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The impact of GDP, human development, unemployment, and globalization on obesity

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ABSTRACT

This paper examines the impact of GDP, human development, unemployment and globalization on obesity rates in EU countries from 1990 to 2019. Hausman's test was applied to test for fixed and random effects on the panel data. The Pesaran and Hsiao tests assessed cross-sectional dependence and the homogeneity (heterogeneity) of the slope between countries. A second generation unit root test was carried out using the CIPS test by Pesaran, and the Westerlund test was used to test for cointegration. Mean group (MG) and pooled mean group (PMG) estimations were applied to allow for a higher degree of heterogeneity of the parameters in growth regressions. Finally, to detect causality in heterogeneous units, and cross-sectional dependence, we used the Dumitrescu–Hurlin test. The results of the analysis showed that the variables are cross-sectionally dependent and heterogeneous as well as stationary at first difference. The cointegration test results show that obesity and the explanatory variables move together in the long-run for all countries. Human development has a negative impact on obesity for 27 EU countries, while GDP, globalization and unemployment have a positive impact on obesity. Globalization and unemployment are considered to be the most influential factors affecting obesity. Hence, EU governments should pay great attention to these aspects.

Contribution/Originality: The current study contributes to the existing literature by revealing that globalization and unemployment are among the most influential factors affecting obesity, the latter being one of the major threats to public health. The originality of this paper is in the use of sophisticated econometric methods and the inclusion of determinants which have not yet been used by researchers.

1. INTRODUCTION

The World Health Organization (WHO) defines obesity as the excessive accumulation of fat in the body to an extent that harms health. Obesity significantly increases the risk of many chronic diseases, such as arterial hypertension, type 2 diabetes, mellitus cardiovascular diseases, certain types of cancer, obstructive sleep apnea, and osteoarthritis, making it a key factor of morbidity and mortality. Nowadays, more people die from causes related to increased body weight than from causes associated with starvation. Developed and developing countries have experienced an increase in obesity during recent decades. A staggering 1 billion people worldwide are classified as obese. Of these, 650 million are adults and 340 million are children, and these numbers are still growing. Based on the World Health Organization's estimates, about 167 million additional people (adults and children) will be overweight or obese by 2025 (Boutari & Mantzoros, 2022; World Health Organization (WHO), 2022).

Obesity is a chronic and multifactorial disease and is a major global public health problem that manifests in individual, socioeconomic and environmental aspects. Some of the known causes are poor diet, lack of physical activity, automation, urbanization, genetic susceptibility, drug use, mental disorders, economic policies, endocrine disruptions and exposure to chemicals that disrupt the endocrine system. Also, obesity leads to high health care costs for families and society as a whole (Finkelstein, Fiebelkorn, & Wang, 2003). Furthermore, obese people face more challenges in the labor market and are more prone to discrimination and cultural stigma (Brewis, Wutich, Falletta-Cowden, & Rodriguez-Soto, 2011). Realizing the individual and socioeconomic consequences, researchers are interested in determining the social and economic factors of obesity. Given the extreme importance of health and economic costs, obesity is a clear global public health priority. The many factors supporting obesity are crucial to promoting health policy initiatives to combat this epidemic (Ralston et al., 2018). The World Health Organization (WHO) is responding to the global obesity crisis by monitoring global trends and prevalence, developing a wide range of guidelines and providing support for the treatment of overweight and obese people (World Health Organization (WHO), 2022).

1.1. Body Mass Index (BMI)

The body mass index (BMI) is defined as the weight-to-height index (kg/m^2) used to classify adults into overweight and obese categories. The simplicity of its measurement makes it a commonly used tool to correlate the risk of health problems with the burden at the population level. However, it comes with some flaws as it relies simply on height and weight measurements and does not take into account other factors such as the different levels of obesity (of adiposity) based on age, physical activity levels and gender. For this reason, it is expected to overestimate obesity in some cases and underestimate it in others. Other measures, such as waist circumference, can complement BMI estimates (World Health Organization (WHO), 2021).

People are classified as obese when the body mass index is 30.0 or higher kg/m^2. A high BMI is an indicator of risk, but not a direct cause of diseases resulting from a poor diet and lack of physical activity. The BMI was developed as a risk indicator of disease, and when the BMI increases, the risk for certain diseases increases.

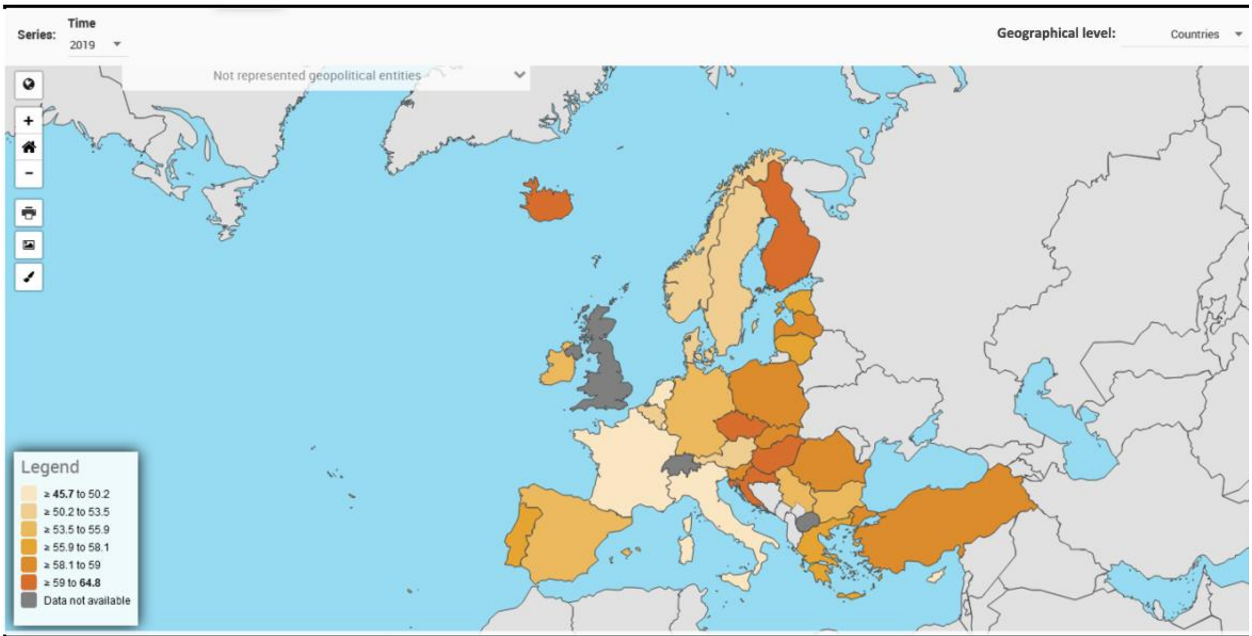

Figure 1. The body mass index (BMI) status in EU countries (2019).

The prevalence of obesity is increasing rapidly, and a large part of the world's population is currently obese, with the "champions" being some of the Arab countries, North America and the USA. In the EU 27, there are significant variations, with the most developed countries having a higher index than the 'newer' EU countries. Figure 1 illustrates the body mass index (BMI) status in EU countries for 2019.

According to the image in Figure 1, the categories of the BMI index for obesity in EU countries are classified as follows:

45.7–50.2 (Belgium, Cyprus, France, Italy, Luxembourg, the Netherlands).

50.2–53.5 (Austria, Denmark, Germany, Sweden).

53.5–55.9 (Bulgaria, Ireland, Spain, Portugal).

55.9–58.1 (Estonia, Greece, Lithuania, Poland, Slovenia).

58.1–59 (Latvia, Romania, Finland, Slovakia).

59–64.8 (Croatia, Czechia, Hungary, Malta).

It is particularly worrying that the phenomenon of obesity is growing in EU countries, with no sign of reduction. If this situation continues, it poses risks to the level of public health and also to the medical care system, which will not be able to meet demand, since obesity is associated with several diseases. The recognition of obesity as a chronic disease offers the opportunity to integrate it into both public health policy and medical care, since the benefits that can be provided by interventions are significant and are proportional to the loss of body weight (Kyle, Dhurandhar, & Allison, 2016).

The cost of obesity is high, but it also incorporates other diseases such as diabetes or cardiovascular diseases. The financial burden of medical services is a function of BMI; the greater the BMI, the greater the cost. More than 8%–9% of health costs are due to obesity, a rate that is particularly large and almost equal to the cost of neoplasms or diabetes. Therefore, health costs rise to >10%, while the impact on the general economy is equally significant, with losses due to obesity amounting to about half a trillion. This includes not only medical costs, whether direct or indirect, but also a fall in the standard of living, absence from work, as well as other problems related to social activities. The benefits of a comprehensive intervention regarding weight loss make it a significant investment in public health (Tremmel, Gerdtham, Nilsson, & Saha, 2017).

The programs currently implemented in the EU focus on reducing BMI through diet and physical exercise. However, the difficulties are great and the results are meagre, as research in many EU countries shows, and the results of a therapeutic approach are also meagre, either because they do not reach the population or because they are not accessible to a large part of the population. The European action plan should be enriched with socioeconomic interventions in order to have a multifactorial shape that gives results. The problem affects 50% of the European population and cannot be tackled by public health and medical care measures alone (Boutari & Mantzoros, 2022).

For adults who are 20 years of age and older, the body mass index BMI is interpreted using standard weight status categories. These categories are the same for men and women of all body types and ages. Table 1 below shows the BMI values for the EU countries between 2008 and 2019.

According to the data for 2019 and the categories of the BMI index, the EU countries are classified as follows:

BMI categories:

Underweight = < 18.5

Normal weight = 18.5–24.9

Overweight = 25–29.9

Obese = BMI of 30 or greater.

Obesity is frequently subdivided into categories:

Class 1: BMI of 30 to < 35

Class 2: BMI of 35 to < 40

Class 3: BMI of 40 or higher. Class 3 obesity is categorized as "severe" obesity in Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Malta Latvia, Lithuania, Luxembourg, Netherland, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden.

Table 1. Body mass index (BMI) values for EU countries.

Country/Area	2008	2014	2017	2019
EURO AREA – 19 countries (from 2015)			49.8	
EURO AREA – 18 countries (2014)			49.7	
Belgium	47.5	49.3	48.7	50.2
Bulgaria	50.8	54.0	59.5	54.9
Czechia	56.6	56.8	62.3	60.0
Denmark		47.7		50.4
Germany (Until 1990 former territory of the FRG)	52.1	52.1		53.5
Estonia	51.0	53.9	56.1	56.7
Ireland		55.7	57.1	54.4
Greece	56.3	56.7		57.6
Spain	53.0	52.4	51.7	53.7
France	43.6	47.2	46.1	47.2
Croatia		57.4	60.9	64.8
Italy		44.9		45.7
Cyprus	51.3	48.3	52.7	49.8
Latvia	54.9	56.5	57	58.3
Lithuania		55.6	56.2	56.8
Luxembourg		48.0	49.3	48.4
Hungary	54.9	55.2	56.3	59.9
Malta	59.7	61.0	62.2	64.8
Netherlands		49.4	47.0	50.0
Austria	49.3	48.0	50.0	52.2
Poland	54.0	54.7	56.0	58.1
Portugal		53.6	53.3	55.9
Romania	50.3	55.8	62.9	58.7
Slovenia	56.6	56.6	52.5	58.1
Slovakia	50.7	54.2	54.5	58.7
Finland		54.7	61.1	59.0
Sweden		49.9		51.3

In the existing literature, the absence of studies that combine longitudinal data to estimate the relationship between globalization, GDP, unemployment and human development with obesity is evident. Although some previous studies have investigated the role of individual, national, macro-economic variables regarding the prevalence of obesity, none have examined the role of a set of variables and their relationship with the prevalence of obesity. The aim of our work is to determine the relationship between globalization, GDP, unemployment and human development and obesity. For this purpose, modern econometric techniques are used that take cross-sectional dependence and heterogeneity into account among the 27 EU countries. The present paper responds to an important research question about the most likely factors that can affect obesity.

1.2. Research Questions and Hypotheses

The research questions and hypotheses that will be examined regarding the correlation of obesity with GDP, globalization, unemployment, and human development in EU countries are as follows:

RQ1: What is the relationship between GDP and obesity in EU countries?

H01: There is no statistically significant relationship between GDP and obesity.

Ha1: There is a statistically significant relationship between GDP and obesity.

RQ2: What is the relationship between globalization and obesity in EU countries?

H02: There is no statistically significant relationship between globalization and obesity.

Ha2: There is a statistically significant relationship between globalization and obesity.

