruption, government instability, religious tension, and poor socioeconomic condition could erode food security by mainly reducing food production and food access.

Although many studies analyze the determinants of food security, few of them focus on the analysis of the hunger trap and the absolute and or conditional convergence of countries towards a specific level of food security, which are the added values of this paper. Therefore, the following section will present the methodology used to assess the existence of a hunger trap and the associated results.

3 Methodology

This paper aims to assess whether some developing countries may be caught in a hunger trap. Specifically, we test the hypothesis of an unconditional hunger trap and then the the combination of fundamentals and factors that may affect food insecurity. To that end, we use the Markov transition matrix and the ergodic distribution to test the unconditional hunger trap, and the conditional inference regression tree analysis to assess the key determinants of food insecurity. Thus, in this section, we first describe the Markov transition matrix and the ergodic distribution, and then conditional inference regression tree. We conclude by presenting the data used.

3.1 Markov transition matrix and ergodic distribution

In this subsection, we focus on the transition probabilities of different levels of food insecurity by using the Markov transition matrix and ergodic distribution (Quah et al., 1992). This allows us to see where the distribution is headed if the current dynamics hold. Therefore, this distribution approach allows one to check what happens to the entire shape of the distribution, instead of only showing what happens to its mean as in β -convergence studies (Abreu et al., 2005), and dispersion as in σ -convergence studies (Furceri, 2005).

A transition matrix is defined as a square matrix that describes the transition probabilities from one state to another. In our case, it means the probabilities of moving from one group or one level of food insecurity to another and from one period to the next.

Let P_t be a $(n * 1)$ vector of the number of DFD levels distinguished to represent the distribution at time t. We have:

$$P_{t+1} = F * P_t \tag{1}$$

Where F is the transition Matrix allowing P_t transformation into P_{t+1} , the distribution for $t + 1$. Four levels of food insecurity gives the following form for our matrix:

$$F = \begin{pmatrix} l_{11} & l_{12} & l_{13} & l_{14} \\ l_{21} & l_{22} & l_{23} & l_{24} \\ l_{31} & l_{32} & l_{33} & l_{34} \\ l_{41} & l_{42} & l_{43} & l_{44} \end{pmatrix} \quad (2)$$

Each element l_{ij} of F provides the probability of moving from level i during the initial period to level j during the next. Specifically, l_{11} gives the probability to remain in the first level of food insecurity, in our case in the severe food insecurity level over a period, while l_{12} provides the probability of moving from level 1 (severe food insecurity level) to level 2 (high food insecurity level). To analyze this transition matrix, we also assume that on average the probabilities of switching to another group are similar for all countries in a given category of food insecurity.

$$P_{t+d} = (F^d) * P_t \xrightarrow{d \rightarrow \infty} \bar{P} \quad (3)$$

Following the transition matrix results, we can easily assess the probability of switching from one food insecurity level to another. Now, through the ergodic distribution, we will see whether countries in any group could end up in a low level of food insecurity.

If this matrix remains the same over time, the distribution after d periods could be obtained by repeating equation 1 d number of times.

$$P_{t+d} = (F^d)(P_t) \quad (4)$$

When d^2 goes to infinity, the distribution converges to an ergodic distribution or steady-state distribution \bar{P} .

The equation below allows us to get the expected time for a country belonging to other levels of food insecurity to move to the steady-state (low food insecurity).

$$t(i, j) = 1 + \sum_{k \neq j} l_{i,k} \times t(k, j) \quad (5)$$

Where $t(i, j)$ is the expected time to move from level i to the steady-state j , and $l_{i,k}$, the probability

²In this analysis, d was equal to 1000.

to move from level i to k . k represents each intermediate level between i and j .

The transition matrix results and ergodic distribution allow us to test whether an unconditional hunger trap exist. A country with a severe, high or moderate levels of food insecurity that grows at the average or median rate of the group will not become a low food insecure country. Suppose the results allow us to reject the hypothesis of unconditional hunger trap. In that case, we will then perform the conditional inference regression tree analysis to identify the key determinants of food insecurity.

3.2 Conditional inference regression tree analysis

Several methods have been used to assess the determinants of food security and their impacts. These methods include scenario simulations, panel probit or logit model, local projection approach, synthetic control, etc. However, these methods present some limits. The probit model requires a normal distribution for all unobserved components, while a logit model needs a logistic distribution. These parametric methods assume that the population can be adequately modeled by a probability distribution that has a fixed set of parameters which may lead to the transformation of data. In addition, they are sensitive to outliers, missing values, and cannot be performed with too many variables. The synthetic control method is mostly used for comparison purposes and therefore focuses on the effect of an event or policy. Therefore, to identify the key determinants of food insecurity we consider in this paper, the conditional regression tree method, a non-parametric method. Contrary to a parametric method, a non-parametric method does not need any assumption regarding the data generation process. Moreover, it is robust to outliers, missing data, and can be performed with many variables³ which is advantageous for our study, as there are many factors that could affect food insecurity.

The regression tree method (Breiman et al., 2017) is a machine learning method that can be explained following two processes. Firstly, the algorithm looks for the split point of the predictor that best predicts food security, then this particular predictor and splitting point makes two children's branches grow from the parent node. Secondly, the algorithm divides each of the child nodes until further division does not improve predictability. In the final tree, each observation will result in one of the end nodes. The expected level for each end node is simply the average of the countries belonging to that node. Therefore, for prediction purposes, we first determine the final node of a country based on the values of its fundamentals. Then the food security level of that final node will be assigned to the expected level for that country. So, this method will allow us to find which proposed determinants of food security are the most relevant.

³It can be performed with more than 20 variables.

Moreover, by using this method, we can manipulate many variables without making assumptions about the distribution of the random shocks. Likewise, trees can be graphically displayed and are easier to explain than linear regression. Finally, compared to linear regression analysis, this technique does not require any transformation of variables. It is robust to outliers and has a greater tolerance of missing data without having to impute values. However, the regression tree analysis results are potentially sensitive to changes in the sample.

Specifically, we use the conditional inference regression tree (Hothorn et al., 2006) a non-parametric classification technique. It corresponds to a refinement of the regression tree analysis that brings a tested hypothesis in the decision of each split. A split is performed if the null hypothesis that the proposed split does not improve the predictive power can be rejected. Because it makes splitting a predictor conditional on other correlated predictors, it pulls through the criticisms of traditional regression tree analysis that favors choosing correlated predictors to perform the splitting method.

This method separately searches for the best predictor to perform the split and the search for the optimal split value. First, based on the linear statistics (Strasser and Weber, 1999), the relationship between a variable and the response evaluated by the permutation tests follows a χ^2 distribution. The null hypothesis is no association between a predictor and the response. With a smaller p-value, the probability of falsely rejecting the null hypothesis is lower. Therefore, the variable with the smallest p-value is chosen to perform the split in the first step. The best cut-off point for the most significant variable chosen in the first step is determined in the second step. For each of the two branches associated with the first split, another variable with the strongest association with the response is sought among all the variables. The other branches of the tree will grow in the same way. Thus, the conditional inference regression tree allows classifying and finding the most relevant determinants for each level of food insecurity. It does not directly determine causal effects, but it is a step toward identifying causal variables. Specifically, it is a classification exercise that looks for combinations of policy and fundamental variables that separate countries with low levels of food insecurity from those with high levels. Thus, if a variable is not considered by the regression tree method to be a predictor of food insecurity, it is unlikely to be a cause.

We can find a relationship between the regression tree and the linear Bayesian Model Averaging (BMA) approach (Hinne et al., 2020). The linear BMA approach imposes a linear relationship between food security and potential correlates. However, the regression tree approach allows for all deviations from linearity in a very flexible manner, and the existence of any non-linearity is subject to statistical testing. A variable that is robust in the linear BMA may not be robust in the regression tree. Similarly, a variable

that is not robust in the linear BMA may be relevant in some combination with other variables in a regression tree.

3.3 Data

We perform these analyses by using 110 developing countries from 1992 to 2016 and several variables. As a dependent variable, we use the depth of food deficit. Following the determinants of food security mentioned above, we considered variables related to the population structure, economic structure, renewable energy production, weather and climate change, and conflicts and institutional conditions.

3.3.1 Population structure

Predictors related to population structure are the annual population growth (%) and age dependency ratio (% of working-age population). According to the literature (Jenkins and Scanlan, 2001; Tilman et al., 2001), the larger and younger the population, the greater the negative impact on food security because this situation could increase food demand and reduce food access. However, other studies suggest that this could be beneficial to food security in the sense that more people mean a larger labor force for food production. We, therefore, expect our results to indicate a threshold below and above which their effect on food security could vary.

3.3.2 Economic structure

Those linked to the country's economic structure include the gross domestic product (GDP) per capita (constant 2010 US\$), trade openness, socioeconomic conditions index, investment profile index, government stability index, wage and salaried workers (% of female employment), wage and salaried workers (% of male employment), contributing family workers(% of total employment), manufacturing value-added, access to electricity (% pf population), food net export, agricultural land and employment in agriculture. We assume that for these variables the higher they are, the better for food security (Barrett, 2002; Devereux et al., 1993; Magrini et al., 2017). We also include total of unemployment (% of total labor force), corruption index, and the total external debt stocks (% of GDP). We suppose that for these variables the lower they are, the better for food security. Moreover, we consider natural resource rent and extractive dependence index. Following the dutch disease theory, we suppose that these variables can have a positive or negative impact on food security under some specific conditions. Natural resource rent could lead to an appreciation of national currency, which would benefit net food-importing countries (Comunale, 2017; Huchet-Bourdon

et al., 2013). Thus, our result will provide a threshold below and above which natural resources rent impact on food security could differ.

