UNIVERSITY OF TWENTE.

Does renewable energy alleviate energy poverty in the European Union?

MASTER'S THESIS

ALAN RIOS RIOS
Faculty of Behavioral, Management and Social Sciences (BMS)
Master's degree in Environmental and Energy Management (MEEM) 2023

FLORENCE METZ
First supervisor

EWERT AUKES
Second supervisor

Table of contents

1. INTRODUCTION *8*

2. LITERATURE REVIEW *10*

2.1. Energy poverty definition in the EU **10**

2.2. Energy poverty measurement **10**

2.2.1. General indicators taxonomy 11

2.2.1.1. Expenditure approach 11

2.2.1.2. Consensual approach 11

2.2.1.3. Direct measurement approach 11

2.2.2. Energy poverty indicators in the EU 12

2.2.2.1. Expenditure approach 12

2.2.2.2. Consensual approach 12

2.3. The energy transition and energy poverty **13**

2.3.1. Affordable energy prices 13

2.3.2. Energy Security 13

2.3.2.1. Security from external resources 14

2.3.2.2. Energy availability 14

2.3.3. Reduction of income inequalities 15

3. METHODOLOGY *17*

3.1. Case selection **17**

3.2. Energy poverty empirical model **18**

3.3. Dependent variables operationalization **20**

3.4. Depended variable data overview **20**

3.5. Independent variables operationalization **21**

3.5.1. Renewable electricity consumption by households 21

3.5.2. Renewable electricity production 21

3.5.3. Affordable energy prices 22

3.5.4. Energy security 22

3.5.5. Reduction of income inequality 22

3.5.6. Control variable 22

3.6. Energy poverty generalized linear models **23**

3.6.1. Models' selection criteria **23**

3.6.2. Energy poverty generalized linear models **24**

4. RESULTS *25*

4.1. Energy poverty in the EU **25**

4.1.1. Energy poverty situation in the EU 25

4.1.2. EU energy poverty model results 27

4.1.2.1. Inability to keep home adequately warm (IKW) 27

4.1.2.2. Arrears on utility bill (AUB) 27

4.1.2.3. Housing conditions (HC) 28

4.1.2.4. Energy poverty combined index (EPCI) 28

4.2. Energy poverty in Denmark **28**

4.2.1. Energy poverty situation in Denmark 28

4.2.2. Energy poverty model results 29

4.2.2.1. Inability to keep home adequately warm (IKW) 30

4.3. Energy poverty in Greece **30**
4.3.1. Energy poverty situation in Greece 30
4.3.2. Energy poverty model results 32
4.3.2.1. Inability to keep home adequately warm (IKW) 32
4.3.2.2. Arrears on utility bill (AUB) 32
4.3.2.3. Housing conditions (HC) 32
5. RESULTS DISCUSSIONS ***34***
5.1. Energy poverty measurement **34**
5.2. The effects of renewable electricity on energy poverty **35**
6. CONCLUSIONS AND RECOMMENDATIONS ***38***
6.1. Conclusions **38**
6.2. Recommendations **39**
REFERENCES ***40***
APPENDIX 1 ..... ***45***
APPENDIX 2 ..... ***46***
APPENDIX 3 ..... ***50***
APPENDIX 4 ..... ***54***
APPENDIX 5 ..... ***56***

<u>List of figures</u>

Figure 1 Energy poverty 2020 indicators ranking (source: own elaboration / data source: EUROSTAT) 17
Figure 2 Share of renewable sources over the total electricity consumption in the EU (source: own elaboration/ data from EUROSTAT) 18
Figure 3 Empirical energy poverty model structure (source: own elaboration) 19
Figure 4 Energy poverty GLMs (source: own elaboration) 23
Figure 5 Energy poverty vs renewable consumption and production in the EU in % (source: own elaboration) 25
Figure 6 Energy poverty geographic distribution in the EU in 2020 %households (source: own elaboration) 26
Figure 7 Energy poverty vs renewable consumption and production in Denmark in % (source: own elaboration) 29
Figure 8 Energy poverty vs renewable consumption and production in Greece in % (source: own elaboration) 31