RQ3: What is the relationship between unemployment and obesity in EU countries?

H03: There is no statistically significant relationship between unemployment and obesity.

Ha3: There is a statistically significant relationship between unemployment and obesity.

RQ4: What is the relationship between human development and obesity in EU countries?

H04: There is no statistically significant relationship between human development and obesity.

Ha4: There is a statistically significant relationship between human development and obesity.

The analysis confirms the findings of existing empirical studies that have been settled but have not focused on all the factors that affect obesity. This work achieves an important research objective with regard to the role of the various factors that can contribute to the reduction of obesity in EU member states. In addition, the current analysis can be characterized as innovative as it complements the innovative elements by exploring the empirical impact of all the considered factors that cause obesity, to which EU policymakers should pay more attention.

Regarding the limitations of the research, the current model uses (at the individual level) only some of the possible explanatory variables of obesity, namely income, gender, education, age, place of residence, work and marital status. These characteristics are considered relevant to the risk of obesity and therefore can be used as explanatory variables (Zhou, 2019).

The rest of the paper is organized as follows: Section 2 presents the factors that affect obesity, and a brief literature review; Section 3 presents the data; Section 4 presents the methodology and explains the main results of the study; and Section 5 presents a discussion and the conclusion of our research.

2. FACTORS THAT EFFECT OBESITY

There are several factors that influence obesity, such as genetic, behavioral, environmental and medical. Given the differences among countries in many aspects, such as body composition, eating habits, and cultural and environmental factors, the relationship between obesity and these factors may vary. However, there are common factors that affect obesity and can be measured for each country. These factors are analyzed below:

2.1. GDP

Income as an indicator of socioeconomic status was found to be inversely related to obesity, although this relationship can be interpreted in two ways:

1) The causal link hypothesis that explains lower income as a cause of subsequent obesity.

2) The prospect of an inverse causality in which obesity is the cause rather than the result of lower income (Flegal, Kit, Orpana, & Graubard, 2013).

On the contrary, an important argument for reverse causality is stigma. Previous research reveals that people who are regarded as obese are more prone to a lazy, failed, weak and undisciplined lifestyle. Based on these negative stereotypes, obese people usually face higher job insecurity, lower chances of getting a job and general discrimination than non-obese people (Caliendo & Gehrsitz, 2016).

When trying to understand the social factors that make people with lower income more susceptible to obesity, research shows that material conditions limit individuals' access to healthy food and health care, while also influencing health-related behaviors and psychosocial factors derived from relative deprivation (Laaksonen, Prättälä, Helasoja, Uutela, & Lahelma, 2003); (Dinsa, Goryakin, Fumagalli, & Suhrcke, 2012).

In addition, lower income is associated with higher levels of psychosocial stressors that include reduced control of life and higher insecurity, social isolation, stress and mental disorders. In low-income areas that reach or even exceed the poverty line, people buy cheap foods full of salt, sugar and partially hydrogenated oils (i.e., foods that are categorized as "junk food") and consume little to no vegetables and fruits. Those in a dire financial position do not have much room for choice, experts admit. Other economic factors contributing to the increase in obesity are unemployment, cigarette prices, many restaurants, and food vouchers for those in the economically weaker categories of the population.

Cheap foods and those that are rich in calories are responsible for the rapid 59% increase in severe obesity between 1990 and 2010 (Fryar & Ervin, 2013). According to the results of relevant work published by the National Bureau of

Economic Research, behind obesity lie the cheap foods that are low in nutrition that the huge supermarkets sell. Contrary to the period sketches that show the representatives of capital fat and well-fed, in the reality of modern economics, obesity is directly linked to the poor economic situation. The poorer people are, the more they resort to cheap, emergency food solutions, with health being the first type of "collateral damage", especially in children.

Obesity seems to accompany the social strata with a low income, while the data on the quality of nutrition, both in adults and children, are similar. In particular, the Fabian Commission's 2016 report on food and poverty has shown that people with lower incomes consume less fruit and vegetables and more salt, sugar, saturated fat and processed foods. Poorer households prioritize calories and put their health second, choosing to spend their money on foods that are simply "filling", often indifferent to how healthy they are. According to the same research, there is an increase in cases of anemia in poorer people because they are unable to procure fruits and vegetables. The report cites other scientific studies that show that, per calorie, healthy foods are three times more expensive than less healthy ones and that special offers in supermarkets tend to favor products that are less healthy. One in three low- and middle-income families is affected by the phenomenon, according to experts from the World Health Organization (WHO). The cause of both problems is the same: the lack of nutritious food. Some children have very little food, while others consume too many empty calories. The high-fat, salty and sugary snacks that are abundant in rich countries are now available in almost every village in the world and have been incorporated into the diets of even the poorest families. A series of reports published in the Lancet medical journal by experts, including WHO scientists, report that more than a third of low- and middle-income countries are affected by this dual problem of poor nutrition (World Health Organization (WHO), 2019).

Previous and ongoing studies show that over the past 30 years, there have been significant changes in average body weight, nutrition and physical activity along with progressive economic growth in developing countries. It is very likely that obesity and its comorbidities will continue to affect an increasing number of populations in these areas. Lifestyle and environmental factors act in a synergistic way to fuel the obesity epidemic.

In Western societies, where the social fabric endures, economic poverty is rarely manifested in the form of malnutrition in the clinical sense, but rather in the form of weight gain, even obesity. This phenomenon was first formulated scientifically in 2005 as "the obesity paradox". Studies show that, in adults, the lower the income, the higher the average body weight. They also show that the obesity rate of the poor is higher than that of the non-poor, and the most striking thing is that even in homeless people, the obesity rate is similar to that of the general population (Hruby & Hu, 2015). The exact mechanisms by which economic hardship causes obesity are still under investigation, but the following are likely, according to the research so far:

1. Food prices.
2. Overeating.
3. Food insecurity.
4. The lack of education and proper nutrition practices.
5. The lack of opportunities for physical exercise (accessibility to gyms, etc.).
6. Cheap entertainment with home TV.
7. The stress of financial impoverishment.
8. Other unknown factors.

In particular, as far as food prices are concerned, financial hardship leads families to resort to junk food and fast food that are very cheap but contain many calories (a lot of energy) without being healthy, leading to weight gain.

Based on current data, it can be predicted that the obesity pandemic will persist, and low-income countries will face the current obesity trends observed in high-income countries. In fact, education is the socioeconomic indicator that has been reported to be the most important predictor of nutrition quality (Moher, Liberati, Tetzlaff, Altman, & PRISMA Group, 2009).

2.2. Coping with the Double Burden of Malnutrition

Many low and middle-income countries now face a "double burden" of malnutrition.

- While these countries continue to address the problems of infectious diseases and malnutrition, they are also experiencing a rapid increase in risk factors of non-communicable diseases, such as obesity, particularly in urban areas.
- It is not uncommon to encounter malnutrition and obesity coexisting in the same country, in the same community, and in the same household.

Children in low and middle-income countries are the most vulnerable to inadequate nutrition in the prenatal, infant and child stages. At the same time, these children are exposed to energy-dense foods that are high in fat, sugar and salt, poor in micronutrients, and tend to be lower in cost but also low in quality nutrients. These dietary patterns, combined with low levels of physical activity, result in sharp increases in childhood obesity, while the malnutrition issues remain unresolved.

Studies investigating the relationship between income and obesity are reported for a single country and many countries. Egger, Swinburn, and Islam (2012) examined the relationship between GDP per capita and body weight levels as well as environmental impacts, such as carbon dioxide emissions, in 175 countries. The results of their work showed that GDP is positively related to body mass index and carbon dioxide emissions. Rybnikova and Portnov (2017) investigated the association between rates of obesity at the country level and exposure to artificial light at night. In their paper they argue that high per capita incomes can reduce obesity rates by allowing for greater access to healthy food and nutrition education, while, on the other hand, high per capita incomes can increase exposure to artificial light at night.

Talukdar, Seenivasan, Cameron, and Sacks (2020) used a Bayes model to calculate the relationship between national income and the prevalence of obesity in 147 countries. The results showed that during the 1975–2014 period the prevalence of obesity increased relative to income in the countries under investigation. In addition, forecasts for the years 2019–2024 based on income showed that the prevalence of obesity will continue to increase at an average annual rate of 2.47%. Bu, Popovic, Huang, Fu, and Gardasevic (2021) evaluated the relationship between economic growth and body mass index in children and adolescents in China using data from 1986–2019. Their results showed a linear increase in body mass index in children and adolescents aged 5–19 years over the years in relation to economic growth.

2.3. Human Development Index

Human development is measured by various indicators, the most popular of which is the Human Development Index (HDI) published by the United Nations Development Programme. The HDI was created by economist Ul Haq (1990) based on the work of Nobel Prize-winning economist Amartya Sen on human abilities. The HDI has since been used by the UN in the annual Report on Human Development.

The HDI is a statistical indicator used to classify countries on the basis of 'human development'. It is a complex measure constructed on the basis of three sub-indicators relating to life expectancy, degree of education and quality of life. Based on the HDI, a country is classified as underdeveloped, developing or developed. It is also used to measure the impact of economic policies on quality of life.

In the 2020 UN report, the indicators used were life expectancy at birth, the expected years of schooling for children, the average school years for adults, and per capita gross national income with purchasing power parity. These indicators are used to create a health index, an education indicator and an income indicator, each with a value between 0 and 1. The geometric mean of the three indicators (that is, the cubic root of the product of the indices) is the indicator of human development. A value above 0.800 is classified as very high, between 0.700 and 0.799 as high, 0.550 to 0.699 as medium, and below 0.550 as low (Human Development Report 2020 United Nations Development Programme). Each year, UN members are registered and ranked according to their HDI.

Various studies have revealed a positive association between the HDI and many chronic diseases, as well as obesity (Ataey, Jafarvand, Adham, & Moradi-Asl, 2020; Khazaei, Sohrabivafa, Darvishi, Naemi, & Goodarzi, 2020; Munir, Zakaria, Alhajj, Salem, & Arshed, 2021). Based on the definition and measurement of human development, the development of obesity can be explained in three different ways. People who receive better education are expected to be aware that obesity is a serious disease.

Educational attainment is the only factor that is significantly related to nutritional knowledge, food purchasing behavior and perceptions of healthy foods. Progress and innovations in the field of health can be an important factor in the fight against obesity. The best level of income can be especially effective in reducing cases of obesity caused by psychological and environmental factors. When all these characteristics of human development are evaluated then we can say that human development has an effect on the reduction of obesity. However, this is not the case. An important example of the positive relationship between the HDI and obesity is demonstrated by the US. Despite high humanitarian development, the US is among the countries with the highest rates of obesity. This means that technological progress and the comforts brought about by human development make people less motivated and more inactive.

In contrast, low socioeconomic status has been associated with a higher prevalence of obesity and chronic diseases in developed countries. Recently, the relationship between socioeconomic status and obesity in developing countries has been reported to have similarities with that in developed countries (Kumanyika, Jeffery, Morabia, Ritenbaugh, & Antipatis, 2002).

In every country worldwide, whether in transitional or developed economies, non-communicable chronic conditions such as obesity are either increasing or have already reached alarming levels (Prentice, 2006). Some of the papers exploring the relationship between human development and obesity are listed below.

Roskam et al. (2010) described educational inequalities in relation to being overweight and obese in 19 European countries. They used a multivariate regression to measure educational inequalities in overweight and obese people based on body mass index. GDP per capita was used as a measure of the level of socioeconomic development. The results of their work showed that higher education was related to lower rates of overweight and obese people, especially among women in Mediterranean countries.

Faeh, Braun, and Bopp (2011) examined the prevalence of overweight by socioeconomic position (SEP) in Swiss men and women for the period from 1992–2007. Socioeconomic position is defined by three indicators –educational level, household income and work status. The results show that for the period under examination, the total prevalence of overweight increased from 37.4% to 41.4% for men and from 18.8% to 21.9% for women. The prevalence of obesity increased from 7.2% to 9.7% in men and from 5.4% to 8.6% in women. Finally, they point out that the indicator of education in relation to overweight was stronger in women.

Devaux and Sassi (2013) provided a broad international comparison of inequalities by educational level, socioeconomic status and obesity in men and women in 11 OECD countries (members of the Organization for Economic Co-operation and Development) and used regression analysis to assess the differences between social groups.

The results of their work showed great social inequalities among women in all countries under examination. The highest rates of obesity were found in the USA and England. The authors concluded that large social inequalities in obesity exist by level of education and socioeconomic status in all OECD countries, with greater inequalities shown in women rather than in men. The work of Ataey et al. (2020) on the relationship of obesity, overweight and the human development index in Eastern Mediterranean countries showed that there is a significant positive correlation between them.