3.3.3 Renewable energy production

As renewable energy production variable, we choose biofuel production (1000 barrels per day). Based on the literature, we assume that under some conditions, biofuel production can positively or negatively affect food security (Ewing and Msangi, 2009; Zilberman et al., 2013). Therefore, we suppose that a threshold exist, below and above which Biofuel production can favor food security or it increase hunger.

3.3.4 Weather and climate change

We consider temperature, precipitation, evapotranspiration, the occurrence of extreme weather events, and natural shock index, to assess weather conditions and extreme weather events. Further to the literature, we can suspect there is a line below and above which the impact of precipitation, temperature, and evapotranspiration on food security can differ. Indeed, several studies point out that too much rain harms food production while others suggest that too low rain also hurts food production. The same applies for temperature and evapotranspiration. Furthermore, the occurrence of extreme weather events and natural shock index negatively impact food production and access (Harvey, 2011; Schwab and Sala-i Martin, 2015).

3.3.5 Conflicts and institutional conditions

To assess the effects of armed conflicts and events, the following predictors were added: internal conflict index, external conflict index, military in politics, number of battles, explosions, riots, violence against civils and religious tensions. These variables negatively affect food security (Martin-Shields and Stojetz, 2019; Bode, 2018) through the negative effect they can have on each dimension of food security mainly availability and access.

3.3.6 Other predictors

Furthermore, we take into account the shock sub-index and the exposure sub-index. The shock sub-index can be defined as the weighted average of 3 indexes (the victims of natural disasters, the instability in the export of goods and services, and the instability in agricultural production. Therefore, this predictor can be linked to those related to economic structure, and extreme weather events. This variable has a negative impact on food security as when the victim of natural disasters is important this may reduce food

production, access and food security. The same goes for instability in the export of goods and agricultural. The exposure sub-index is the weighted average of 5 indexes such as population size, remoteness from the world market, exports concentration, the share of agriculture, forestry and fishery in the GDP, and the share of population living in the low elevated coastal zone. Thus, it can be associated with the predictors of economic and population structure. Each of these variables affects at least one of the dimensions of food security (availability, access, utilization, and stability). We assume that the lower it is, the better for food security. The table [A.4](#) provides the descriptive statistics and table [A.6](#) the source of each variable.

4 Results

For our analyses, we computed five-year periods and considered the value at the beginning of each period and the thresholds previously defined to categorize countries in a level of food insecurity. This section presents the results of the transition matrix and the ergodic distribution. Then, based on their results, we also performed the conditional inference regression tree.

4.1 Markov transition matrix and ergodic distribution

The table below displays the results of the transition matrix⁴. Specifically, the first cell shows that a country classified as severely food insecure has a 50.00% probability of staying in the same level. The second cell indicates that the probability of moving to the level of high food insecurity is 50.00%. The remaining cells in the first row allow concluding there is zero probability of becoming moderate or low food insecure. The same explanation applies to other rows. For a country that started as low food insecure, the probability of remaining in the same level is 92.7%, while the probability of getting back to a level of moderate food insecurity is 7.30%. These results highlight the fact that the probability of obtaining an improvement in the food security situation is higher than the opposite.

Given the ergodic distribution result, we can be ensured that in the long run, all countries of our sample belonging to the severe (, high, and moderate level of food insecurity will end up at the low level. In addition, on average, a country in a situation of severe (Ethiopia, Djibouti or Haiti), high (Mozambique, Central African Republic or Sierra Leone) or moderate (Bolivia, Cambodia or Cameroun) levels of food insecurity has more than 50% chance of having a negative growth rate of the DFD (table [A.4](#)) which means an improvement of their level of food security. Thus, all the countries considered in this analysis, are always expected to move to the low level of food insecurity. Since the thresholds used to categorize the

⁴These probabilities have been calculated over the whole period, and the sum per raw is 100%.

Table 1: Average transition matrix (in %)

	Severe FI	High FI	Moderate FI	Low FI
Severe food insecurity	50.00	50.00	0.00	0.00
High food insecurity	2.17	43.48	52.17	2.18
Moderate food insecurity	0.00	3.90	78.54	17.56
Low food insecurity	0.00	0.00	7.30	92.70
Ergodic distribution	0.00	0.00	0.00	100.00
Average expected time to move to Low FI(years)	9	8	5.3	
Expected time for 50% of observations (years)	6.7	6.7	5	
Expected time for 75% of observations (years)	9.3	7.5	5.2	

level of food insecurity are exogenous, we modified their values to see if this could have a significant impact on the unconditional hunger trap hypothesis we are testing. The results indicate some small variations of the probabilities, however, the ergodic distribution findings remain the same; which enable us to be confident that in the long run, all states will converge to the low level of food insecurity.

We might then ask how long does it take for a set of countries at one level (severe, high, or moderate) to move to low food insecurity? According to the transition matrix results, it will take an average of 9 years⁵ for a severe food insecure country to move to the low level. Similarly, it will take 8 and 5.3 years, for a high and moderate food-insecure country to reach the low level. Furthermore, to take into account the distribution of countries, we considered in each group of food insecurity, the country-period having a level of the depth of the food deficit below the median (50%) and the third quartile (75%) value.

As the results allow us to reject the unconditional "hunger trap" hypothesis, and given that each country presents specific contexts and characteristics, it is essential to check the conditional hunger trap or determine the conditions under which a country could find itself in a high level of food insecurity. In other words, it is necessary to identify the key determinants of food insecurity or the combinations of fundamentals that can distinguish countries with low levels of food insecurity from those with high levels of food insecurity. Thus, the non-parametric method, conditional inference regression tree, described above will provide the main conditions and variables for which a country could be at a low or high level of food insecurity.

⁵The results give us 1.8 periods, and as mentioned above (see data section), we considered periods of five years; therefore, $1.8 \times 5 = 9$. Furthermore, it will take an average of 1.6 and 1.06 periods for high and moderate food-insecure countries, respectively.

4.2 Conditional inference regression tree analysis

This section is divided into three subsections. First, we present the result of the conditional inference regression tree performed in the overall sample and then the results in the sub-sample of low and high food insecure countries.

4.2.1 Overall sample

Figure 3 shows the conditional inference regression trees for the overall sample with the variables used for each split and the associated p-values. For each division, the right branch displays the result when the values of the division variable are above a threshold value of the parent node, while the left branch shows the result when the values are below or equal to the threshold. The final nodes indicate the number of observations and the predicted value of the depth of food deficit obtained with the relevant combination of the preceding variable values. The predicted value of the depth of food deficit corresponds to the median values over 5 years. The results indicate that among all the variables considered for this analysis, the most critical variables for their level of food deficit are: GDP per capita, evapotranspiration, natural shock index, employment in agriculture, socioeconomic condition index, access to electricity (% of the population), exposure sub-index, age dependency ratio, and food net export. However, biofuel production does not appear in the tree. The variable considered most relevant to determine the depth of the food deficit is GDP per capita. This variable competed with all other variables in explaining the level of the food deficit and was found to have the highest explanatory power. Thus, any country-period whose GDP per capita (log) exceeds 7.77 (2368.47\$US per capita ⁶ such as Argentina Turkey, Brazil, Mexico and Ecuador), is classified in the right-hand branch group and the others (Ethiopia, Mozambique, Djibouti, Cambodia, Cameroon and Haiti) in the left one. After the first split, all variables compete to perform the next split until the regression tree attains the stopping criterion. Thus, for countries with a GDP per capita value (log), less than or equal to 8.783 (6522.42 \$US per capita), the depth of the food deficit will also depend on the percent of the population having access to electricity. If this percent is less than or equal to 97.195, the predicted average value of the log of our dependent variable will be 4.5, or about 90.017 kilocalories per person per day⁷. Some of the country-periods in node 17 include Ecuador in 2012 and Brazil in 2002. By doing this systematically, all observations classified into the same final nodes share the same range of explanatory variables and have similar food deficit depth values. The regression tree technique allows

⁶ $e^{7.77} = 2368.47$

⁷ $e^{4.5} = 90.017$

threshold and interactive effects to be handled flexibly. It favors one variable to contribute to our food security variable only after another variable has reached certain levels. For example, does a low exposure index contribute to food security? The regression tree results indicate that this is correct, but it also requires a high level of GDP per capita.