List of tables

Table 1 Energy poverty indicators (source: own elaboration) 12
Table 2 HC indicators GLM regressions details (source: own elaboration) 20
Table 3 Dependent variables probabilities (source: own elaboration / data source: EUROSTAT) 21
Table 4 EU GLM regressions details (source: own elaboration) 24
Table 5 Denmark GLM regressions detail (source: own elaboration) 24
Table 6 Greece GLM regressions detail (source: own elaboration) 24
Table 7 EU GLM regressions independent vs dependent variables detail (source: own elaboration) 27
Table 8 Denmark GLM regressions independent vs dependent variables detail (source: own elaboration) 30
Table 9 Greece GLM regressions dependent variable vs independent variable (source: own elaboration) 32

List of abbreviations

ARP	:	**At-risk-of-poverty rate**
AUB	**:**	**Arrears on utility bill**
IKW	**:**	**Inability to keep home adequately warm**
EID	**:**	**Energy import dependency by products**
ELP	**:**	**Electricity prices**
EP	**:**	**Energy poverty**
EPAH	**:**	**Energy Poverty Advisory Hub**
EPCI	**:**	**Energy poverty combined index**
EPEC	**:**	**Energy poverty empirical model**
EC	**:**	**European Commission**
EU	**:**	**European Union**
EUROSTAT	**:**	**Statistical Office of the European Union**
GC	**:**	**Gini coefficient**
GLM	**:**	**Generalized linear models**
HC	**:**	**Housing conditions**
HEC	**:**	**Households' electricity consumption**
RREC	**:**	**Renewable electricity consumption**
RREP	**:**	**Renewable electricity production**
TLE	**:**	**Electricity taxes and levies**

Acknowledgement

I would like to acknowledge the following people for helping with this master's thesis:
To my supervisors, Dr. Florence Metz and Dr. Ewert Aukes, for sharing with me their valuable academic knowledge, support and feedback during the development of this research. Without them, this master's thesis would not have been possible. In addition, I would like to give a special mention to Dr. Joy Clancy for being the person who motivated me to conduct research on energy poverty.

With special love I would like to thank my mother, Rosario, for being the beacon of light that has guided me on this journey. To my dear aunts, Socorro and Teresa for their family support, and to my two great friends, Lorena and Katia for always being present

ABSTRACT

This master thesis tries to determinate whether the increase in the consumption and production of renewable electricity can mitigate energy poverty (EP) in the European Union (EU) between 2013 and 2022. Employing a quantitative method the research seeks for determinate the statistical relationship between EP indicators and the consumption and production of renewable electricity in three geographic units: the EU, Denmark and Greece. To achieve the objectives of the research an empirical energy poverty model was built based on the literature review. In general, to estimate the correlation between the independent and dependent variables I used Generalized Linear Models (GLM).

EP was measured using three single indicators, and a combination of them following Rodriguez-Alvarez et al. (2021). They were also used to examine the context of energy poverty in the EU. Thus, it was concluded that EP represents a complex socio-economic phenomenon that cannot be measured using a single indicator. Likewise, the large gaps between indicators at supranational and national levels show that this challenge must be addressed from a local perspective to avoid erroneous generalizations.

The independent variables are composed by three mechanisms through energy transition can alleviate EP, the rate of consumption and production of renewable electricity, and one control variable. To analyze the statistical relevance of them I run 12 GLM. The models' results elucidate that the reduction of EP is more linked to socio-economic factors than to the consumption and production of renewable electricity. Thus, controlling electricity costs, reducing income inequalities and mitigating monetary poverty show greater influence on EP levels. Furthermore, the results can be framed in two different approaches to tackling EP in the EU. The first one implemented in countries like Denmark where the use of energy subsidies has kept EP levels low. And the second applied in countries such as Greece where policies have been developed to attack the causes of this challenge such as high electricity prices or low levels of energy security. In summary, the results suggest the need to approach EP from a local rather than a supranational perspective. They also emphasize high electricity prices and socio-economic conditions as the factors that have had the greatest impact on energy poverty levels in the EU.