In conclusion, there is a significant positive correlation between the HDI and obesity. As policymakers strive to improve people's general well-being, it is advisable to be aware of possible adverse effects of development on the risk of obesity and the overweight population.

2.4. Globalization Index

According to Dreher, Gaston, and Martens (2008), globalization is defined as the integration of the market by the creation of networks connected between actors at multicontinental distances, through flows, between people, the information of funds, and goods. Globalization is a process that abolishes national borders, integrates national economies, cultures, technologies and produces complex relationships of mutual interdependence.

The phenomenon of globalization cannot be measured one-dimensionally because it is the product of multiple factors of interaction. The measurement of economic globalization usually focuses on elements of a country's commercial activity, such as GDP, investment, and income per capita. However, other indicators try to illustrate globalization by taking into account other factors of a political, social, cultural and environmental nature (Vujakovic, 2010). In this work, we use the KOF Index created on the basis of the economic, social, and political characteristics of countries, and has been used in several studies (see Costa-Font and Mas (2016)). The KOF Index was developed by the Swiss Economic Institute and has been used in studies on the effect of globalization on health (Goryakin, Lobstein, Philip, & Suhrcke, 2015; De Soysa & de Soysa, 2018).

The economic dimension of the KOF Index includes, inter alia, international trade, foreign direct investment, financial investment, and foreign currency payments, all defined as a percentage of GDP. The number of embassies per country, participation in international organizations, participation in the United Nations, missions to the Security Council and the number of international treaties signed are incorporated into the political dimension of the KOF. As far as the social dimension of the KOF is concerned, it consists of, inter alia, outgoing telephone traffic (in minutes per 1000 inhabitants), international tourism (population ratio), foreign residents (percentage of total population), international charters (per capita), television users (per 1000 inhabitants), internet users (per 1000 inhabitants), and the newspaper and book trade (as a percentage of GDP).

Since the early 1980s, economic globalization in developing countries has led to changes in dietary patterns and food choices and has greatly influenced people's eating habits. Before globalization, people ate a lot of local and seasonal foods. Nowadays, the global economy has given people access to foods from all over the world. The nutritional transition between countries through foreign trade and investment have changed the eating habits of populations, resulting in increased obesity (De Vogli, Kouvonen, Elovainio, & Marmot, 2014).

Many studies have linked globalization to obesity (Costa-Font & Mas, 2016; De Vogli et al., 2014). Globalization has the potential to increase energy consumption and lower energy expenditure. It leads to a more abundant supply and a higher intake of cheaper processed foods with higher calories and creates more opportunities for lifestyle enjoyment with reduced energy expenditure (such as more car use and more indoor activities).

About 1.1 billion of the Earth's population are overweight, and this number is constantly growing, as announced by the International Institute for Obesity in Washington, D.C. For the first time in world history, the majority of adults in many countries are overweight. Specifically overweight are 61% of Americans, 54% of Russians and 51% of Britons. The figure for Germans is around 50%, while half of Europeans between the ages of 35 and 65 have a weight above what doctors recommend. In the throes of globalization, more and more people need to work faster, more efficiently, and longer hours.

Thus, contact with family, friends, the environment is lost, with anxiety prevailing in all grades. The result of anxiety is an increase in mental illnesses, which do not appear as purely mental disorders, but as psychosomatic diseases, such as obesity, diabetes, heart disease, allergies, asthma or dermatoses, according to scientists. Stress is definitely an important factor that increases the chances of a heart attack; however, it should not be overestimated. The explosive development of technology linked to globalization has profoundly changed the working environment, with the result that we often forget how things were ten years ago.

A significant amount of evidence in the literature has highlighted that globalization promotes obesity. More specifically, Costa-Font and Mas (2016) examined the impact of globalization on obesity from an economic and social point of view and their results suggest a strong positive relationship between the two. Specifically, an increase of one standard deviation in globalization is associated with a 23.8% increase in obesity. However, they found that the main leverage is the social rather than the economic dimension.

Fox, Feng, and Asal (2019) used a two-way fixed effects OLS regression in panel data for 190 countries between 1980 and 2008 where they evaluated the effect of globalization on weight gain. The authors found that domestic factors associated with modernization, urbanization, and women's empowerment were associated with an increase in the average weight index over time. On the other hand, economic globalization did not show a significant increase in the average weight, and cultural globalization showed mixed results.

Sudeshna (2019) examined the impact of globalization, with its social and economic dimensions, on obesity in a set of Asian countries, which were divided into two groups based on their income classification, between 1985 and 2015. The findings suggest that social globalization for low- and middle-income countries positively affects obesity. However, when it comes to the richest Asian nations, globalization was found to have a negative impact on obesity, particularly in its social dimension.

According to the literature review, the economic, political and social dimensions of the KOF index showed an increase in overweight and obesity. Social globalization exhibited polynomial behavior, while in political and economic globalization, a concave relationship was found. As a result, we can conclude that all three dimensions of globalization have a positive correlation with overweight and obesity (Goryakin et al., 2015; Hawkes, 2006; Miljkovic, Shaik, Miranda, Barabanov, & Liogier, 2015; Popkin, 2006).

2.5. Unemployment

One factor that is considered to have significant social and economic consequences for obesity is the status of the labor market. Reduced income due to involuntary job loss can negatively affect health, as it often leads to people consuming obesogenic diets. In the long term, unemployment seems to be an important risk factor for the prevalence of obesity (Antelo, Pilar, Reboredo, & Reyes-Santias, 2020).

There is a strong correlation between unemployment and the increased risk of both poor health and mortality. These associations arise in part through behaviors that have adverse effects on health, mainly smoking, poor diet, lack of exercise, and alcohol consumption caused by limited income, change in daily routine, and psychosocial stress that usually accompany job loss (Roelfs, Shor, Davidson, & Schwartz, 2011). While there is evidence of increases in smoking after unemployment, the correlation between unemployment, other health behaviors and indicators such as body mass index and obesity, is minimal (Arcaya, Glymour, Christakis, Kawachi, & Subramanian, 2014).

Research has been carried out that found an increase in BMI due to unemployment (Monsivais, Martin, Suhrcke, Forouhi, & Wareham, 2015) and others who report the fall of BMI during unemployment (Jónsdóttir & Ásgeirsdóttir, 2014). The reasons for these mixed results are unknown, but the ambiguous results could be explained by a previously overlooked 'U-shaped' association of unemployment and BMI and that jobseekers are at increased risk of being both underweight and obese. Both underweight and obesity are associated with psychosocial stress of which unemployment is an established source (Jahoda, 1981). It is known that economic developments can affect human health positively or negatively. People with lower incomes and lower spending opportunities are turning to cheap and unhealthy foods. The unemployed with lower spending opportunities are negatively affected by the increasing availability of unhealthy fast food. The effects of unemployment on obesity can be explained in economic and psychological terms. When a person's income decreases, the quality of his diet will also decrease. Low income and long-term unemployment contribute to the manifestation of physical and mental illnesses. Psychological conditions and factors, such as smoking, alcohol use, irregular diet and insomnia, can lead to weight problems related to stress. Abrupt loss of income and long-term unemployment make people more vulnerable to disease but are less likely to use health services. As a result, unemployment and obesity are two concepts that are expected to affect each other due to the stress and low income that unemployment brings.

Hughes and Kumari (2017) investigated whether there is a U-shaped correlation of unemployment and BMI in a sample of 10,737 adults of working age in the UK. Using polynomial models, they concluded that jobseekers were underweight and that unemployment was related to obesity.

Colman and Dave (2018) examined the effects of unemployment and non-employment on a range of health behaviors in a period of recession. The results of their work revealed that becoming unemployed is associated with a slight increase in exercise during leisure time, a moderate decrease in smoking, and a significant decrease in overall physical activity.

Bramming et al. (2019) studied the hypotheses of whether people with obesity are at higher risk of unemployment and are less likely to work compared to people of a normal weight in a sample of 87,796 people in Denmark over a five-year period. The results of their work showed that the risk of unemployment was 95% higher for people with obesity.

Tobing (2023) explored the effect of unemployment on obesity in two US states during the recession period due to the Covid-19 pandemic. The results of her work show a pro-cyclical relationship between unemployment and obesity. This positive relationship may be related to the lack of access to public leisure and fitness facilities during the pandemic.

Campbell et al. (2021) investigated the impact of BMI on employment in a total of 230,791 people in the UK comprising men aged 40–64 and women aged 40–59. The results of their work showed that the indicator of body mass exerts a causal effect on work status while greatly affecting the health of a person. It was concluded that the obesity epidemic contributes to the rise in unemployment and imposes a significant social burden.

3. DATA

To study the relationship between obesity, GDP, the globalization index, the human development index and unemployment in the 27 EU countries, we analyze a model panel for the period from 1990–2019. The mean body mass index (BMI) is used as the dependent variable, which is taken as the average for men and women at the country level.

The global burden, which measures the metabolic risk factors of chronic diseases, was compiled from various sources, consisting mainly of household surveys, such as demographic and health surveys, based on biomarkers of height and weight, estimated by a Bayesian hierarchical model to provide accurate estimates by country years. The BMI index is available for around 200 countries between 1980 and 2019. BMI data are reported separately for men and women. However, in addition to the estimates by gender, we calculated the average male and female BMIs to produce an estimate of the total BMI in a country.

For the independent variables we use gross domestic product (GDP) measured in millions of US dollars at constant 2015 prices; the KOF globalization index created on the basis of the economic, social, and political characteristics of a country; the human development index that measures three sub-indicators related to life expectancy; the degree of education and quality of life; as well as the unemployment rate of the countries considered in this study.

The sample under investigation includes data from 27 EU member countries – Austria (AUT), Belgium (BEL), Bulgaria (BGR), Cyprus (CYP), Czech Republic (CZE), Germany (DEU), Denmark (DNK), Spain (ESP), Estonia (EST), Finland (FIN), France (FRA), Greece (GRC), Croatia (HRV), Hungary (HUN), Ireland (IRL), Italy (ITA), Lithuania (LTU), Luxembourg (LUX), Latvia (LVA), Malta (MLT), Netherlands (NLD), Poland (POL), Portugal (PRT), Romania (ROU), Slovak Republic (SVK), Slovenia (SVN), and Sweden (SWE).

For the purpose of the current analysis, we use annual data for the 1990–2019 period and the Stata 14.0 statistical package and EViews 12.0. All variables alongside their symbols as well as their data sources are presented in Table 2 below.

Table 2. Description of the data used for the analysis

Variable	Period	Database	Explanation
obs	1990–2019	World Health Organization (WHO) Last update: Feb 24, 2022	Body mass index (BMI) percentage (total) (Overweight BMI = 25–29.9).
gdp	1990–2019	World Development Indicators Last update: Feb 15, 2022	Gross domestic product measured in millions of constant 2015 US dollars.
glob	1990–2019	SWISS Economic Institute KOF	Globalization was measured using the Swiss Economic Institute (KOF) index of economic globalization.
hdi	1990–2019	Source: HDRO calculations based on data from UNDESA (2019), UNESCO Institute for Statistics (2020), United Nations Statistics Division Department of Economic and Social Affairs Statistics (2020), World Bank (2020), Barro and Lee (2018) and the IMF Annual Report (2020).	A composite index measuring the average achievement in three basic dimensions of human development – a long and healthy life, knowledge, and a decent standard of living (see Technical note 1 at http://hdr.undp.org/sites/default/files/hdr2020_technical_notes.pdf for details on how the HDI is calculated).
unm	1990–2019	World Development Indicators Last update: Feb 24, 2022	Unemployment measured as a percentage of the total labor force.

Appendix A presents the diagrams of all variables from the 27 EU member states as well as the detailed descriptive statistics for the variables under examination.

4. METHODOLOGY AND EMPIRICAL RESULTS

In order to determine the suitable functional form which better reflects the relationship between OBS, GDP, GLOB, HDI and UNM, we estimated the models separately for three functional forms. The linear, quadratic and logarithmic models were compared using the mean absolute percentage errors, and the logarithmic model was found to be the most suitable. Equation 1 presents the model used in the current study in its logarithmic form:

$$\ln obs_{it} = \alpha_0 + \beta_1 \ln gdp_{it} + \beta_2 \ln glob_{it} + \beta_3 \ln hdi_{it} + \beta_4 \ln unm_{it} + u_{it} \quad (1)$$

Where $t = 1,...,T$ and $i = 1,...N$ are the time series and cross-sectional units, respectively; $\ln obs$ is the natural logarithm of obesity; $\ln gdp$ is the natural logarithm of GDP; $\ln glob$ is the natural logarithm of globalization; $\ln hdi$ is the natural logarithm of human development; $\ln unm$ is the natural logarithm of unemployment; and u_{it} is the error term including all unobserved factors. In the model below, coefficients β_1, β_2, β_3 and β_4 are the coefficients which respectively measure the impact of GDP, globalization, human development, and unemployment on obesity.