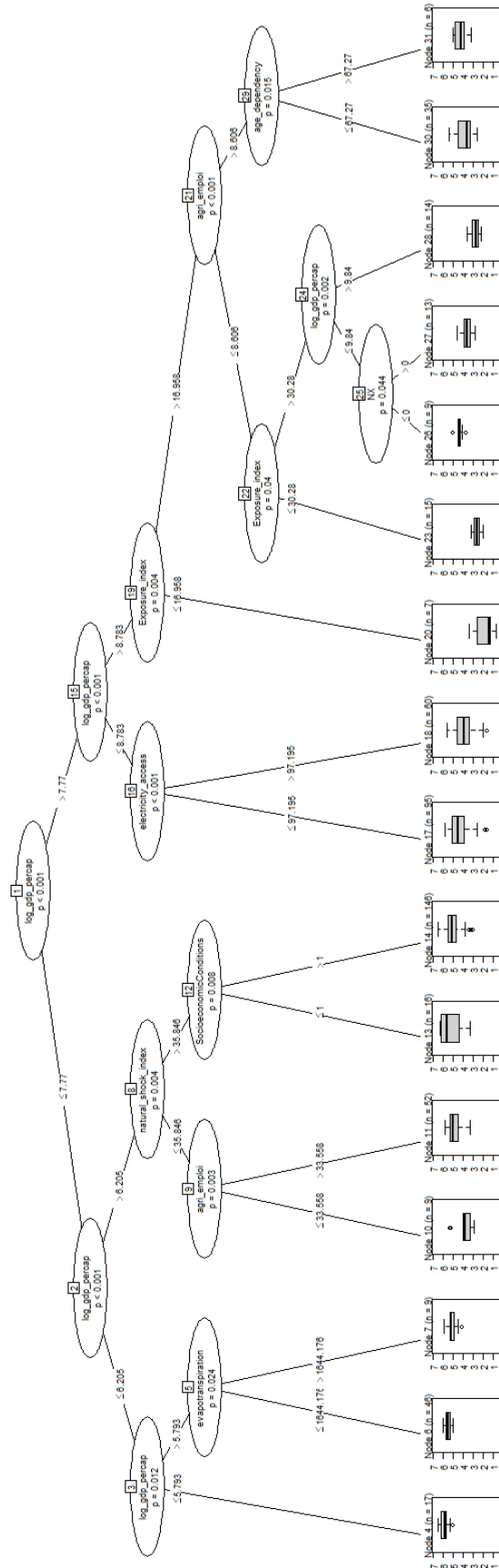


Figure 3: Conditional inference regression tree in the overall sample

4.2.2 High food insecurity

Since we assume that all countries in our sample aim to become low food insecure and then achieve food security, we group severe, high, and moderate food insecure countries together. Thus, figure 4 provides the conditional inference regression tree result in the countries labelled as highly food insecure. Of all the variables considered for this analysis, the relevant variables for categorizing their level of the depth of the food deficit are the level of GDP per capita, age dependency ratio, precipitation, socioeconomic conditions, and corruption index. The most important variable is GDP per capita, and biofuel production is not among the determinants revealed by the tree as with the overall sample. A low level of GDP per capita favors food insecurity; indeed, country-periods with a GDP per capita (log) less than or equal to 5.462 will have the highest depth of food deficit. As we can see in figure 4, this characteristic leads to node 3, and some of the country-periods involved are Mozambique in 1992 and Ethiopia in 1997 (see table A.1). Then, for those with a GDP per capita (log) greater than 6.077, their level of the depth of the food deficit will also depend on the socioeconomic conditions. If the socioeconomic condition index is less than or equal to 1, the average predicted value of the log of our dependent variable would be 6.05 or about 424.11 kilocalories per person per day. However, suppose the level of the index is higher than or equal to 1, and the level of annual precipitation is higher than 1738.988 mm, as we can see in figure 4. In that case, the country-period in node 15 will have the lowest median value of the depth of the food deficit. Some of the country-periods concerned are Cambodia and Cameroon in 2007 (see table A.1). The predicted value of DFD is 4.90 or about 134.3 kilocalories per person per day, and the associated predicted error is low, attesting to a good prediction of the DFD by this method.

Even if they did not specify a threshold, several studies assess the role of GDP per capita on food security. Baer-Nawrocka and Sadowski (2019) analysis displays that countries with the lowest GDP per capita, mainly from Sub-Saharan Africa and Central Asia, presented the lowest energy supply per capita; while countries with the highest GDP per capita presented the largest energy supply per capita. They also indicated that worldwide, general economic growth contributes to reducing famine. Additionally, Luan et al. (2013) showed that a seriously unbalanced domestic economy but also large disparities between rich and poor determine low food self-sufficiency. Moreover, for Smith et al. (2017), low socioeconomic conditions through low levels of education, poorly developed social networks and low social capital make food insecurity a much more likely experience.

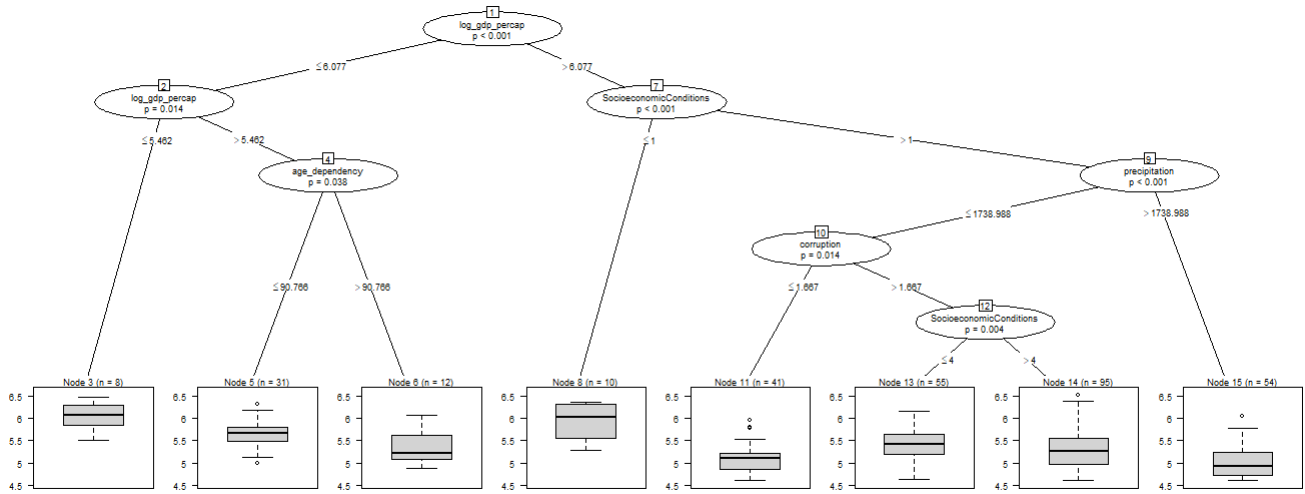


Figure 4: Conditional inference regression tree in high food-insecure countries

4.2.3 Low food insecurity

Figure 5 shows the conditional inference regression tree results for low food-insecure countries. As for the overall sample and high food-insecure countries, the most important determinant of the depth of the food deficit is the GDP per capita. Otherwise, among all the variables used to perform the analysis, the relevant variables to categorize the level of the depth of the food deficit include GDP per capita, precipitation, exposure sub-index, and conflict events such as explosions. Biofuel production again does not appear in figure 5. These results still highlight the importance of high GDP per capita for food security. Indeed, the low predicted values of the depth of the food deficit appear for country-period with a GDP per capita (log) higher than 8.783 (6522.42 \$US per capita). Then, country-period with a level of exposure sub-index less than or equal to 16.95 will end in node 12 with a median predicted value of the depth of the food deficit (log) of around 1.5 or 4.48 kilocalories per capita per day. Countries of node 12 include Turkey and Mexico. Table A.2 and A.1 provide some examples of country-period per final node with the absolute value of the predicted error⁸. We notice that the predicted errors are pretty low, indicating a good prediction of the outcome and the relevance of the identified determinants.

As presented in the data section, exposure sub-index is the weighted average of indexes including population size and remoteness from the world market; therefore, The lower its value, the better for food security. This finding is in line with Jenkins and Scanlan (2001), who displayed that population pressure hurts food security and that most of the countries with the highest number of undernourished people also

⁸The predicted error is the absolute value of the difference between the real and the predicted value of the DFD.

5.1 Boosted Random forests

The random forest technique considers and examines sensitivity to each sub-samples (Breiman, 2001; Hapfelmeier, 2012). This is a combination of trees, each constructed based on an independently drawn random sub-sample. This method construct a forest of decision trees on bootstrapped training samples. Whenever a split in a tree is considered, a random sample of X predictors is chosen as split candidates from the full set of p predictors. The number of predictors at each split is approximately one-third of the total number of predictors.

$$X = \frac{p}{3} \quad (6)$$

Random forests solve the problem of heteroscedasticity that may occur by considering only a subset of the predictors for each division. However, it requires many decision trees because fewer decision trees reduce performance. Therefore, when applied on a small scale, it cannot retain its generality. This is why boosting is introduced in the random forest (Mishina et al., 2015).

Boosting is a general approach that aims at improving the predictions resulting from the decision tree, and can be applied to statistical learning methods for regression or classification (James et al., 2013). With this method, trees are grown sequentially by using information from previously grown trees. Specifically, the boosting combines many decision trees⁹ $\hat{f}^1, \dots, \hat{f}^B$. In contrast to fitting a single large decision tree to the data, which would mean strictly fitting the data and potentially overfitting it, the boosting approach learns slowly. It fits a decision tree to the residuals in the model. In other words, the procedure is to fit a tree using the current residuals, rather than the Y result, as the answer. Then we add this new regression tree to the fitted function to update the residuals. Each of these trees can be quite small, with only a few terminal nodes determined by the parameter d of the algorithm. Boosting results allow us to get the relative influence of each variable on the outcome and thereby check if they are in line with the conditional inference regression tree results.

The boosting has three settings. First, the number B of trees selected with cross-validation. Second, the shrinkage parameter ρ whose typical values are 0.01 or 0.001 controls the boosting learns rate. A very small ρ may require using a huge value of B to achieve good performance.

The boosting results in figure A.1 show us the relative influence of each variable on our food security indicator in the overall sample. Hence, giving the results, we can be ensured that, like in the conditional inference regression tree, the most important determinant is the level of GDP per capita, then the em-

⁹In this study, the number of decision trees was 5000.

ployment in agriculture (% of total employment) and exposure sub-index. Although biofuel production appears among the variables that could influence food security in the long run, its influence is very low around 0.01%. These results can allow us to think that biofuels' long-run effects on food security can be negligible. The other key determinants revealed by the boosting results include the level of wage and salaried workers (% of female employment), precipitation, evapotranspiration, agricultural land, age dependency ratio, external debt, contributing family workers (% of total employment), socioeconomic conditions, access to electricity, food net export, shock sub-index, climate events occurrence, government stability, external conflict, corruption, conflict events such as explosions and protests.

We also run this model on the sample of high and low food-insecure countries (see figure A.4 and 5); the results reveal that GDP per capita is among the three main determinants. However, it seems that employment in agriculture and exposure sub-index are respectively the most relevant for high and low food insecure countries. Furthermore, the biofuel production effect appears again negligible. Its relative influence on the outcome compared to the other variables is 0.12% in the high level sample and 0.66% for the sample of low food insecure countries.