1. INTRODUCTION

The invasion of Ukraine by Russia set off the alarms of the energy vulnerability in Europe. The European Union's dependence on Russian gas created the perfect environment to make visible a social problem whose definition was introduced into academic debates after the 1973 oil crisis, energy poverty. According to the Commission Recommendation (EU) 2023/2407 on energy poverty in 2022 around 40 million Europeans lived under energy poverty threshold. The efforts of the EU to address this challenge started in 2009 when the European Commission (EC) introduced its first definition. Also, by using EC recommendations and creating institutions such as The Energy Poverty Advisory Hub (EPAH) EU Member States have implemented tools to measure and mitigate its effects.

The definition of energy poverty is on a continue debate between scholars, according to Castaño-Rosa et al. (2019) this term is used to identify the vulnerability and lack of access to energy in a domestic scale. Moreover, the scholars highlights that the use of the term energy poverty depends on geographic location. Therefore, EP is more related to the Global North because even when there is fully access to energy services, some socio-economic aspects can limit the capacity of households to meet their energy needs. Whereas in the Global South the term energy vulnerability fits better due to the lack of access to energy infrastructure. In the academic literature is possible to find energy access as one of the most studied reasons of energy poverty. However, Thomson et al. (2017) present energy poverty as multidimensional challenge that depends on socio-economic aspects like genre and income inequality among other socio-economic gaps. Based on this and the focus of this research on the EU, socioeconomic challenges such as energy affordability, security and income inequality were addressed as EP drivers.

The repercussions of this challenge are not only limited to economic aspects, but also to health. On one hand, Pye et al. (2015) claim that energy poverty represents a threat to EU Member States highlighting its serious economic impacts on the welfare of the most disadvantaged households. While Churchill & Russell (2021) concluded that EP have a deep negative effect on adult people's health. All this presents EP as a significant challenge to be faced by the EU Member States in the context of an energy crisis and Climate Change. Thus, the EU has been promoting different strategies to deal with it, one of them being the energy transition. As it is a broad process that includes power generation, electrification, among others, the focus of this research is on the consumption and production of renewable electricity. The effectiveness of this measure has been analyzed in several academic studies with positive and negative results. On the one hand, Süsser & Kannen (2017) and Li (2005) highlight the benefits of renewable energies in the reduction of energy prices, income inequalities and energy insecurity. On the other hand, Primc & Slabe-Erker (2020) concludes that the introduction of renewable sources has increased the economic burden on households generating increases in EP. On this basis, in this master's thesis I will analyze whether renewable electricity can contribute to mitigate the causes of EP and thus contribute to its reduction.

According to data from the Statistical Office of the European Union (EUROSTAT), energy poverty levels in the EU show a geographical trend. While northern countries have the lowest rates, southern countries have the highest. In addition, with different growth rates the consumption and production of renewable electricity has increased across the EU. Based on these trends, three geographic units were selected to run the research which are: the EU as a supranational entity, and Denmark, and Greece. Thus, this research has one main objective: **analyze how renewable energies can alleviate energy poverty in the European Union**. Also, it has four subobjectives:

a) **Examine a definition of energy poverty in the European Union**

b) **Reflect and examine how energy poverty can be measured**

c) **Analyze by which mechanism the energy transition can alleviate energy poverty**

d) **Compare the effects of renewable electricity on energy poverty levels at the supranational and Member State levels**

To meet the goals, I am going to address the following research question: **What are the impacts of more consumption and production of renewable electricity on the reduction of energy poverty?** and two sub-research question:

a) **How different were the effects of increasing renewable electricity between the EU and its Member States on reducing energy poverty?**

b) **How different were the effects of renewable electricity between countries with high and low levels of energy poverty on reducing energy poverty?**

To achieve the research's objective and the research questions, I am going to use a quantitative, deductive, and explanatory method. Using descriptive statistics, I am going to analyze the current situation of energy poverty in the EU. Likewise, by means of an empirical energy poverty model I will determinate the statistical correlation between EP as a dependent variable, and a set of explanatory variables (consumption and production of renewable electricity, electricity prices, income inequalities, among others). Generalized Lineal Models will be used for this purpose, which will be run in Eviews 12. All this with the aim of analyzing and reflecting on the impacts of more renewable electricity consumption and production on the reduction of energy poverty.