4.1. Preliminary Tests

To determine the most suitable panel model, the following preliminary tests should be applied:

4.1.1. Random Effects vs. Fixed Effects Estimation

Econometric modelling of panel data usually applies two main approaches, fixed and random effects. To determine the suitability between the fixed and random effects models, the Hausman test (Hausman, 1978) is used. Table 3 presents the results of the Hausman test, which shows that the fixed effects model is the most appropriate.

Table 3. Hausman test.

Test summary	Chi-Sq. statistic	Chi-Sq. d.f.	Prob.
Cross-section random	21.211	4	0.0003

4.1.2. Cross-Sectional Dependence and Slope Homogeneity Tests

While panel models are capable of capturing the complex behavior of macroeconomic variables, as they contain more degrees of freedom and a larger sample variance from time series data of a country, at the same time they suffer from cross-sectional dependence and heterogeneity. Recent econometric approaches are used that take into account both cross-sectional dependence issues and heterogeneity to find the most suitable panel models.

In order to check the cross-sections between the residuals, we use the Breusch and Pagan (1980); Pesaran (2004) and Baltagi, Feng, and Kao (2011) bias-corrected scaled LM tests. The results are presented in Table 4.

Table 4. Cross-sectional dependence.

Cross-sectional dependence test (H_0: No cross-sectional dependence)		
Test	**Statistic**	**P-value**
Breusch–Pagan LM	3806.931	0.000
Pesaran scaled LM_s	130.4357	0.000
Bias-corrected scaled LM_p	129.9702	0.000
Pesaran CD_{BC}	42.72851	0.000

The findings in the table above show that the null hypothesis of no cross-sectional dependence is rejected, even at the 1% significance level. Therefore, we need to employ checks and assessment techniques that can take cross-sectional dependency into account.

For the country heterogeneity test, the Hsiao test (Hsiao, 2014) is applied. According to Hsiao (2014), the homogeneity test can be conducted based on the following three hypotheses:

$$(1)\begin{cases} H_0^1 : \alpha_i = \alpha \quad and \quad \beta_i = \beta \quad \forall i \in [1, N] \\ H_1^1 : \alpha_i \neq \alpha_j \quad or \quad \beta_i \neq \beta_j \quad \exists (i, j) \in [1, N] \end{cases}$$

If we accept the null hypothesis, there is homogeneity between sectional individuals.

The Hsiao test for homogeneity slope on panel data is presented in Table 5.

Table 5. Homogeneity test results.

Hypothesis	F-stat	P-value
H_1	68.019	0.000
H_2	14.660	1.4E-117
H_3	99.674	2.2E-227

From Table 5 we can see that the estimated statistical checks and corresponding values indicate that the null hypothesis of homogeneous slopes should be rejected, and it suggests that it is important to take into account the heterogeneity of the slope and of the constant.

4.2. Panel Unit Root Tests

If the hypotheses of cross-sectional independence and homogeneity (slope and the constant) in our data are rejected, we can use the covariate augmented Dickey–Fuller (CADF) test of the second generation unit root of the Pesaran (2007) cross-sectionally augmented Im–Pesaran–Shin (CIPS). Equation 2 shows how the unit root CADF test can be achieved:

$$y_{it} = (1-\varphi_i)\mu_i + \varphi_i y_{it-1} + u_{it} \quad \text{for } i = 1,\ldots,N \text{ and } t = 1,\ldots,T \tag{2}$$

Where μ_i and φ_i are parameters, and u_{it} is an error term with a single common structure of factors shown in Equation 3:

$$u_{it} = \gamma_i f_t + \varepsilon_{it} \tag{3}$$

Where $\varepsilon_{i,t}$ is assumed to be distributed independently for $i = 1,\ldots,N$ as well as $t = 1,\ldots,T$ with means equal to zero and σ_i^2.

Equation 2 can be re-written as Equation 4:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i f_t + \varepsilon_{it} \tag{4}$$

where $\Delta y_{it} = y_{it} - y_{i,t-1}$, $\alpha_i = (1-\varphi_i)\mu_i$, $\beta_i = \varphi_i - 1$

The null hypothesis is:

$H_0 : \beta_i = 0$ for every i.

The alternative hypothesis is:

$H_1 : \beta_i < 0 \quad i = 1,2,\ldots,N_1 \quad \beta_i = 0,\ i = N_1 + 1, N_2 + 2,\ldots,N$

According to Pesaran (2006), the cross-sectional mean of Δy_{it} and $y_{i,t-1}$ can be used as a proxy for the unobserved common factor f_t. Pesaran (2007) uses the results of his work to extract the statistical tests on the hypotheses and proposes the cross-sectional augmented Dickey–Fuller (CADF) regression model presented in Equation 5:

$$\Delta y_{it} = \alpha_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta\bar{y}_t + e_{it} \tag{5}$$

where $\bar{y}_{t-1} = N^{-1}\sum_{i=1}^{N} y_{i,t-1}$ and $\Delta\bar{y}_t = N^{-1}\sum_{i=1}^{N}\Delta y_{it}$

Ratio t of the OLS b_i estimate in Equation 5, which is defined by $t_i(N,T)$, refers to the CADF statistic for i and the average of ratio t.

$$CIPS(N,T) = N^{-1}\sum_{i=1}^{N} t_i(N,T) \tag{6}$$

Equation 6 gives the test statistic of the panel unit root. CIPS(N,T) is an augmented cross-sectional version of the statistic test proposed by Im, Pesaran, and Shin (2003) and is referred to as the statistic CIPS.

While the determinant term in Equation 5 is only the constant, it can easily be extended to a model including the linear temporal trend as shown in Equation 7:

$$\Delta y_{it} = \alpha_i + \delta_i t + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta\bar{y}_t + e_{it} \tag{7}$$

Although the distributions of both statistical CADF and CIPS are non-standard, the critical values in the cases of both constant only and the linear time trend are shown in Table 6.

Thus, we use the second generation unit root test of the Pesaran (2007) CIPS that takes into consideration both cross-sectional dependence and heterogeneity.

Table 6. Pesaran CADF panel unit root test.

Variable	Pesaran-CIPS			
	Intercept		Intercept and trend	
	T-stat	Prob.	T-stat	Prob.
LOBS	-1.040	>0.10	-0.762	>0.10
LGDP	-1.002	>0.10	-1.822	>0.10
LGLOB	-1.737	>0.10	-2.149	>0.10
LHDI	-1.651	>0.10	-1.991	>0.10
LUNM	-0.826	>0.10	-1.601	>0.10
Δ LOBS	-0.254	>0.10	-7.043*	<0.01
Δ LGDP	-2.582*	<0.01	-3.069*	<0.01
Δ LGLOB	-3.529*	<0.01	-3.241*	<0.01
Δ LHDI	-2.837*	<0.01	-2.961*	<0.01
Δ LUNM	-1.963	>0.10	-4.127*	<0.01

Note: Critical values: -2.36, -2.18, -2.08 (intercept), and -2.88, -2.70, -2.60 (intercept and trend). * indicates the 1% level of significance. Δ is first difference. The lag lengths from the cross sections were selected using the Modified Akaike Information Criterion (MAIC).

As shown in the table above, the null hypothesis of the unit root is rejected in the first differences. Therefore, all variables are integrated of first order I(1). Therefore, to control for cointegration, we use the Westerlund (2007) control, which allows for heterogeneity and cross-sectional dependence between panel units, since it assumes that all variables used in the panel data are integrated of first order.

4.3. Panel Cointegration Tests

The Westerlund (2007) test examines the existence of cointegrated vectors in panel data by applying an error correction model. The error correction model presented in Equation 8, as suggested by Westerlund (2007), takes the following form:

$$\Delta y_{it} = \delta_i' d_t + \alpha_i \left(y_{i,t-1} + \beta_i' x_{i,t-1} \right) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{p_i} \vartheta_{ij} \Delta x_{i,t-j} + e_{it} \quad (8)$$

Where y_{it} is the endogenous variable, $x_{i,t}$ represents a set of exogenous variables, α_i is the adjustment coefficient, d_t represents the determinant factors, δ_t' is the vector parameters, and e_{it} is the white noise residual.

Using the bootstrap method, Equation 8 could be estimated with the error correction model $\left(y_{i,t-1} + \beta_i' x_{i,t-1} \right)$ and be written as follows in Equation 9:

$$\Delta y_{it} = \delta_i' d_t + \alpha_i y_{i,t-1} + \lambda_i' x_{i,t-1} + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{p_i} \vartheta_{ij} \Delta x_{i,t-j} + e_{it} \quad (9)$$

where $\lambda_i' = -\alpha_i \beta_i'$.

Parameter α_i determines the adaptation speed with which the system corrects the equilibrium relationship between $(y_{i,t-1} + \beta_i' x_{i,t-1})$ after a sudden shock.

If $\alpha_i < 0$ then there is an error correction, which implies that variables y_{it} and x_{it} are cointegrated.

If $\alpha_i = 0$ then there is no error correction, which implies that variables y_{it} and x_{it} are not cointegrated.

Westerlund (2007) proposed two different types of tests in order to examine the null hypothesis H_0 (of no cointegration) for the error correction model. The first category consists of the G_t and G_α group means tests, which implies that $H_0 : \alpha_i = 0$ (there is no cointegration for all i), as opposed to the alternative hypothesis $H_1 : \alpha_i < 0$ (there is cointegration for a specific unit of at least on one i). In the second category, panel test statistics P_t and P_α imply $H_0 : \alpha_i = 0$ (there is no cointegration for all i), as opposed to $H_1 : \alpha_i = \alpha < 0$ (there is cointegration for all i).

Table 7 presents the results of the Westerlund cointegration test.

Table 7. Westerlund ECM panel cointegration test results (H_0: No cointegration).

Statistic	Value of the test	Z-value	P-value
Deterministic specification: Constant			
G_t	-2.485	-2.817	0.001*
G_a	-7.214	-4.417	0.075
P_t	-8.231	-3.129	0.005*
P_a	-10.518	-4.574	0.001*
Deterministic specification: Constant & trend			
G_t	-2.396	-3.721	0.017**
G_a	-8.414	-5.174	0.049**
P_t	-9.101	-3.043	0.006*
P_a	-10.221	-4.535	0.003*

Note: * and ** indicate the 1% and 5% levels of significance, respectively.

The results presented in Table 7 reject the null hypothesis of non-cointegration for the cross-sectional units and the panel as a whole, which means that there is a stable and long-term relationship between these variables.

4.4. Estimating Long-Run Relationships from Dynamic Heterogeneous Panels

Pesaran, Shin, and Smith (1999) proposed two assessment procedures as solutions for heterogeneity bias caused by heterogeneous slopes in dynamic panels. The mean group (MG) and the pooled mean group (PMG) allow for a higher degree of heterogeneity of parameters in growth regressions.

The MG estimator has the least restrictive procedure and allows for the heterogeneity of all coefficients, constants and slopes by estimating a separate equation for each country, while the coefficients for the entire panel are calculated as unweighted averages of the individual coefficients. The MG estimator extracts the long-term parameters from the autoregressive distribution lag (ARDL) models for individual countries.

Therefore, the MG estimator estimates individual regressions for each country. The ARDL model is presented in Equation 10:

$$Y_{it} = \alpha_i + \gamma_1 Y_{i,t-1} + \beta_i X_{it} + u_{it} \qquad (10)$$

For country i, where $i = 1, 2, \ldots, N$

The long-term coefficient ϑ_i for every country i would be:

$$\vartheta_i = \frac{\beta_i}{1-\gamma_i}$$

And the MG estimators for the whole panel can be given by:

$$\hat{\vartheta} = \frac{1}{N}\sum_{i=1}^{N}\vartheta_i \text{ and } \hat{\alpha} = \frac{1}{N}\sum_{i=1}^{N}\alpha_i$$

The pooled mean group (PMG) estimator considers a lower degree of heterogeneity, since it imposes homogeneity on long-term coefficients while still allowing heterogeneity in short-term coefficients and error variances. The unlimited specification for the ARDL equation system for $t = 1, 2, \ldots T$ time periods and $i = 1, 2, \ldots, N$ countries for the dependent variable Y_{it} is shown in Equation 11:

$$Y_{it} = \sum_{j=1}^{p}\lambda_{ij} Y_{i,t-j} + \sum_{j=1}^{q}\gamma_{ij} X_{i,t-j} + \mu_i + u_{it} \qquad (11)$$

Where $X_{i,t-j}$ and $k \times 1$ are vectors of the explanatory variables for group i.