To assess the model accuracy, we also compute the mean squared error (MSE) through the equation below:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{f}(x_i))^2 \quad (7)$$

Where $\hat{f}(x_i)$ gives the prediction for the i th observation and y_i the real value of the depth of the food deficit for the i th observation. Therefore, the MSE allows quantification of the extent to which the predicted value for an observation is close to its true response value. The lower the MSE, the better the prediction. Since, on average, we are primarily interested in the accuracy of the predictions we obtain by applying our method to unseen test data rather than the effectiveness of the method on the training data, we divided our dataset into two, training and a test dataset. Specifically, we want to know if the predictive value of the depth of the food deficit is very close to its real value for an unseen test observation. For the overall sample, the results of the MSE computed on the test and training dataset respectively show 0.47 and 0.22. For the sample of high food insecurity, the results of the MSE computed on the test and training dataset respectively give 0.14 and 0.06. In the low food insecurity sample, we get 0.43 and 0.13 for the MSE computed on the test and training dataset. As the MSE value in the test and the training data is very low, we can be ensured on the model's prediction quality and robustness.

5.2 Other dependent variables: prevalence of underweight (% of children under 5) and the global hunger index

In addition to the depth of the food deficit, the prevalence of underweight as a percentage of children under 5 and the global hunger index are two other main indicators of hunger.

- Prevalence of underweight

The prevalence of underweight measures the share of children under 5 who are underweight over a long period of time. It can include children who are stunted, wasted, or suffering from insufficient energy intake. It is one of the two indicators used to monitor the hunger target of the Millennium Development Goals (MDGs) (Hickel, 2016). Figure A.7 draw through data coming from the World Development Indicators database the evolution of the underweight children from 2000 to 2020. We can notice worldwide a decrease in the prevalence of underweight, however, it is still high in Sub-Saharan Africa and low and middle-income groups. This points out the fact that food insecurity is a crucial challenge mainly for the developing world.

Considering this indicator as our dependent variable, we performed the conditional inference regression tree in the overall sample. As for the previous results, we can see that the most important variable to predict the level of the prevalence of underweight is the GDP per capita; While biofuel production does not appear. Hence, the higher the level of GDP per capita, the lower the level of food insecurity. Figure 6 also shows other key determinants to food insecurity such as agricultural land, the occurrence of extreme weather events, female wage, food net export, evapotranspiration, access to electricity, precipitation, external conflict index, Socioeconomic condition index, age dependency ratio and contributing family workers. Following node 40, we can see that the combination of a high level of GDP per capita, female wage, precipitation, socioeconomic condition with a low corruption index and age dependency ratio, allow getting a predicted value of the prevalence lower than 5%. Examples of countries in node 40 are Argentina, Brazil, Turkey and Mexico.

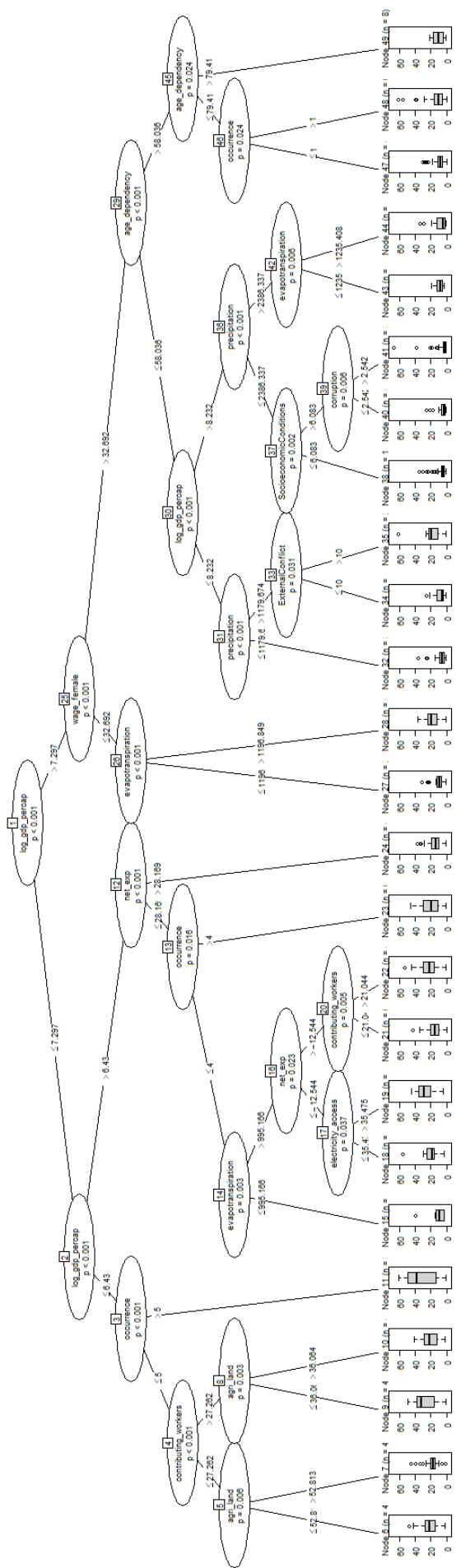


Figure 6: Conditional inference regression tree in the overall sample

- Global hunger index

There are many indicators to track progress on malnutrition. In order to capture and track progress with a single measure, the International Food Policy Research Institute (IFPRI) defined the Global Hunger Index (GHI). It is designed to comprehensively assess and track hunger at the global, regional and national levels (Von Grebmer et al., 2017). It attempts to assess the multidimensional nature of hunger, combining four key indicators of malnutrition: the proportion of undernourished people as a percentage of the population, the proportion of children under the age of five who suffer from wasting, the proportion of children under the age of five who suffer from stunting, and the mortality rate of children under the age of five. The index is based on a scale of 0 to 100 where 0 is the highest score. Although it provides good tracking of hunger by region, country and globally, it is less used in empirical analyzes due to the high rate of missing values.

Using this indicator as our dependent variable, the conditional inference regression tree results (see figure 7) indicate that a high level of GDP per capita is the most important determinant of food security. Furthermore, we also have other factors similar to the previous results such as age dependency ratio, female wage, the occurrence of extreme weather events, access to electricity, and employment in agriculture. Following node 7, we can see that a high level of age dependency ratio ($>80.9\%$) combined with a low level of GDP per capita (log value <5.8) leads to a high level of food insecurity as the predicted value of GHI is higher than 40. Countries in node 7 also include Ethiopia, Mozambique and Djibouti. Moreover, as was the case when considering the prevalence of underweight and depth of the food deficit, biofuels are not among the major determinants of food insecurity.

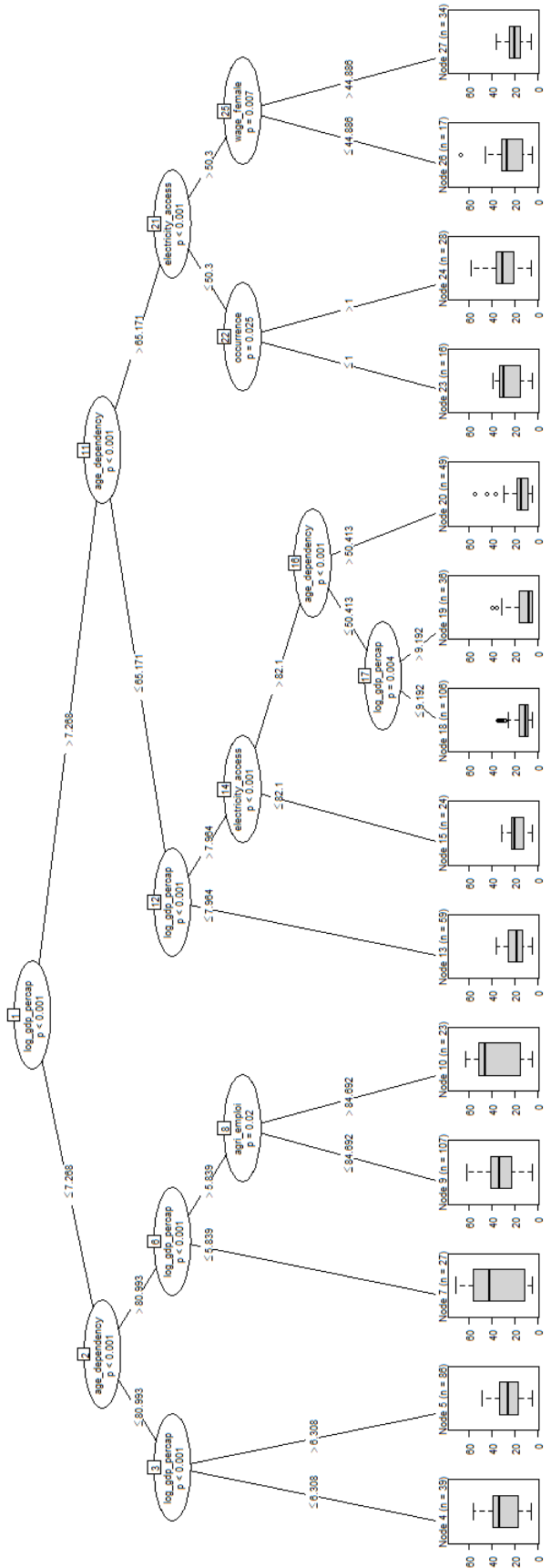


Figure 7: Conditional inference regression tree in the overall sample

5.3 Additional explanatory variables: real effective exchange rate, and net official development assistance and official aid received per capita

To test the robustness of our results we also include additional predictors such as the real effective exchange rate, and the net official development assistance and official aid received per capita.