The present thesis is broken down into six parts. In the literature review I am going to examine the definition and causes of energy poverty in the EU. In the same chapter the ways to measure energy poverty and the mechanism through the energy transition can mitigate it will be analyzed. In addition, the chapter 3 explains the methodology followed in the research Moreover, the models' results will be presented in the chapter 4, and their discussion in the chapter 5. Finally, the conclusions, and the recommendations for further research will be introduced in the chapter 6.

2. LITERATURE REVIEW

2.1. Energy poverty definition in the EU

Energy poverty conceptualization started to being developed in 1973 in the context of the oil embargo with the name of fuel poverty. However, it was not until 1991 when Dr. Brenda Boardman set its first definition as the impossibility of households to warm their homes as result of an inadequate services. The scholar set a maximum value of 10% of the cost of the energy services over the household income as indicator to measure EP. Which became the most widely used measurement benchmark until the concept of energy poverty was developed with new research and the incorporation of new indicators. The first attempt to introduce a definition for EP in the EU can be found in the Directive 2009/72/EC on concerning common rules for the internal market in electricity as *"Member State shall define the concept of vulnerable customers which may refer to energy poverty and, inter alia, to the prohibition of disconnection of electricity to such customers in critical times"* (Directive 2009/72). This statement frames EP in relation to energy security, concept that has been updated with the inclusion of more social aspects.

In addition, in 2019 through Directive (EU) 2019/944 on common rules for the internal market for electricity the EU introduced the requirement for its Member States to make public the criteria chosen to measure EP. In 2020 The EC under the Commission Recommendation (EU) 2020/1563 on energy poverty set a pool of indicators through the European Energy Poverty Observatory to assess energy poverty. Also, this institution was transformed into The Energy Poverty Advisory Hub (EPAH) in 2021. This became a platform which purpose is share information and knowledge between experts, authorities and stakeholders committed to eradicating energy poverty in the EU.

Thus, the current definition of EP was developed in 2023. It is derived from the point 1 Article 2 of the Regulation (EU) 2023/955 establishing a Social Climate Fund and amending Regulation (EU) 2021/1060 as *"household's lack of access to essential energy services that underpin a decent standard of living and health, including adequate warmth, cooling, lighting, and energy to power appliances, in the relevant national context, existing social policy and other relevant policies"* (Regulation 2023/955). Likewise, the causes of energy poverty are set out in Article 2, point 48 of the Directive (EU) 2023/1791 on energy efficiency and amending Regulation (EU) 2023/955 (recast) as "*caused by a combination of factors, including but not limited to non-affordability, insufficient disposable income, high energy expenditure and poor energy efficiency of homes"* (Directive 2023/1791).

Furthermore, the EC through the Commission Recommendation (EU 2023/2407) on energy poverty presents the energy transition as one of the most effective tools to eradicate EP. Also, this institution incorporates other social aspects such as gender or health conditions as possible causes of EP. This shows EP as a socio-economic challenge of great relevance for the EU. Moreover, this recommendation lists four mechanisms that must be improved to combat EP: energy affordability, energy security, energy efficiency, and sufficient incomes disposal.

2.2. Energy poverty measurement

Thomson et al. (2017) developed three general approaches: expenditure, consensual and direct measurement to categorize all EP's indicators. Moreover, following this the indicators recommended by Commission Recommendation (EU) 2020/1563 on energy poverty and the EPAH were categorized. Finally, the objective of this part is to identify the indicators that will be used to estimate the levels of energy poverty in the EU.