Equation 11 can be reformulated as the VECM system, presented in Equation 12:

$$\Delta y_{it} = \vartheta_i (y_{i,t-1} - \beta_i' x_{i,t-1}) + \sum_{j=1}^{p-1}\lambda_{ij}\Delta y_{i,t-j} + \sum_{j=1}^{q-1}\gamma_{ij}'\Delta x_{i,t-j} + \mu_i + e_{it} \qquad (12)$$

Where β_i represents the long-term parameters and ϑ_i represents the parameters of equilibrium correction (or error). The error correction term indicates the setting of the speed to restore equilibrium to the dynamics of the model. To select the lag length for the MG and PMG estimates, we use the Akaike Information Criterion (AIC).

Table 8 shows the results of the MG and PMG estimates for Equation 9. The MG's estimates are the unweighted means of individual regressions in each country.

The PMG assessor estimates common long-term coefficients and different short-term coefficients below the average of the short-term coefficients. The PMG calculations were obtained by estimating a common ARDL (4,4,4,4,4) for all EU countries according to the AIC. Appendix B contains all the estimates of the ARDL models in accordance with the AIC.

Table 8. MG (mean group) and PMG (pooled mean group) empirical results.

(Dependent variable: D(LOBS) Selected model: ARDL (4, 4, 4, 4, 4) AIC = -7.77 BIC = -4.46 Long-run equation								
Variable	Mean group estimates				Pooled mean group estimates			
	Coefficient	Std. error	T-stat.	Prob.	Coefficient	Std. error	T-stat.	Prob.
LGDP	0.2045*	0.0972	2.5112	0.013	0.1912**	0.0817	2.3411	0.0200
LGLOB	0.6571**	0.6721	2.1833	0.042	0.7895***	0.4169	1.8938	0.0594
LHDI	-2.4276**	1.7191	-1.993	0.057	-3.0629***	1.6357	-1.8725	0.0623
LUNM	0.0487***	0.0234	1.8321	0.071	0.0221***	0.0127	1.7448	0.0823
ECT	-0.0413*	0.0452	-2.164	0.049	-0.0406***	0.0231	-1.7507	0.0813
Hausman test								
Chi-square					P-value			
9.15					0.015			

Note: *, ** and *** indicate the 1%, 5% and 10% levels of significance, respectively.

The findings of PMG-ARDL and MG-ARDL show that human development has a negative impact on obesity in the 27 EU countries, while GDP, globalization and unemployment have a positive effect on obesity in the long term, according to both the PMG and MG estimators.

The ARDL model (4,4,4,4,4) has suggested four lags in all variables in the MG and PMG assessment tests. The lags of all variables have a significant effect on obesity by 5% and 10%. This shows that GDP, globalization, human development and unemployment will affect obesity after four years. The error correction term indicates the setting of the speed to restore equilibrium to the dynamics of the model. The error correction factor shows how quickly the variables converge/diverge in equilibrium and should have a statically significant factor with a negative sign. The error correction term confirms the existence of a stable long-term relationship. Hausman's audit shows that the null hypothesis is rejected, so we can say that the MG estimator is preferable to the PMG estimator.

4.5. Causality Test

Dumitrescu and Hurlin (2012) causality testing on panel data is an advanced causality check by Granger (1969) that can be applied to balanced and heterogeneous panels with or without cross-sectional dependence. The regression suggested by Dumitrescu and Hurlin (2012) to detect causality in panel data is depicted in Equation 13:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_{ik} y_{i,t-k} + \sum_{k=1}^{K} \beta_{ik} x_{i,t-k} + e_{i,t} \quad \text{with} \quad i = 1,\ldots,N \ \text{and} \ t = 1,\ldots,T \tag{13}$$

Where $y_{i,t}$ and $x_{i,t}$ are the observations for the two stationary variables for individual i in time t. Constant α_i and coefficients $\beta_i = (\beta_{i1},\ldots,\beta_{ik})'$ allow differences between individuals but are regarded as unchanged over time. We assume that the autoregressive coefficient γ_{ik} and the estimators of the regression coefficients β_{ik} vary between cross sections. The order of lag K is the same for all individuals and the panel should be balanced.

The null hypothesis, H_0, is the following:

$H_0 : \beta_i = 0 \quad \forall i = 1,\ldots,N$ (There is no causal relationship for any cross-sectional unit homogenous non-causality hypothesis).

The alternative hypothesis, H_1, is defined as the heterogeneous non-causality hypothesis. In the alternative hypothesis, we have two cross-sectional sub-groups:

$$H_1^A : \beta_i \neq 0 \quad \forall i = 1,\dots, N_1.$$

$$H_1^B : \beta_i \neq 0 \quad \forall i = N_1+1, N_1+2,\dots, N.$$

Unidirectional causality from variable x toward variable y in the first sub-group exists but not in the second sub-group. If there is no causal relationship from variable x toward variable y for the second sub-group, then we use a heterogeneous panel data model assuming constant group estimations for the empirical analysis.

We assume that β_i could differ between the cross-sectional groups, and there are $N_1 < N$ individual procedures without causality from variable x toward variable y. The unknown individual procedure N_1 is determined by the relationship $0 \leq N_1 / N < 1$. According to Dumitrescu and Hurlin (2012), this hypothesis leads to the average statistics $W_{N,T}^{HNC}$. The mean statistics for homogenous non-causality (HNC) are shown in Equation 14:

$$W_{N,T}^{HNC} = \frac{1}{N}\sum_{i=1}^{N} W_{i,T} \tag{14}$$

Where $W_{i,T}$ shows the individual cross-sectional Wald statistics for the ith cross-sectional unit, which corresponds to the individual test $H_0 : \beta_i = 0$. The null hypothesis of no causality reveals that each single Wald statistic congregates a χ^2 distribution with K degrees of freedom for $T \longrightarrow \infty$. This harmonized statistic $Z_{N,T}^{HNC}$ for T, and $N \longrightarrow \infty$ is given by Equation 15:

$$Z_{N,T}^{HNC} = \sqrt{\frac{N}{2K}}\left(W_{N,T}^{HNC} - K\right) \rightarrow N(0,1) \tag{15}$$

The harmonized statistic $\overline{Z}_{N,T}^{HNC}$ for fixed T samples is given in Equation 16:

$$\overline{Z}_{N,T}^{HNC} = \sqrt{\frac{N(T-2K-5)}{2K(T-K-3)}}\left[\frac{(T-2K-3)}{(T-2K-1)}W_{N,T}^{HNC} - K\right] \rightarrow N(0,1) \tag{16}$$

where $W_{N,T}^{HNC} = \frac{1}{N}\sum_{i=1}^{N} W_{i,T}$ (see Dumitrescu and Hurlin (2012)). The Dumitrescu and Hurlin (2012) test uses two separate distributions, the asymptotic distribution of the mean statistic $W_{N,T}^{HNC}$ and the semi-asymptotic distribution. The asymptotic distribution is used when T>N and the semi-asymptotic distribution when N>T.

Table 9. Dumitrescu and Hurlin test results.

Null hypothesis	W-stat.	Zbar-stat.	Prob.
1. DLGDP does not homogeneously cause DLOBS	1.67933	-1.11237	0.2660
2. DLOBS does not homogeneously cause DLGDP	0.27453	-4.11359*	4.E-05
3. DLGLOB does not homogeneously cause DLOBS	1.54237	-1.60496***	0.1070
4. DLOBS does not homogeneously cause DLGLOB	2.24256	0.09092	0.9276
5. DLHDI does not homogeneously cause DLOBS	0.96934	-2.62920*	0.0086
6. DLOBS does not homogeneously cause DLHDI	1.44437	-1.61432***	0.1065
7. DLUNM does not homogeneously cause DLOBS	1.37629	-1.75977***	0.0784
8. DLOBS does not homogeneously cause DLUNM	0.96899	-2.62994*	0.0085
9. DLGLOB does not homogeneously cause DLGDP	1.82784	-0.79509	0.4266
10. DLGDP does not homogeneously cause DLGLOB	1.50098	-1.49340	0.1353
11. DLHDI does not homogeneously cause DLGDP	1.96608	-0.49975	0.6172
12. DLGDP does not homogeneously cause DLHDI	1.90812	-0.62357	0.5329
13. DLUNM does not homogeneously cause DLGDP	2.25528	0.11810	0.9060
14. DLGDP does not homogeneously cause DLUNM	3.42220	2.61112*	0.0090
15. DLHDI does not homogeneously cause DLGLOB	2.93196	1.56376	0.1179
16. DLGLOB does not homogeneously cause DLHDI	3.58372	2.95619*	0.0031
17. DLUNM does not homogeneously cause DLGLOB	2.06480	-0.28884	0.7727
18. DLGLOB does not homogeneously cause DLUNM	2.93886	1.57850	0.1145
19. DLUNM does not homogeneously cause DLHDI	3.27084	2.28775**	0.0222
20. DLHDI does not homogeneously cause DLUNM	2.44605	0.52567	0.5991

Note: *, ** and *** indicate the 1%, 5% and 10% levels of significance, respectively. We used the test with lag = 2.
Where DLGDP is the first difference of the log GDP; DLOBS is the first difference of the log for obesity; DLGLOB is the first difference of the log for globalization; DLHDI is the first difference of the log for the human development index; and DLUNM is the first difference of the log for unemployment.

The causality between obesity, globalization GDP, human development and unemployment for EU countries appears in Table 9. Dumitrescu and Hurlin (2012), tests can be calculated in three different statistic values. The global panel statistic W-Stat, the standardized statistic Zbar-Stat, and corresponding p-values based on the N(0,1).

Table 9 presents the results of the Dumitrescu–Hurlin Granger non-causality test with two lags. Including two lags means that the test is based on the individual averaged Wald statistics for the following model 17:

$$y_{i,t} = \alpha_i + \gamma_{1i} y_{i,t-1} + \gamma_{2i} y_{i,t-2} + \beta_{1i} x_{i,t-1} + \beta_{2i} x_{i,t-2} + \varepsilon_{i,t} \quad (17)$$

As seen in the second row in Table 9, there is a unilateral causal relationship between obesity and economic growth. In other words, we claim that obesity causes growth at the 1% level of significance. In row 3, there is a unilateral causal relationship between obesity and globalization. In rows 5 and 6, there is a bilateral relationship between human development and obesity, and it seems that human development has a robust effect on obesity in EU countries.

As seen in rows 7 and 8, there is a bilateral relationship between unemployment and obesity; obesity strongly affects unemployment and is affected by unemployment on a smaller scale. A significant unilateral causal relationship between unemployment and economic growth with a direction from economic growth to unemployment is found in row 14.

Similarly, a significant unilateral causal relationship between globalization and human growth with a direction from globalization to human growth is found in row 16. In row 19, there is a unilateral causal relationship between unemployment and human growth.

Figure 2 shows the Dumitrescu and Hurlin (2012) causality for the connection between the variables for the EU countries.

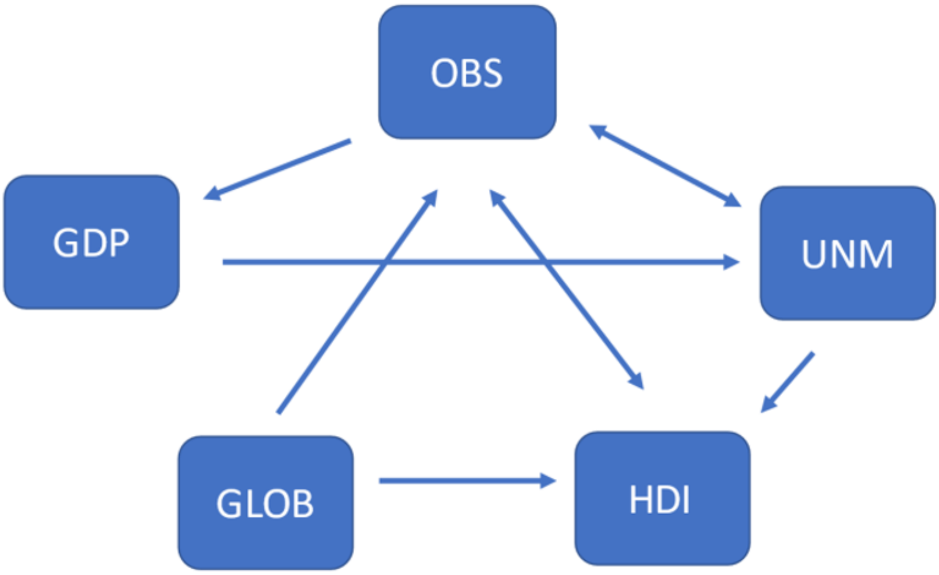

Figure 2. Dumitrescu and Hurlin (2012) causality test.