According to the literature on the determinant of food security, the exchange rate can have a significant impact on food security, especially for vulnerable developing countries (Laroche-Dupraz et al., 2013). Specifically, Huchet-Bourdon et al. (2013) shows, in the short run, a depreciation of the national currency contributes to a deterioration of food security due to the increase in the food import bill and the decline in net export earnings; while an appreciation of national currency leads to improve food security, mainly in net importer countries. Hence, the real effective exchange rate was considered as a predictor related to the economic structure. Otherwise, following the literature on the rent of natural resources and the Dutch disease, the exchange rate makes it possible to capture the effect of the rent of natural resources. Indeed, the exploitation of resources favors the appreciation of the national currency (Comunale, 2017). Therefore, in this subsection, we run the conditional inference regression tree analysis by adding the real exchange rate and removing the natural resource rent and extractive dependency index.

We also deemed the net official development assistance and official aid received per capita. Following the literature, aid has a positive impact on food security through an improvement in the level of food supply and access. Clover (2003); Blizkovsky and Emelin (2020) analysis show that the aid received leads to a significant increase in food production by means of the enhancement of agricultural performance and its contribution to the economy of developing countries. Some studies, though, point to the negative effect of foreign aid on institutions and economic growth, which they describe as the aid curse (Djankov et al., 2008; Lensink and Morrissey, 2000). A large influx of aid does not necessarily increase well-being. High levels of aid can make it difficult to resolve the collective action problems inherent in reform efforts, creating moral hazard for recipients and donors alike. Therefore, when income does not depend on taxes collected from citizens and businesses, there are fewer incentives to responsibility. At the same time, corrupt government officials will try to perpetuate their rent-seeking activities involving low economic growth and food insecurity. Wooster (1997) explains that the civil war in Somalia was caused by the desire of different actors to control the large amount of food aid the country was receiving. We therefore assume the existence of a threshold above and below which the effect of the aid may vary.

Figure 8 provides the conditional inference regression tree results performed in the overall sample and including the real effective exchange rate and the official development assistance among the predictors.

We can see that the main determinants of food security remains the GDP per capita and that biofuel production do not appear. Furthermore, official development assistance has an impact on food security, and it seems that the lower it is the better for food security. In fact, the low level of DFD is observed for country with a level of aid received per capita lower than or equal to 5.82\$, such as Turkey, Argentina or Brazil.

The real effective exchange rate does not appear in the tree (figure 8), but the boosting model performed (see figure A.6) allows us to conclude that even if its relative influence is low (1.51%), the exchange rate can be considered among the long-term determinants of food security. Furthermore, the relative influence of the aid received per inhabitant is also low, around 1.55%. As noted in previous sections, the most influential variable is again GDP per capita with the same level 30% and biofuels have the weakest influence (0.02%), which highlights the robustness of our results.

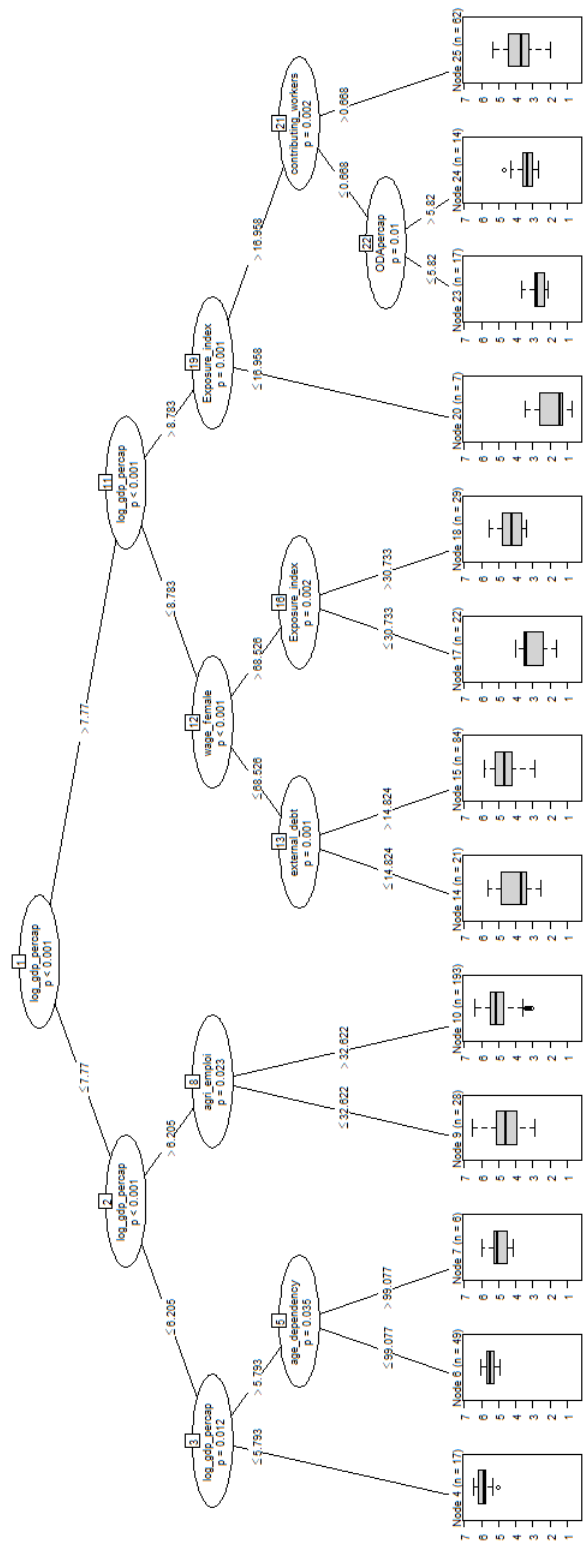


Figure 8: Conditional inference regression tree in the overall sample

5.4 Parametric method: panel data quantile regression

Since we used a non parametric method, the conditional inference regression tree, to test the existence of a conditional hunger trap by determining the key factors of food insecurity, in this subsection, we consider a parametric method, the quantile regression (Koenker and Hallock, 2001; Koenker, 2004) to check the accuracy of determinants of food insecurity identified. This method is less robust than the non parametric carried out above because it cannot take too many variables, however, it will allow us to test the effect of GDP per capita and biofuel production, and their significance on the level of the depth of the food deficit.

Quantile regressions are statistical tools whose purpose is to describe the impact of independent variables on specific percentiles of a variable of interest. They allow a higher description than classical linear regressions, since they are interested in the entire conditional distribution of the variable of interest and not just the average of it. It is, therefore, a tool available to the econometrician to address the inherent limitations of the mean. Moreover, they can be more adapted for certain types of data including censored or truncated variables, presence of values extremes, non-linear models, etc. This method has two main advantages over least-squares regression. It can make no assumptions about the distribution of the target variable and tends to resist the influence of outliers. Many studies considered this method in their analysis. Charnoz et al. (2011) used it on french data to study the determinants of wage inequality and Corneic (2014) used it to forecast economic conditions.

Following Machado and Silva (2019), we apply a panel data quantile regression model. More precisely and as mentioned above, we are interested in estimating the conditional quantiles of the depth of the food deficit whose distribution is conditioned on a vector of covariates including GDP per capita and biofuel production, via the equation below:

$$DFD_{it} = \alpha_i + \beta X_{it} + (\phi_i + Zit\gamma)U_{it} \quad (8)$$

where DFD_{it} is our dependent variable, the depth of the food deficit; X_{it} is the k-vector of covariates; Z is a k-vector of known differentiable transformations of the components of X ; U_{it} is an unobserved random variable, independent and identically distributed across i and t , and independent of X_{it} ; α_i and ϕ_i two parameters capturing fixed effects; with $Pr\phi_i + Zit\gamma > 0 = 1$.

The results of quantile regression for our two variables of interest, GDP per capita and biofuel production, have been presented graphically (Figure 9) with the 95% confidence interval (shaded area) and in table A.3. As described in the previous section, the level of GDP per capita has a relatively large and

significant influence on food security. The coefficient corresponding to GDP per capita is always negative (figure 8), which means that it shifts the overall distribution of the depth of the food deficit downwards and thus contributes to improving the level of food security. Its effect decreases sharply with the decile. Thus, the decrease in the first decile of the distribution of the conditional DFD following a 1% increase in GDP per capita is, once controlled by the other variables, 0.35% (significant at 10%), against 0.5% for the last decile. Therefore, this result highlights the importance of GDP per capita in reducing food insecurity, mainly for the country belonging to the last decile. These countries are considered highly food insecure because their level of food deficit depth is greater than 297 kilocalories per capita per day. Finally, as for the boosted results, figure 9 shows that the coefficient associated with the production of biofuels is not significant, which means that the relative influence of biofuels is small.