2.2.1. General indicators taxonomy

2.2.1.1.Expenditure approach

It analyzes the portion of households budget allocated on energy bills. The most used indicator in this approach establishes a threshold limit of 10% for the ratio of energy expenditure to households' incomes. In other words, households that allocate more 10% of their incomes on energy bills are considered energy poor. Moreover, two new developments were introduced with the passage of time. The first claims, if a household's share of energy bills over its income is more than twice the national median is energy poor. The second claims, if a household's absolute energy expenditure is less than the half of the national median expenditure can be considered as energy poor.

Thomson et al. (2017) make a critical observation about the upsides and disadvantages of this approach. For instance, the 10% threshold developed in 1991 has not followed the trend of the current energy prices. Therefore, after the energy crisis of 2022, this indicator could show that a significant part of Europeans would live under EP. Also, the use of rents in new developments may distort the result, as rents could include social subsidies. Thus, low-income households would be mostly dependent on them to pay their energy bills. Moreover, the energy expenditure depends on the consumption, which in turn depends on many factors such as the size of the house or energy efficiency. Therefore, even when people can cover their energy needs can be considered as energy poor just because their consumption is low. However, when it comes to showing an advantage of this approach is easy to conclude that these indicators are objective and can be quantified effortless.

2.2.1.2.Consensual approach

This approach employs a set of self-reporting tools to inform the capacity to heat or cool households' dwelling, to pay the energy utilities on time, and houses' physical conditions. Thomson et al. (2017) highlight that one of the most significant contributions of this approach is the possibility to collect data directly from households. Moreover, with this approach data can be standardized to assess the level of EP at supranational levels such as the EU.

Among its disadvantages Thomson et. al (2017) and Castaño-Rosa et al. (2019) highlight the subjectivity of the households to identify themselves as energy poor. For instance, households could try to hide they do not have the capacity to heat their houses properly during the winter. Thus, identifying whether a house is adequately heated can be influenced by cultural, socioeconomic and geographic characteristics. For example, the tolerance to low temperatures would be higher for Scandinavians than for Mediterranean. Thus, the lack of standards leaves it to the subjectivity of households to agree or disagree with the use of heating or air conditioning in some specific situations. This could lead to some of them being classified as energy poor even if they can cover their energy needs.

2.2.1.3.Direct measurement approach

This approach has the aim to measure if households can access to adequate levels of energy services such as lightening or cooling, for which some determined standard has been developed. As a first glance the most difficult part is how to implement a procedure to measure the access to energy services directly. Also, the standards can be different depending on different factors such as the geographic location, cultural, economic, and technical aspects. Therefore, Castaño-Rosa et al. (2019) argues that given the impossibility of obtaining standardized data at the European level, this approach would not be appropriate for measuring EP in the EU.

2.2.2. Energy poverty indicators in the EU

2.2.2.1.Expenditure approach

These indicators are focused on determinate EP level by collecting information about the households' consumption patterns. This gives tools to measure estimate the expenditures on energy bills. This data is collected from the European Union Household Budget Survey.

2.2.2.2.Consensual approach

These indicators have been developed on based of the access to energy service households' self-reporting. This data is collected from the European Union Survey on Income and Living Conditions (EU-SILC).

The Table 1 shows a short list of the most used indicators, identifying their units, timeline data available and their approaches classification.

Table 1 Energy poverty indicators (source: own elaboration)

Indicator name	Approach	Timeline data	Geopolitical entity	Unit	Time frequency
Arrears on utility bill	Expenditure	2004-2022	EU and Member States	Households (%)	Annual
Low absolute energy expenditure	Expenditure	2011-2015	EU and Member States	Household (%)	Annual
High share of energy expenditure incomes	Expenditure	2010-2015	EU and Member States	Household (%)	Annual
Inability to keep home adequately warm	Consensual	2004-2022	EU and Member States	Households (%)	Annual
Household electricity prices	Consensual	2007-2022	EU and Member States	€/kWh	Annual
Household natural gas prices	Consensual	2007-2022	EU and Member States	€/kWh	Annual
At risk of poverty or social exclusion	Consensual	2004-2022	EU and Member States	Population (%)	Annual
Pop. Liv. Dwelling with presence of leak, damp and rot windows.	Consensual	2003-2020	EU and Member States	Households (%)	Annual

Thomson & Snell (2013) after to analyze a wide range of EP indicators recommend using three of them belonging to the consensual approach. Those indicators are inability to keep home adequately warm (IKW), arrears on utility bill (AUB), and population living in dwelling with presence of leak, damp and rot windows. The latter was named as housing conditions (HC) for practical reasons. The research is going to follow this recommendation to estimate EP.