5. DISCUSSION AND CONCLUSION

Overweight and obesity have been widely recognized as key risk factors for the health of the population and the global economy for at least two decades. Obesity has more than doubled worldwide since 1980, and the prevalence of obesity is increasing for both sexes. As economic transition advances progress, it is predicted that the current trends of the average Body Mass Index reflected in developing countries will exceed the maximum average Body Mass Index values reported in developed countries. However, alternative explanations include domestic factors such as increases in the consumption of unhealthy foods in response to an increase in income and the higher participation of women in the labor force of economically growing countries. Despite some policies implemented by EU countries, the multifaceted causes that support the obesity epidemic have not yet been fully addressed and, so far, new policies have not been able to stop the epidemic (OECD, 2019).

Researchers have attributed the increase in obesity rates to factors related to economic growth, unemployment, and globalization processes, which are believed to contribute to obesity from the markets of low-income countries, with cheap but fattening Western-style fast food (Fox et al., 2019). Such an increase in excess weight can be attributed to significant changes in eating habits and lower levels of physical activity caused by socioeconomic influences. The use of screen time has been associated with other equally unhealthy behaviors, such as mindlessly eating unhealthy foods. Watching TV is associated with high cholesterol levels and unhealthy diets, and it also influences unhealthy diets through advertisements (Shang et al., 2015).

Instead of focusing on obesity as an individual chronic behavioral condition, current scientific evidence suggests the examination of an interdisciplinary approach aimed at the immediate environment of the obese in broader socioeconomic contexts. For such an undertaking to be fruitful in developing countries, incentives at various levels of organizations, the media and educational institutions, along with changes in food policies and distribution, should be provided to low-income populations (Hruby & Hu, 2015).

While some results have already been achieved, even more needs to be done in many EU countries. New technologies, advances in forecasting techniques and policies to modify the environment in which we live can offer exciting opportunities to promote healthier behavior. More needs to be done to promote an active lifestyle throughout the day, from commuting to the workplace to leisure activities.

This study assesses the influence of GDP, human development, unemployment and globalization on obesity in EU countries for the period from 1990 to 2019.

To achieve this goal, we initially determine the most suitable functional form which better reflects the relationship among obesity, GDP, human growth, unemployment and globalization. For this reason, we estimated the models separately in three functional forms (linear, quadratic and logarithmic) and compared these models using the mean absolute percentage errors. Based on the results, it was concluded that the logarithmic model was best suited to this study. The Hausman test (Hausman, 1978) was then applied to determine if the fixed or random effects model is best. Pesaran's test (Pesaran, 2004) was also applied to test for cross-sectional dependence among the EU countries as well as Hsiao's test (Hsiao, 2014) for heterogeneity. These preliminary tests found that the fixed effects model is the most appropriate and that there is cross-sectional dependence and heterogeneity between the EU countries.

For the integration order of the variables, we used the second generation CIPS unit root test of Pesaran (2007) because the preliminary tests showed that there is cross-sectional dependence and heterogeneity among the EU countries. The test results showed that the variables are integrated of first order I(1). The long-run relationship between obesity and the explanatory variables was examined using the Westerlund test (Westerlund, 2007), which allows for heterogeneity and cross-sectional dependence among the panel units. The test results showed that there is a fixed and long-run relationship among these variables.

Afterwards, the Pesaran et al. (1999) test was applied for the estimations among the variables with two evaluation procedures, the mean group (MG) and the pooled mean group (PMG), allowing for a higher degree of heterogeneity of the parameters for the growth regressions. The MG estimator extracts the long-term parameters from the autoregressive distribution lag (ARDL) models for individual countries, while the PMG estimator estimates common long-term coefficients. The calculations of the MG and PMG estimators were determined by the ARDL (4,4,4,4) model, according to the Akaike criterion. The results of PMG-ARDL estimators showed a positive and statistically significant relationship between GDP and obesity in the EU countries. This result agreed with Egger et al. (2012); Talukdar et al. (2020) and Bu et al. (2021), proving that GDP is positively related with body mass index. Furthermore, the results of the PMG-ARDL and MG-ARDL estimators denoted a positive relationship between globalization and obesity. This result is in accordance with the papers of Goryakin et al. (2015); Hawkes (2006); Miljkovic et al. (2015); Popkin (2006) and Costa-Font and Mas (2016), while the papers of Fox et al. (2019) and Sudeshna (2019) show mixed results for cultural and social globalization. Moreover, the results of the PMG-ARDL and MG-ARDL estimators denoted a negative relationship between human development and obesity in the EU countries. This result does not agree with the papers of Ataey et al. (2020); Khazaei et al. (2020) and Munir et al. (2021). The results of our paper partially agree with Roskam et al. (2010); Faeh et al. (2011) and Devaux and Sassi (2013), where human development is estimated in terms of education level and socioeconomic condition. Finally, the results of the PMG-ARDL and MG-ARDL estimators demonstrate a positive relationship between unemployment and obesity in the EU countries. This agrees with the papers of Hughes and Kumari (2017); Bramming et al. (2019); Tobing (2023) and Campbell et al. (2021).

For the causal relationship between the variables, the Dumitrescu and Hurlin (2012) test was applied, which can be used for balanced and heterogeneous panel data with or without cross-sectional dependence. The causality results showed a significant unidirectional causal relationship between obesity and GDP with the direction running from obesity to GDP as well as between globalization and obesity with the direction running from globalization to obesity. This suggests that obesity is causing the economic development of EU countries. Therefore, the reduction of obesity rates in EU countries will result in the development of a healthier lifestyle that will cause an increase in the prosperity of EU countries. Also, the unidirectional causality that links globalization with obesity is caused by fast food businesses that have become widespread in all EU countries. This situation has changed the consumption habits of individuals as they adopt unhealthy lifestyles through changing their eating habits, thus causing an increase in obesity rates.

Also, according to the results of the causality of work, there is a bidirectional causality linking obesity to human development. This suggests that the EU's technological progress and the comforts brought about by human development make people less motivated and more inactive. There is also a bidirectional causal relationship between obesity and unemployment. This suggests that, in the EU, obesity causes people to become unemployed, as well as the unemployed to become obese. Policymakers are therefore advised to fight obesity in order to control unemployment.

Obesity is not a theoretical health problem that concerns the scientific world, but a real problem caused by many factors, with the "protagonists" being the lack of physical activity and a poor diet. Its treatment should be organized primarily by the state in preventive and therapeutic dimensions based mainly on correct and continuous public information. In recent years, initiatives have doubled to mitigate obesity; however, these were met with little or no success. Therefore, the effectiveness of current intervention programmes should be reassessed and put into perspective in order to better address the increasing prevalence of obesity (Joslyn & Haider-Markel, 2019).

This study is instrumental in devising a strategy for the modification and transformation of health in EU countries. Higher obesity will affect the productivity of EU members, so policymakers need to encourage people not to migrate to cities to help the rural population to alleviate obesity. Educational attainment is the only factor that is significantly related to nutritional knowledge, food purchasing behavior and perceptions of healthy foods. The best level of income can be especially effective in reducing cases of obesity caused by psychological and environmental factors. When all the features of human development are evaluated, we can say that human development has an effect on the reduction of obesity.

Traditionally, the prevention of obesity is aimed at behavioral changes and lifestyle modification. We risk believing that obesity is a matter of personal responsibility, while critical opportunities are being missed to make key environmental changes that will have a greater impact on the prevention of obesity. Relevant policies, nutrition education and physical activity programmes should be implemented on a large scale in all countries. At the same time, the quality of nutrition from preparation to sale should be strictly monitored to ensure the equal and adequate distribution of foods with a high content of nutrients, especially in low-income populations. Some of these interventions may, of course, have a direct impact on industry and businesses by increasing production costs or affecting sales. Even if these costs take the social perspective into account, the benefits of public health actions are likely to outweigh the costs, especially if actions aimed at minimizing the impact on businesses and the food industry are implemented. The simplicity of dietary choices and the physical work that is mainly subjected to agricultural occupations can reduce the average value of the indicator of obesity (BMI) (Hruby & Hu, 2015).

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Authors' Contributions: Both authors contributed equally to the conception and design of the study.

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APPENDIX A

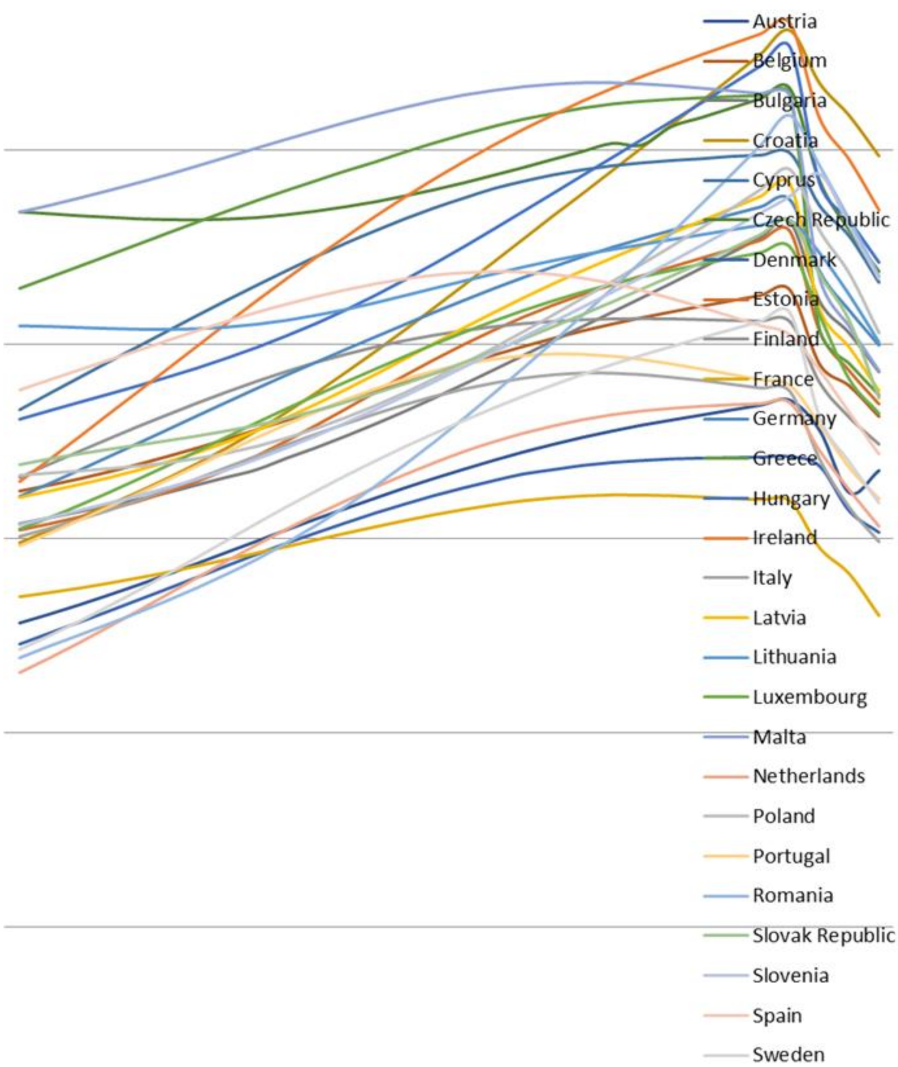

Figure 1A. Mean body mass index (BMI) for the countries under investigation.