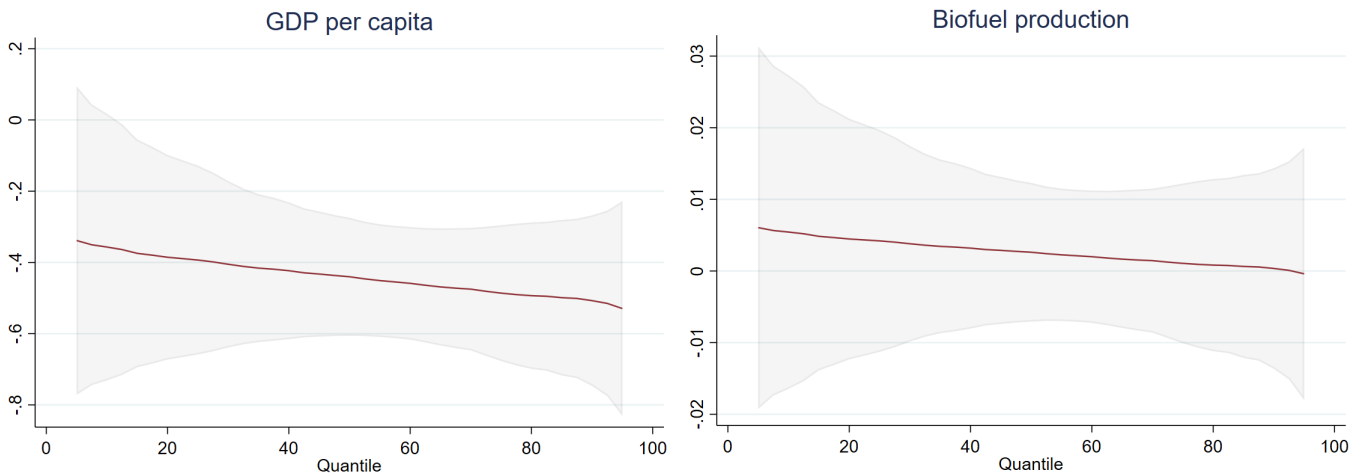


Figure 9: Quantile regression

6 Conclusion and Discussion

Given the increasing programs supporting food security, and the improvement of agricultural techniques and production, many people worldwide and mainly in developing countries face food insecurity. This raises some questions on the key drivers of food insecurity and the existence of an unconditional hunger trap. Therefore, in this paper, we considered the depth of the food deficit as our dependant variable and performed several analyses to answer these questions.

The Markov transition matrix performed allowed us to test the unconditional hunger trap hypothesis. Findings gave us the probability to move from one state to another, and revealed through the ergodic

distribution that all countries of our sample belonging to the severe, high, and moderate level of food insecurity will end up to the low level. Results also showed that it will take around 9 years to move from the severe level of food insecurity to the low one. Therefore, we can reject the hypothesis of an unconditional hunger trap. The only trap that could exist is the food security trap because, on average, a country is always expected to move to a low level of food insecurity. In addition, a country in a situation of severe, high or moderate level of food insecurity has more than 50% chance of having a negative growth rate of the depth of the food deficit that means an improvement of their level of food security. Thus, as we reject the hypothesis, it becomes necessary to identify the key drivers for each level of food insecurity.

The conditional inference regression inference tree provided the optimal decision tree for each level of food insecurity. Thus, it showed that critical factors of food insecurity are mainly related to the economic structure. Indeed, the most relevant variable is a low GDP per capita. However, for a country-period with a high level of food insecurity, the key determinants, in addition to GDP per capita, are the age dependency ratio, low precipitation, low socioeconomic conditions, and high corruption index. For a country with a low level of food insecurity, the key variables influencing their level include GDP per capita, precipitation, exposure sub-index, and conflict events. Food insecurity determinants seem closer to the capability approach developed by Sen than to the Malthusian approach.

Specifically, according to the results, low predicted values of the level of the food deficit appear for country-periods with a GDP per capita of more than US\$6,550 such as Turkey and Mexico. Then, country-periods with an exposure sub-index level less than or equal to 16.95 will have an average predicted value of the magnitude of the food deficit of about 4.48 kilocalories per capita per day. These results are in line with some authors showing that poverty, economic structure, trade openness, unemployment, and climate change are among the determinants of food insecurity. Hence, this analysis strengthens and contributes to the literature on food security determinants. Specifically, this paper allows us to conclude we need to combine policies and programs supporting food security with those contributing to improving poverty, economic growth, competitiveness and trade openness of countries, and climate change mitigation. In addition, policymakers could ensure that food security objectives are integrated into national poverty reduction strategies. The results also highlight the importance of armed conflict on food insecurity. In light of the resurgence of conflicts, particularly in Africa where populations are also the most food insecure, policymakers could reinforce the resilience of populations and measures to promote better access to food for displaced people.

To test the precision of our results, we performed the conditional inference regression tree using the

global hunger index and the prevalence of underweight (percentage of children under 5) as dependent variables, and considering the additional predictors such as the real effective exchange rate and the net official development assistance and official aid received per capita, the boosted random forest, and the panel data quantile regression as robustness check. Findings had also led to the conclusion that GDP per capita is the key determinants of food security as its influence is higher than other drivers. Furthermore, boosting results also highlight the relative importance of women wage. Hence, they should be specifically targeted in food security initiatives. Among others, this can be done by facilitating their access to public food procurement initiatives.

Contrary to some studies on the high negative effect of biofuel production on food security, the conditional inference regression tree results revealed that biofuels are not among the long-run key determinant of food insecurity. This finding was further enhanced with the panel data quantile regression because we did not find any significance of biofuels on food security. In addition, boosting model displayed that among the variables, biofuels have the lowest relative influence rate (0.01%) for the overall sample. As a result, to achieve the 13th objective of Sustainable Development Goals (Climate Action) without reducing food security, biofuel production can be a solution to save our planet by reducing dependency to fossil fuels.

As food security is multidimensional, these analyses can be extended by using other indicators as dependent variables or computing a synthetic index of food security with its indicators. A variable related to the covid-19 pandemic can also be included among the predictor variables. This study assesses the hunger trap and difference in terms of food insecurity between countries. Consequently, it could be performed at the micro level, focusing on analysing hunger trap and food insecurity determinants within a country.

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7 Appendix

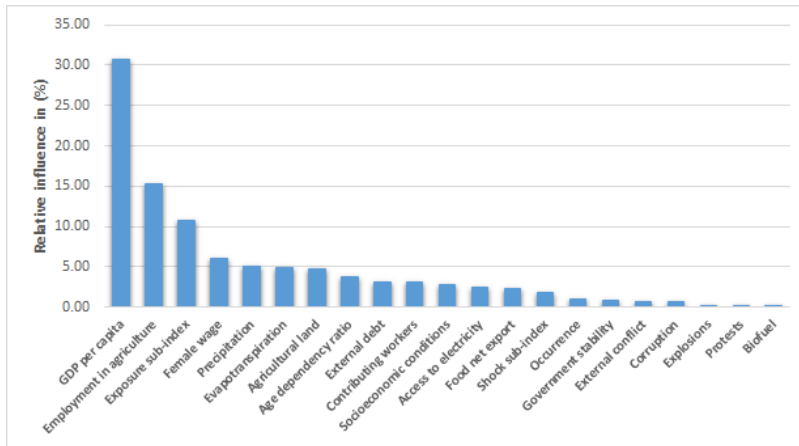


Figure A.1: Boosting model in the overall sample: relative influence of each predictor variable

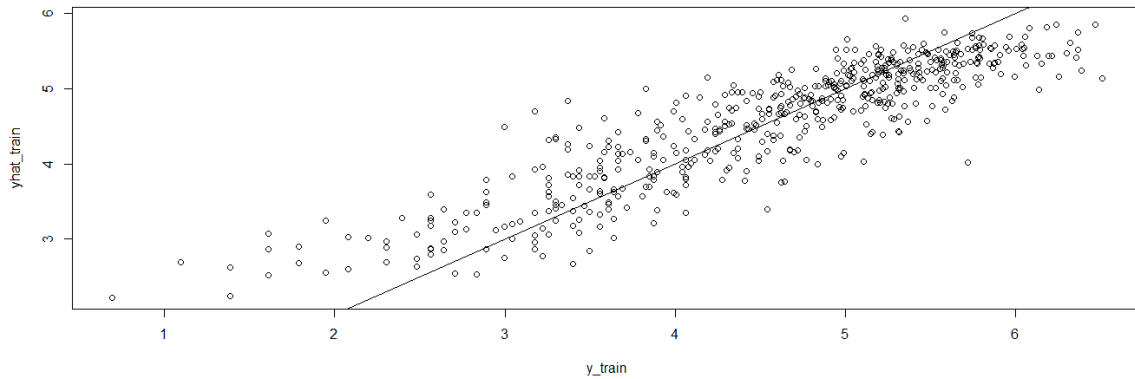


Figure A.2: Boosting model in the overall sample: actual (y) vs prediction value (\hat{y}) of the outcome (depth of the food deficit) on the training dataset

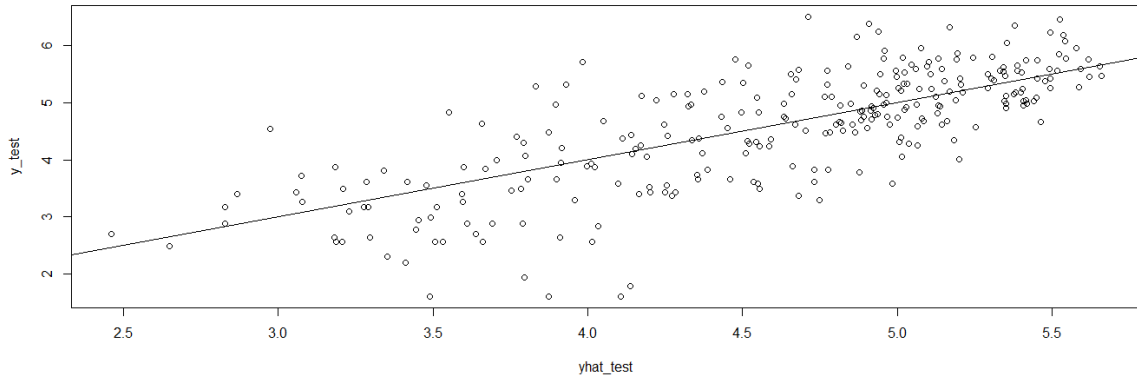


Figure A.3: Boosting model in the overall sample: actual (y) vs prediction value ($yhat$) of the outcome (depth of the food deficit) on the testing dataset