2.3.The energy transition and energy poverty

Starting from the causes of EP identified by the European Commission, this part will develop the mechanisms through which the energy transition can address them and thus reduce the effects of EP.

2.3.1. Affordable energy prices

Bonatz et al. (2019) define energy affordability as one of dimensions of EP highlighting that household can live under its effects if they are not able to afford energy bills. According to IRENA (2022) the electricity levelized cost from utility-scale plants of solar PV and wind energy dropped on average 14% from 2020 to 2021 reaching fossil fuel's levelized cost range. Also, since 2010 until 2021 solar PV levelized cost fell by 89%, and onshore wind levelized cost decreased by 68% in the same period. In addition, comparing the average levelized cost of electricity at utility scales between solar PV and natural gas in Europe, the former is getting cheaper than the latter since 2020. By 2021 electricity levelized cost from natural gas was 6 times more expensive than solar PV. This argument shows the positive effect of renewable energies on the reduction of electricity prices improving its affordability which can be translated into lower energy poverty levels. Furthermore, IRENA (2022) shows that the significant reduction in the renewable's electricity levelized cost came from installation and commissioning costs, which accounted for more than 50% of the reductions. Other factors that are catalyzing the renewable electricity' competitiveness is the higher prices of fossil fuels. As well as the revenue recovered by capital invested. Thus, solar photovoltaic and wind energy recorded capital recoveries 7 times higher than those of fossil fuels in Germany and the United Kingdom in 2021.

However, the energy transition faces a crucial challenge, the capacity to store energy using batteries. This requires the consumption of scare minerals such as lithium or rare earths undermining renewable energies' competitiveness. However, according to IRENA (2017) since 1991 until 2005 the lithium-ion cells cost has dropped more than 500 in $/Wh due to the technological development. Also, the institution estimates that by 2030 the use of batteries for power storage will increase substantially reducing more their prices. Is certain is that the batteries technology represents the biggest obstacle for the diffusion of the renewable energies. As well as its future prices performance depends on many aspects like minerals availability, more efficient supply chains, market demand, and synergies with other relevant fields such as the e-vehicles. Moreover, the role of governments is vital to enhance renewables energies' competitiveness is vital and ensure a just transition. This requires the development of effective policies to provide financing to households and to projects where public and private equities do not see business opportunities.

Without prejudice to the latter, the improvement in renewable electricity prices at utilities level in the EU illustrate that renewable energies are getting competitive to replace traditional energies carriers. This can improve the affordability of energy prices, preventing households from ending up living below the EP threshold.

2.3.2. Energy Security

Energy security can be defined as *"the uninterrupted availability of energy sources at an affordable price"* (IEA 2014). On this basis, energy security was approached from two perspectives. The first was security from external resources, and the second was energy availability.

2.3.2.1.Security from external resources

This challenge has gained importance across all European countries. A case in point is Germany, where its citizens' energy security and wellbeing was in risk for many months because of less natural gas supply from Russia. The dependency on imported fossil fuels in the EU has been stressed since many years ago. Umbach (2010) warned about the fragile energy security in Europe after the conflict between Russia and Ukraine in 2006. The scholar claimed almost two decades ago that the Kremlin was developing a geopolitical weapon by monopolizing the European gas market, a weapon that used in 2022 generating a new energy crisis.