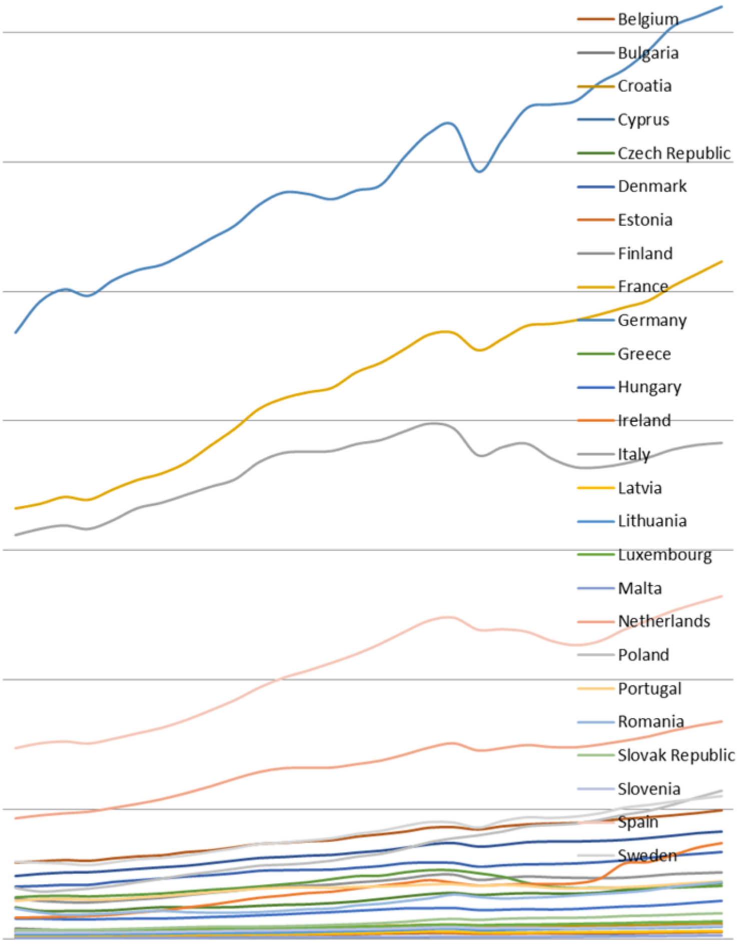

Figure 2A. Gross domestic product (GDP) for the countries under investigation.

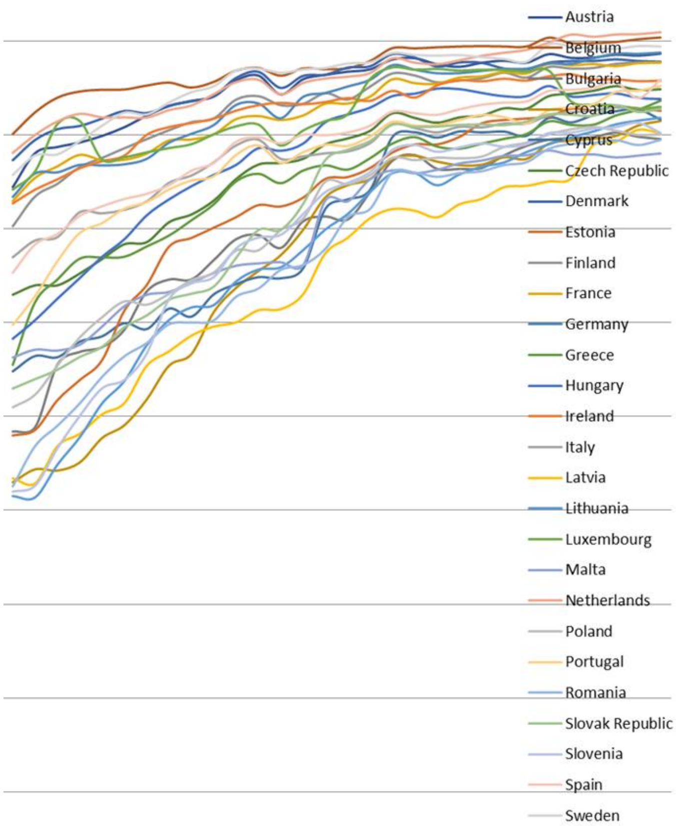

Figure 3A. Globalization index (KOF) for the countries under investigation.

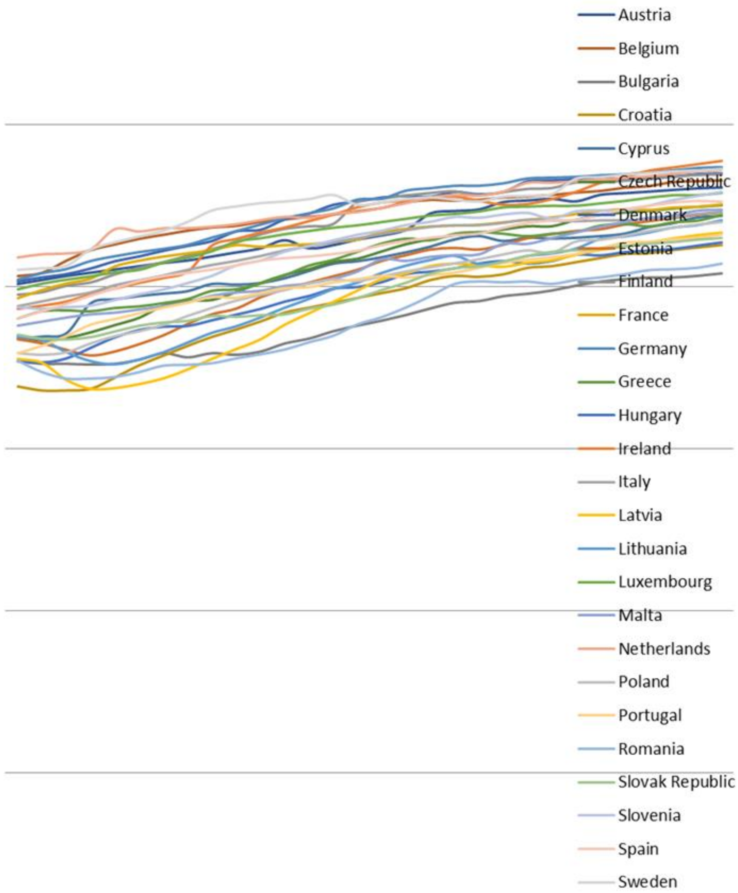

Figure 4A. Human development index (HDI) for the countries under investigation.

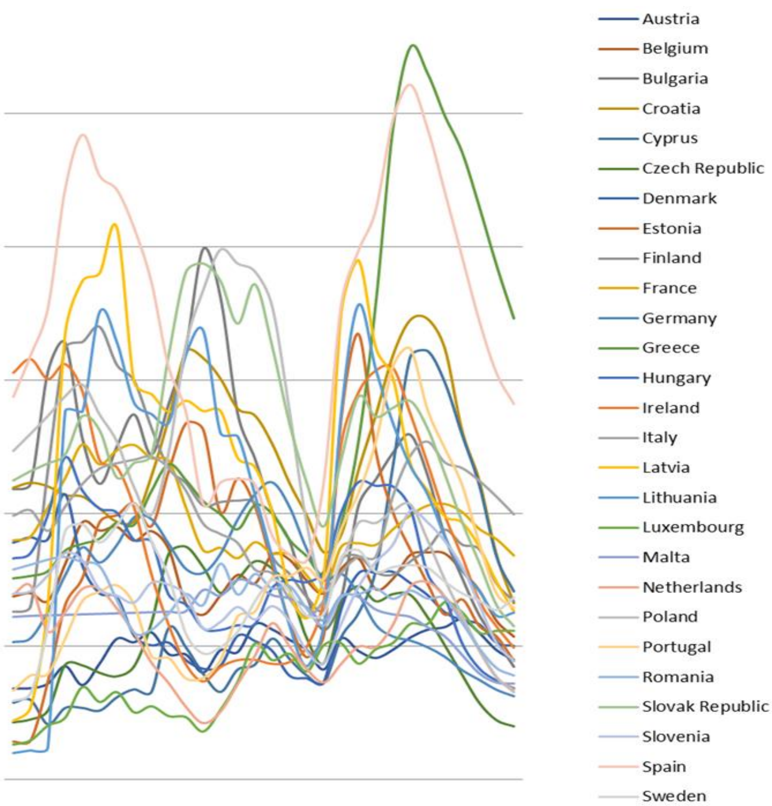

Figure 5A. Unemployment rate (UNEM) for the countries under investigation.

Table 1A. Basic descriptive statistical analysis for the countries under investigation.

Economies variables	Austria (AUT)					Belgium (BEL)					Bulgaria (BGR)				
	Obs	Gdp	Glob	Hdi	Unm	Obs	Gdp	Glob	Hdi	Unm	Obs	Gdp	Glob	Hdi	Unm
Mean	25.2	3.30	85.4	0.86	4.81	25.7	3.92	87.1	0.88	7.74	25.7	4.12	69.9	0.75	11.2
Max.	25.7	4.14	89.0	0.92	6.01	26.2	4.95	90.0	0.93	9.65	26.6	5.74	80.0	0.81	19.9
Min.	24.5	2.41	75.0	0.80	3.41	25.2	2.93	80.0	0.81	5.36	25.1	2.90	48.0	0.70	4.23
Std. dev.	0.35	5.26	3.72	0.03	0.73	0.32	6.31	2.54	0.03	1.08	0.47	8.78	9.57	0.04	3.83
Skewness	-0.3	-0.2	-1.2	-0.0	-0.4	-0.1	-0.1	-0.8	-0.7	-0.1	0.17	0.22	-0.7	0.08	0.11
Kurtosis	1.88	1.76	3.48	1.53	2.33	1.78	1.70	3.41	2.68	2.37	1.77	1.61	2.61	1.42	2.62
Jarque–Bera	2.31	2.12	7.70	2.68	1.43	1.89	2.15	4.06	2.84	0.55	2.01	2.67	3.35	3.15	0.24

gdp=3.30E+11, gdp(S.D)=5.26E+10 gdp=3.92E+11, gdp(S.D)=6.31E+10 gdp=4.12E+10, gdp(S.D)=8.78E+09

Economies variables	Croatia (HRV)					Cyprus (CYP)					Czech Republic (CZE)				
	Obs	Gdp	Glob	Hdi	Unm	Obs	Gdp	Glob	Hdi	Unm	Obs	Gdp	Glob	Hdi	Unm
Mean	26.2	4.45	66.9	0.77	12.2	26.5	1.74	70.6	0.82	6.24	26.8	1.51	76.8	0.82	5.44
Max.	27.6	5.72	81.0	0.85	17.3	26.9	2.49	83.0	0.88	16.1	27.3	2.16	85.0	0.90	8.76
Min.	24.9	2.99	43.0	0.67	6.62	25.6	9.94	55.0	0.73	2.09	26.3	1.06	63.0	0.73	2.01
Std. dev.	0.84	8.56	13.4	0.06	2.81	0.41	4.39	10.2	0.04	4.21	0.22	3.39	7.35	0.05	2.13
Skewness	0.01	-0.3	-0.6	-0.4	0.22	-0.6	-0.2	-0.1	-0.5	1.23	0.56	0.23	-0.5	-0.3	-0.1
Kurtosis	1.61	1.70	1.85	1.89	2.18	2.13	1.82	1.36	2.38	3.23	2.56	1.77	1.95	1.73	1.73
Jarque–Bera	2.41	2.62	3.75	2.75	1.09	2.83	2.06	3.47	2.11	7.73	1.83	2.15	3.16	2.64	2.13

gdp=4.45E+10, gdp(S.D)=8.56E+09 gdp=1.74E+10, gdp(S.D)=4.39E+09 gdp=1.51E+11, gdp(S.D)=3.39E+10

Economies variables	Denmark (DNK)					Estonia (EST)					Finland (FIN)				
	Obs	Gdp	Glob	Hdi	Unm	Obs	Gdp	Glob	Hdi	Unm	Obs	Gdp	Glob	Hdi	Unm
Mean	25.1	2.69	85.4	0.88	6.24	25.8	1.74	72.1	0.81	8.36	25.8	2.06	83.0	0.88	10.0
Max.	25.4	3.35	89.0	0.94	10.7	26.5	2.71	83.0	0.89	16.7	26.1	2.55	88.0	0.94	17.0
Min.	24.4	2.02	77.0	0.80	3.68	25.0	8.88	48.0	0.71	1.43	25.3	1.41	70.0	0.79	6.30
Std. dev.	0.31	3.74	3.10	0.04	1.81	0.49	5.80	11.0	0.05	3.65	0.26	3.85	4.70	0.04	3.22
Skewness	-0.6	-0.2	-1.1	-0.5	0.55	-0.1	-0.1	-0.9	-0.3	0.09	-0.6	-0.4	-1.1	-0.5	0.89
Kurtosis	2.11	2.17	3.22	1.87	2.54	1.69	1.63	2.66	1.64	2.59	2.04	1.73	3.58	1.81	2.65
Jarque–Bera	3.04	1.24	5.72	3.11	1.81	2.17	2.37	4.49	2.78	0.24	3.30	3.20	7.00	3.16	4.18

gdp=2.69E+11, gdp(S.D)=3.74E+10 gdp=1.74E+10, gdp(S.D)=5.80E+09 gdp=2.06E+11, gdp(S.D)=3.85E+10