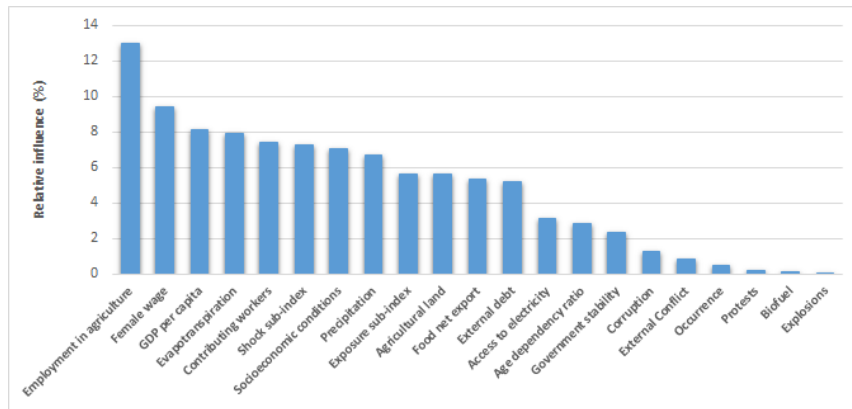


Figure A.4: Boosting model in the sample of high food insecurity: relative influence of each predictor variable

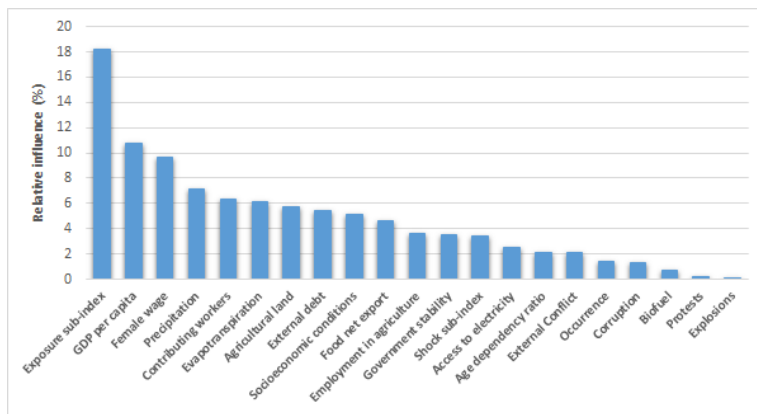


Figure A.5: Boosting model in the sample of low food insecurity: relative influence of each predictor variable

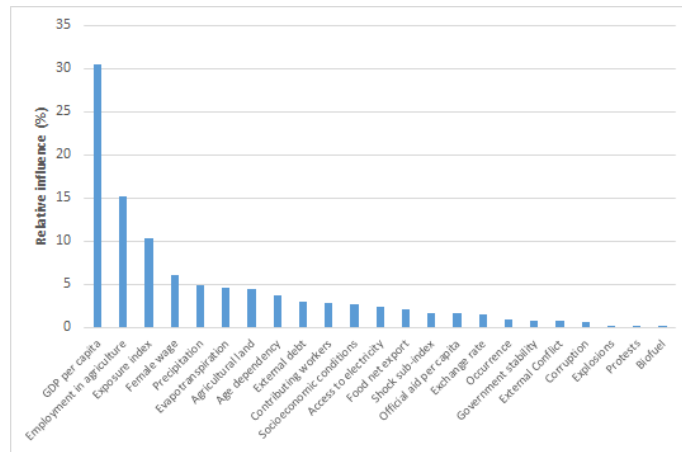


Figure A.6: Boosting model in the overall sample and considering additional predictors

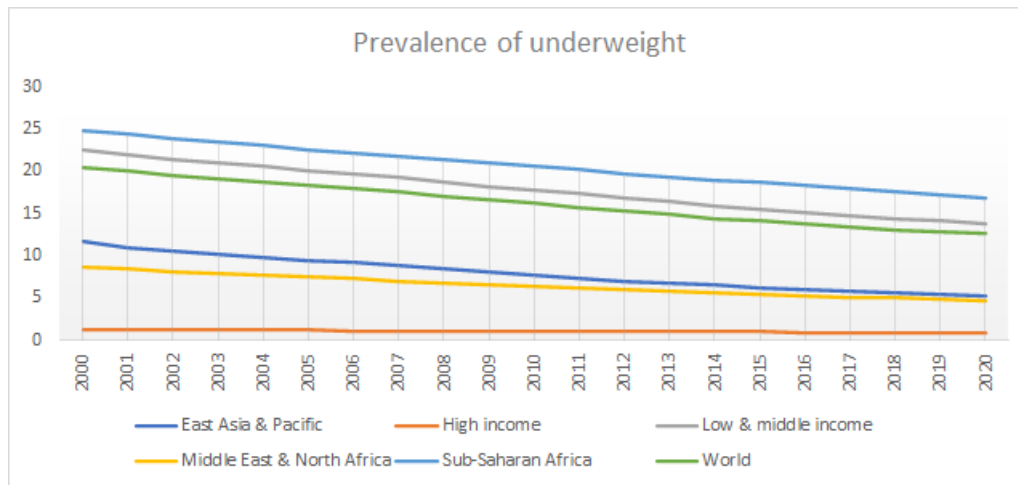


Figure A.7: Evolution of the prevalence of underweight (% of children under 5)

Table A.1: Example of observation per final node in the sample of high food insecurity

Node	Country	Year	DFD (real)	DFD (predict)	Error (abs value)
3	Myanmar	1992	6.24	6.10	0.14
3	Ethiopia	1997	6.36	6.10	0.26
3	Ethiopia	2002	6.05	6.10	0.05
3	Liberia	1997	5.74	6.10	0.36
3	Mozambique	1992	6.08	6.10	0.02
5	Bangladesh	1992	5.51	5.70	0.19
5	Cambodia	1997	5.34	5.70	0.36
5	Central African Rep	2002	5.77	5.70	0.07
5	Central African Rep	2007	5.72	5.70	0.02
5	Liberia	2002	5.68	5.70	0.02
6	Malawi	2002	5.21	5.25	0.04
6	Malawi	2007	5.19	5.25	0.06
6	Niger	1992	5.24	5.25	0.01
6	Uganda	1997	5.21	5.25	0.04
6	Burkina Faso	1992	5.18	5.25	0.07
8	Haiti	1992	6.25	6.05	0.20
8	Haiti	1997	6.35	6.05	0.30
8	Haiti	2002	6.30	6.05	0.25
8	Zimbabwe	2002	5.85	6.05	0.20
8	Zimbabwe	2007	5.77	6.05	0.28
11	Angola	2012	4.79	5.15	0.36
11	Armenia	2002	5.11	5.15	0.04
11	Bolivia	2012	5.10	5.15	0.05
11	Congo, Rep	2012	5.32	5.15	0.17
11	Guyana	1992	5.11	5.15	0.04
13	Angola	2002	5.87	5.50	0.37
13	Angola	2007	5.34	5.50	0.16
13	Botswana	1997	5.35	5.50	0.15
13	Cameroon	1997	5.58	5.50	0.08
13	Cameroon	2002	5.34	5.50	0.16
14	Afghanistan	1992	5.31	5.30	0.01
14	Afghanistan	1997	5.80	5.30	0.50
14	Afghanistan	2007	5.30	5.30	0.00
14	Armenia	1992	5.18	5.30	0.12
14	Bolivia	2002	5.40	5.30	0.10
15	Bangladesh	2002	4.93	4.90	0.03
15	Brazil	1997	4.62	4.90	0.28
15	Cambodia	2007	4.91	4.90	0.01
15	Cameroon	2007	4.92	4.90	0.02
15	Ecuador	1992	4.80	4.90	0.10

Table A.2: Example of observation per final node in the sample of low food insecurity

Node	Country	Year	DFD (real)	DFD (predict)	Error (abs value)
4	Algeria	2012	3.43	3.50	0.07
4	Jordan	2002	3.64	3.50	0.14
4	Morocco	2007	3.66	3.50	0.16
4	South Africa	1992	3.40	3.50	0.10
4	Turkmenistan	2007	3.53	3.50	0.03
5	Armenia	2007	4.06	4.05	0.01
5	Belize	1992	4.06	4.05	0.01
5	Cuba	1992	3.66	4.05	0.39
5	Jamaica	2002	3.89	4.05	0.16
5	Peru	2012	4.26	4.05	0.21
8	Guinea	2007	5.05	4.15	0.90
8	Guinea	2012	4.83	4.15	0.68
8	Cote d'Ivoire	1997	4.29	4.15	0.14
8	Cote d'Ivoire	2007	4.58	4.15	0.43
8	Cote d'Ivoire	2012	4.62	4.15	0.47
9	Cote d'Ivoire	1992	4.19	4.10	0.09
9	Cote d'Ivoire	2002	4.73	4.10	0.63
9	Afghanistan	2012	5.00	4.10	0.90
9	Cabo Verde	1997	4.69	4.10	0.59
9	Nigeria	1997	4.32	4.10	0.22
10	Fiji	1992	3.74	3.80	0.06
10	Fiji	1997	3.56	3.80	0.24
10	Kiribati	1992	3.83	3.80	0.03
10	Kiribati	1997	3.61	3.80	0.19
10	Kyrgyzstan	2012	3.91	3.80	0.11
12	Turkey	1992	1.10	1.50	0.40
12	Turkey	1997	1.39	1.50	0.11
12	Turkey	2002	1.79	1.50	0.29
12	Turkey	2007	1.39	1.50	0.11
12	Mexico	2002	3.43	1.50	1.93
13	Barbados	1997	3.33	3.30	0.03
13	Brazil	2007	3.30	3.30	0.00
13	Chile	2007	3.30	3.30	0.00
13	Costa Rica	2012	3.61	3.30	0.31
13	Uruguay	2002	3.26	3.30	0.04