Economies variables	France (FRA)					Germany (DEU)					Greece (GRC)				
	Obs	Gdp	Glob	Hdi	Unm	Obs	Gdp	Glob	Hdi	Unm	Obs	Gdp	Glob	Hdi	Unm
Mean	25.0	2.14	82.5	0.85	9.75	26.1	2.95	83.3	0.89	7.20	26.8	2.05	74.8	0.83	13.4
Max.	25.2	2.62	88.0	0.90	12.6	26.7	3.60	89.0	0.94	11.1	27.2	2.66	84.0	0.88	27.4
Min.	24.6	1.66	73.0	0.78	7.06	25.2	2.34	73.0	0.80	3.14	25.7	1.58	56.0	0.76	7.57
Std. dev.	0.19	2.99	4.33	0.03	1.52	0.45	3.54	4.83	0.04	2.30	0.44	3.24	6.90	0.04	6.46
Skewness	-0.4	-0.2	-0.4	-0.6	0.53	-0.3	0.15	-0.5	-0.5	-0.1	-0.8	0.42	-0.9	-0.3	1.04
Kurtosis	1.82	1.75	2.07	2.53	2.26	1.93	2.03	1.95	1.81	1.91	2.71	2.15	3.13	1.49	2.53
Jarque–Bera	2.65	2.29	2.19	2.31	2.09	1.86	1.28	2.96	2.95	1.56	3.34	1.76	4.38	3.36	5.72

gdp=2.14E+12, gdp(S.D)=2.29E+11 gdp=2.95E+12, gdp(S.D)=3.54E+11 gdp=2.05E+11, gdp(S.D)=3.24E+10

Economies variables	Hungary (HUN)					Ireland (IRL)					Italy (ITA)				
	Obs	Gdp	Glob	Hdi	Unm	Obs	Gdp	Glob	Hdi	Unm	Obs	Gdp	Glob	Hdi	Unm
Mean	26.4	1.05	77.7	0.79	7.94	26.6	1.90	82.4	0.87	9.48	25.5	1.81	77.7	0.85	9.96
Max.	27.5	1.47	85.0	0.85	12.1	27.6	3.71	86.0	0.95	15.7	25.8	1.99	83.0	0.89	12.6
Min.	25.6	7.59	58.0	0.70	3.42	25.3	8.05	73.0	0.77	3.68	24.9	1.56	67.0	0.77	6.08
Std. dev.	0.57	2.09	8.23	0.04	2.39	0.71	8.04	4.00	0.05	4.49	0.29	1.29	4.63	0.03	1.84
Skewness	0.24	0.11	-1.0	-0.4	-0.1	-0.4	0.50	-1.0	-0.5	0.12	-0.4	-0.7	-0.8	-0.6	-0.4
Kurtosis	1.89	1.92	2.86	1.90	2.04	2.00	2.64	2.91	2.01	1.38	1.72	2.23	2.57	2.04	2.13
Jarque–Bera	1.82	1.51	5.60	2.57	1.25	2.21	1.44	5.55	2.63	3.33	3.14	3.27	3.52	3.28	2.03

gdp=1.05E+11, gdp(S.D)=2.09E+10 gdp=1.90E+11, gdp(S.D)=8.04E+10 gdp=1.81E+12, gdp(S.D)=1.29E+11

Economies variables	Latvia (LVA)					Lithuania (LTU)					Luxembourg (LUX)				
	Obs	Gdp	Glob	Hdi	Unm	Obs	Gdp	Glob	Hdi	Unm	Obs	Gdp	Glob	Hdi	Unm
Mean	25.9	2.06	64.8	0.77	11.9	26.3	3.01	67.3	0.79	10.6	25.8	4.59	82.1	0.86	3.97
Max.	26.8	3.07	81.0	0.86	20.7	26.6	4.82	82.0	0.88	17.8	26.5	6.73	87.0	0.91	6.67
Min.	25.2	1.11	43.0	0.67	2.20	26.0	1.55	41.0	0.70	1.00	25.0	2.52	74.0	0.79	1.32
Std. dev.	0.50	6.76	11.5	0.06	4.92	0.19	1.05	12.6	0.05	5.00	0.45	1.29	3.80	0.03	1.56
Skewness	0.12	-0.1	-0.4	-0.2	-0.1	0.31	0.03	-0.7	-0.2	-0.4	-0.3	-0.6	-0.1	-0.5	-0.1
Kurtosis	1.77	1.47	1.99	1.50	2.21	1.62	1.60	2.38	1.59	2.15	1.86	1.72	2.06	1.94	1.71
Jarque–Bera	1.96	2.93	2.19	3.21	0.84	2.85	2.43	3.26	2.65	2.02	2.05	2.70	1.18	2.82	2.08

gdp=2.06E+10, gdp(S.D)=6.76E+09 gdp=3.01E+10, gdp(S.D)=1.05E+10 gdp=4.59E+10, gdp(S.D)=1.29E+10

Economies variables	Malta (MLT)					Netherlands (NLD)					Poland (POL)				
	Obs	Gdp	Glob	Hdi	Unm	Obs	Gdp	Glob	Hdi	Unm	Obs	Gdp	Glob	Hdi	Unm
Mean	27.0	7.54	69.8	0.82	6.09	25.2	6.63	85.9	0.89	5.14	25.9	3.42	70.8	0.80	11.7
Max.	27.3	1.39	78.0	0.89	7.49	25.7	8.40	91.0	0.94	7.42	26.9	5.70	81.0	0.88	19.6
Min.	25.8	3.57	56.0	0.75	3.62	24.3	4.65	78.0	0.83	2.12	25.3	1.81	51.0	0.71	3.28
Std. dev.	0.38	2.85	7.93	0.04	0.96	0.44	1.13	3.65	0.03	1.54	0.50	1.16	9.36	0.05	4.56
Skewness	-1.5	0.56	-0.3	0.07	-1.3	-0.6	-0.4	-0.3	-0.2	-0.1	0.36	0.28	-0.6	-0.3	0.08
Kurtosis	4.72	2.52	1.59	1.71	4.32	2.10	1.92	2.09	1.98	1.97	1.77	1.91	2.17	1.92	2.28
Jarque–Bera	14.9	1.88	3.16	2.09	11.0	2.83	2.23	1.48	1.59	1.44	2.52	1.88	3.06	1.96	0.67

gdp=7.54E+09, gdp(S.D)=2.85E+09 gdp=6.63E+11, gdp(S.D)=1.13E+11 gdp=3.42E+11, gdp(S.D)=1.16E+11

Economic variables	Portugal (PRT)					Romania (ROU)					Slovak republic (SVK)				
	Obs	Gdp	Glob	Hdi	Unm	Obs	Gdp	Glob	Hdi	Unm	Obs	Gdp	Glob	Hdi	Unm
Mean	25.6	1.89	77.5	0.80	7.76	25.6	1.38	67.1	0.75	6.77	25.9	6.30	72.0	0.79	13.0
Max.	25.9	2.22	85.0	0.86	16.2	27.1	2.17	79.0	0.83	8.36	26.6	9.90	83.0	0.86	19.3
Min.	24.9	1.45	60.0	0.72	3.35	24.3	9.21	43.0	0.68	3.91	25.3	3.44	53.0	0.73	5.75
Std. dev.	0.31	2.26	6.37	0.04	3.54	0.89	3.78	11.1	0.05	1.14	0.38	2.11	10.6	0.04	3.43
Skewness	-0.6	-0.7	-1.1	-0.4	0.88	0.16	0.47	-0.5	-0.0	-0.7	0.36	0.15	-0.5	0.06	0.05
Kurtosis	2.01	2.19	3.68	2.39	2.91	1.64	2.01	2.11	1.32	3.23	1.85	1.60	1.66	1.45	2.78
Jarque–Bera	3.24	3.49	6.94	1.39	3.96	2.43	2.35	2.72	3.49	3.14	2.30	2.54	3.56	3.00	0.07

gdp=1.89E+11, gdp(S.D)=2.26E+10 gdp=1.38E+11, gdp(S.D)=3.78E+10 gdp=6.30E+10, gdp(S.D)=2.11E+10

Economic variables	Slovenia (SVN)					Spain (ESP)					Sweden (SWE)				
	Obs	Gdp	Glob	Hdi	Unm	Obs	Gdp	Glob	Hdi	Unm	Obs	Gdp	Glob	Hdi	Unm
Mean	25.8	3.63	69.1	0.85	6.98	26.1	1.05	78.9	0.84	17.0	25.4	4.04	85.8	0.89	7.12
Max.	26.8	5.02	81.0	0.91	10.1	26.3	1.32	86.0	0.90	26.1	26.1	5.50	90.0	0.94	10.3
Min.	25.1	2.36	42.0	0.77	4.37	25.4	7.37	65.0	0.76	8.23	24.4	2.83	76.0	0.82	2.95
Std. dev.	0.56	8.19	12.5	0.04	1.43	0.24	1.92	5.75	0.04	5.37	0.52	8.42	3.98	0.03	1.79
Skewness	0.14	-0.5	-0.9	-0.4	0.17	-1.0	-0.3	-0.8	-0.3	-0.6	-0.3	0.06	-1.1	-0.8	-0.4
Kurtosis	1.69	1.71	2.48	1.72	2.63	3.45	1.66	2.68	2.15	1.79	1.93	1.75	2.97	2.81	2.87
Jarque–Bera	2.25	2.18	4.41	2.98	0.31	5.48	2.91	3.42	1.42	1.83	1.85	1.95	6.37	3.30	1.03

gdp=3.63E+10, gdp(S.D)=8.19E+09 gdp=1.05E+12, gdp(S.D)=1.92E+11 gdp=4.04E+11, gdp(S.D)=8.42E+10

APPENDIX B

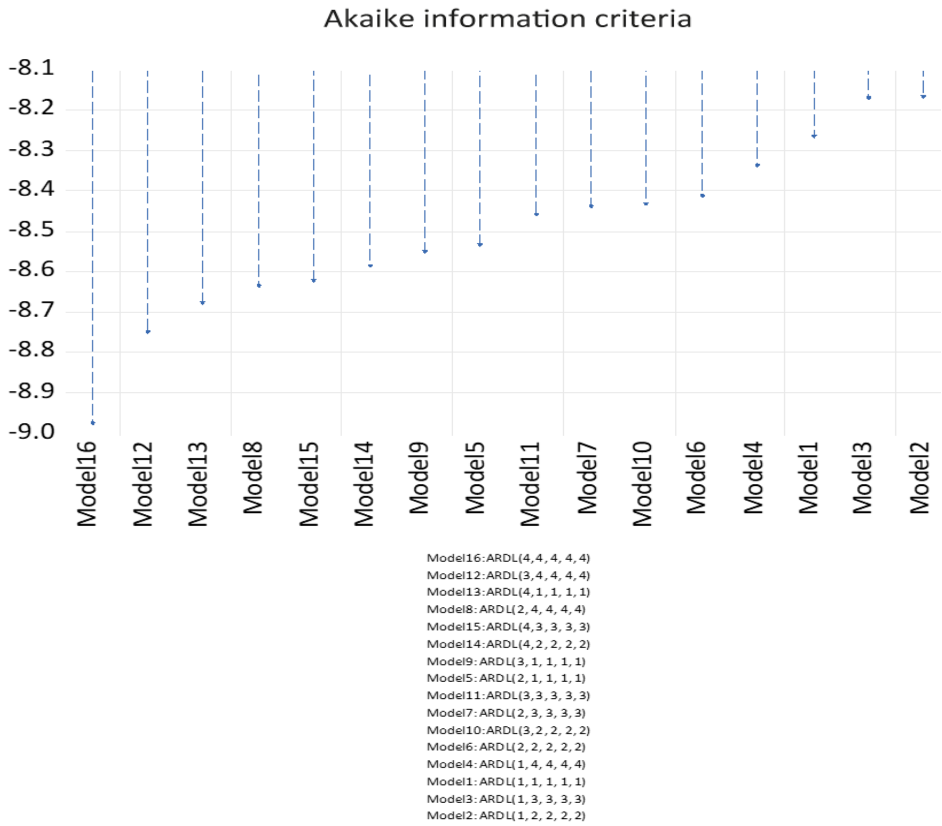

Figure 1B. The estimates of the autoregressive distributed lag (ARDL) models.