Table A.3: Panel data quantile regression

	Quantile (0.25) DFD(log)	Quantile (0.5) DFD(log)	Quantile (0.75) DFD(log)
Biofuel	0.004 (0.008)	0.003 (0.005)	0.001 (0.006)
GDP per capita (log)	-0.393*** (0.135)	-0.440*** (0.085)	-0.486*** (0.097)
Exposure index	0.039*** (0.015)	0.031*** (0.009)	0.023** (0.011)
Evapotranspiration	0.001* (0.001)	0.001*** (0.0004)	0.001** (0.0005)
Female wage	-0.004 (0.008)	-0.007 (0.005)	-0.010* (0.006)
Agricultural land	-0.006 (0.008)	-0.009* (0.005)	-0.012** (0.006)
External debt	-0.0003 (0.0004)	-0.0001 (0.0002)	0.0001 (0.0003)
Corruption	-0.009 (0.035)	-0.011 (0.022)	-0.0124 (0.026)
Precipitation	0.0001 (0.0001)	0.001 (0.0001)	0.0001 (0.0001)
Shock index	-0.003 (0.003)	-0.002 (0.002)	-0.001 (0.002)
Age dependency	-0.013* (0.008)	-0.008 (0.005)	-0.003 (0.005)
Access to electricity	-0.020*** (0.004)	-0.017*** (0.003)	-0.014*** (0.003)
Government stability	0.047*** (0.015)	0.043*** (0.010)	0.039*** (0.011)
Protests	-0.00003 (0.00007)	-0.00001 (0.00005)	0.00001 (0.00006)
Explosions	0.0001 (0.0004)	0.0000 (0.0003)	-0.00004 (0.0003)
Employment in agriculture	-0.013*** (0.004)	-0.014*** (0.003)	-0.015*** (0.003)
<i>N</i>	454	454	454

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Depth of the food deficit	549	4.55	1.05	0.69	6.51
Agricultural land	529	41.31	21.05	0.45	85.39
Employment in agriculture	534	41.39	24.69	0.40	90.83
Contributing workers	534	14.28	13.20	0.01	52.57
Population growth	533	2.03	1.36	-5.09	14.24
Unemployment	534	8.38	6.15	0.16	39.30
Female wage	534	43.77	28.80	0.86	99.59
Male wage	534	47.70	22.86	6.43	97.99
Corruption	408	2.36	0.90	0.00	5.00
External debt	460	58.20	58.46	0.00	517.85
Biofuel production	319	4.29	34.93	0.00	423.74
Temperature	534	22.30	5.91	-0.69	29.11
Precipitation	534	1191.53	862.53	23.24	4601.26
Evapotranspiration	534	1418.30	337.58	769.86	2478.56
Government Stability	408	7.95	1.92	1.83	11.50
Shock sub-index	509	33.90	16.61	3.40	89.39
Exposure sub-index	535	35.78	12.71	4.09	86.08
GDP per capita	538	7.62	1.20	5.09	11.07
Socioeconomic conditions	408	4.88	2.08	0.00	11.00
Investment profile	408	7.18	2.06	0.00	11.50
Internal conflict	408	8.33	2.15	0.00	12.00
External conflict	408	9.78	1.70	2.00	12.00
Military in politics	408	3.11	1.65	0.00	6.00
Battles	170	74.63	229.81	0.00	1902.00
Explosions	170	27.95	224.89	0.00	2853.00
Protest	170	131.90	1082.25	0.00	14022.00
Riots	170	38.11	177.63	0.00	1642.00
Strategic development	170	36.82	315.72	0.00	4098.00
Civil violence	170	80.76	234.56	0.00	2229.00
Age dependency ratio	548	65.61	20.57	15.86	111.25
Trade openness	488	75.36	38.99	0.22	311.35
Natural shock index	513	42.16	17.06	2.25	91.03
Religious tensions	408	4.27	1.39	0.00	6.00
Manufacturing value added	360	579.78	937.11	7.56	10039.09
Natural resources rent	428	10.85	13.06	0.00	74.13
Food net exporter	549	0.74	0.44	0.00	1.00
Occurrence	363	3.42	3.87	1.00	29.00
Extractives dependence index	99	40.63	26.26	4.05	93.26
Access to electricity	302	63.41	33.37	0.01	100
Real effective exchange rate	198	104.39	26.25	41.07	236.02
Net official development assistance	537	62.63	83.16	-27.94	641.06

Table A.5: Evolution of the Depth of the food deficit per country from 1992 to 2016

Country	1992	2016	(%)	Country	1992	2016	(%)
Afghanistan	202	173	-14%	Lebanon	13	29	123%
Algeria	48	20	-58%	Lesotho	99	76	-23%
Angola	499	90	-82%	Liberia	211	256	21%
Argentina	15	2	-87%	Madagascar	180	229	27%
Armenia	177	41	-77%	Malawi	332	139	-58%
Azerbaijan	163	12	-93%	Malaysia	31	14	-55%
Bangladesh	247	116	-53%	Maldives	69	34	-51%
Barbados	16	21	31%	Mali	107	23	-79%
Belize	58	40	-31%	Mauritania	95	36	-62%
Benin	190	48	-75%	Mauritius	57	35	-39%
Bolivia	261	104	-60%	Mexico	46	29	-37%
Botswana	168	177	5%	Mongolia	210	156	-26%
Brazil	110	10	-91%	Morocco	39	31	-21%
Brunei Darussalam	21	12	-43%	Mozambique	437	181	-59%
Burkina Faso	177	167	-6%	Myanmar	511	103	-80%
Cambodia	205	97	-53%	Namibia	252	325	29%
Cameroon	260	63	-76%	Nepal	149	51	-66%
Cape Verde	100	68	-32%	Nicaragua	420	122	-71%
Central African Republic	356	380	7%	Niger	188	56	-70%

Chad	470	261	-44%	Nigeria	140	42	-70%
Chile	60	20	-67%	Oman	118	33	-72%
China	188	74	-61%	Pakistan	179	172	-4%
Colombia	101	62	-39%	Panama	188	66	-65%
Congo, Rep.	322	206	-36%	Paraguay	133	71	-47%
Costa Rica	33	35	6%	Peru	222	50	-77%
Cote d'Ivoire	66	93	41%	Philippines	184	93	-49%
Cuba	39	7	-82%	Rwanda	426	232	-46%
Djibouti	669	118	-82%	Sao Tome and Principe	146	40	-73%
Dominican Republic	247	86	-65%	Saudi Arabia	18	9	-50%
Ecuador	122	70	-43%	Senegal	163	63	-61%
Egypt, Arab Rep.	26	12	-54%	Sierra Leone	333	160	-52%
Ethiopia	644	236	-63%	South Africa	30	13	-57%
Fiji	42	30	-29%	Sri Lanka	228	192	-16%
Gabon	70	18	-74%	Sudan	283		-100%
Gambia, The	86	32	-63%	Suriname	107	56	-48%
Georgia	463	55	-88%	Swaziland	97	192	98%
Ghana	352	19	-95%	Tajikistan	187	250	34%
Guatemala	89	101	13%	Tanzania	157	238	52%
Guinea	165	115	-30%	Thailand	280	53	-81%
Guinea-Bissau	156	143	-8%	Timor-Leste	323	184	-43%
Guyana	166	74	-55%	Togo	268	75	-72%

Haiti	519	546	5%	Trinidad and Tobago	88	55	-38%
Honduras	154	85	-45%	Tunisia	5	3	-40%
India	165	109	-34%	Turkey	3	1	-67%
Indonesia	136	51	-63%	Turkmenistan	57	22	-61%
Iran, Islamic Rep.	31	31	0%	Uganda	150	172	15%
Iraq	46	185	302%	United Arab Emirates	14	18	29%
Jamaica	70	58	-17%	Uruguay	58	24	-59%
Jordan	33	13	-61%	Uzbekistan	20	29	45%
Kazakhstan	18	18	0%	Vanuatu	69	41	-41%
Kenya	209	135	-35%	Venezuela, RB	91	9	-90%
Kiribati	46	22	-52%	Vietnam	368	83	-77%
Kuwait	305	21	-93%	Yemen, Rep.	179	182	2%
Kyrgyzstan	105	40	-62%	Zambia	235	405	72%
Lao PDR	325	128	-61%	Zimbabwe	327	259	-21%

Table A.6: Source of variables

Variables	Source
Dependent variable	
Depth of the food Deficit	World Development Indicators
Global hunger index	International food policy research institute
Prevalence of children underweight	Food and Agriculture Organization
Economic structure	
GDP per capita	World Development Indicators
External debt	International Monetary fund
Contributing family workers	World Development Indicators
Trade openness	World Development Indicators
Socioeconomic conditions	International Country Risk Guide
investment profile	International Country Risk Guide
government stability	International Country Risk Guide
Female wage	World Development Indicators
Male wage	World Development Indicators
Access to electricity	World Development Indicators
Natural resources rent	World Development Indicators
Food net export	World Development Indicators
Unemployment	World Development Indicators
Corruption	International Country Risk Guide
Real Effective Exchange Rate	World Development Indicators
Official Development Assistance	World Development Indicators
Renewable energy	
Biofuels	Energy Information Administration
Weather conditions and events	
Temperature	Center for Studies and Research on International Development
Precipitation	Center for Studies and Research on International Development
Evapotranspiration	Center for Studies and Research on International Development
Occurrence of extreme weather events	Emergency events database
Natural shock index,	World Development Indicators
Agricultural sector	
Agricultural land	World Development Indicators
Employment in agriculture	World Development Indicators
Armed conflicts	
Internal conflict	International Country Risk Guide
External conflict	International Country Risk Guide
Military in politics	International Country Risk Guide
Battles	Armed Conflict Location and Event Data project
Explosions	Armed Conflict Location and Event Data project
Riots	Armed Conflict Location and Event Data project
Violence against civils	Armed Conflict Location and Event Data project
Religious tensions	International Country Risk Guide
Other indexes	
Shock sub-index	Foundation for studies and Research on International Development
Exposure sub-index	Foundation for studies and Research on International Development