Many scholars have made clear the urgent need to diversify the European energy system, one of these is Awerbuch (2006) who highlight the key role of renewables energies for this purpose. The scholar ran different scenarios with different energy mixes. He found that a system with a substantial participation of renewable energies improve energy security providing affordable energy services to European households. Moreover, Heshmati & Abolhosseini (2017) state that the successive energy crisis in the EU since the oil embargo in 1973 are the results of its dependency on fossil fuels produced out of its borders. To address this, renewable energies are presented as reliable sources because they do not require the consumption of foreign natural resources.

Li (2005) stresses the power sources diversification as a tool to guarantee energy supply at affordable prices, and to enhance energy systems reliability through the development of decentralized solutions. A successful example are district heating systems, decentralized solutions that cover heating needs in a flexible way. This technology has seen a significant progress in Denmark, where collective heating system supply enough heating during the winter. Moreover, those solutions require the consumption of local resources such as ground water. Other example of this is the Dutch case. The Dutch government is promoting the use of water as a heat source to replace existing gas heating systems to achieve energy security. Connolly et al. (2016) highlight the environmental benefits of district heating in terms of less greenhouse gas emissions, and its capacity to reduce dependency on imported natural gas. Moreover, these systems can be operated by using renewable electricity generated from local resources, which in turn eliminate the risk of fossil fuel market volatility.

In a context of high energy dependence in Europe, energy transition plays a vital role in developing an energy system that is autonomous from the external geopolitical game and relies on local resources. Thus, as Dong et al. (2021) state, mitigating this challenge can lead to a more independent and competitive energy system. This can provide lower energy prices to households and, in turn, reduce energy poverty.

2.3.2.2.Energy availability

Global Warming is putting at risk the security of the electrical power system in Europe. For instance, water scarcity is reducing the capacity of hydropower plants. Also, the water temperature increase can affect the operation of thermoelectric plants due to less available cooling water to cool nuclear and fossil fuel power plants. Is important to stress that solar and wind can also be affected for the changes in the climate patterns. However, Tobin et al. (2018) conclude that those energy sources would be more resilient to extreme weather changes. Moreover, the increased electricity consumption in the coming decades will test the capacity of the current system. This dilemma raises the need to renovate the European electrical system, which must cover more demand and be flexible to demand patterns. Thus, the energy transition represents a tool to modernize old carbon and nuclear power systems, improving energy availability and keeping the prices affordable.

In this way, Connolly et al. (2016), Child et al. (2019), and Papaefthymiou & Dragoon (2016) analyzed a few scenarios to determinate how possible is to achieve 100% renewable energy system in Europe. All then concluded in different ways that the objective is possible to achieve by 2050, ensuring energy availability to cover future loads requirements. The scholars highlight the capacity of renewable electricity to replace existing fossil fuels and nuclear systems by local renewable resources improving energy security. A transition with these characteristics promotes an integration and synergies between modern energy services and carriers. For instance, mobility can be fully green in the way the electricity require will come from renewables. Furthermore, district heating and cooling could be fostered by using electric heat pumps meeting households' comfort needs. In addition, the studies show that the development of technology in generation, system integration and energy storage could make energies prices more affordable. Also, the revamping of the electrical system will require a significant allocation of capitals. This can generate an increase on employment rates during the installation and commissioning stages, reducing income inequality. And finally, renewable energies have the capacity to develop decentralized systems improving reliability in comparison with centralized power systems. All these advantages would ensure sustainable access to energy in the EU, which in turn is a key to mitigating EP.

However, to develop a system like that the EU faces significant challenges. Spiecker & Weber (2014), Zappa et al. (2019), Connolly et al. (2016), and Child et al. (2019) identify two types of challenges, technical and institutional. The point is more renewable energy sharing more regional energy system integration is needed. In other words, EU member states must make the transition to an intercontinental energy system in which different renewable technologies operate. This requires increased energy storage and more flexible generation systems that integrate these technologies and couple them to complement each other. Therefore, the variability of solar and wind can be managed by hydropower, and big batteries bank. In addition, grid integration across the countries is more than needed to balance the system and meet consumption peak flexibly. Regarding the institutional challenges, is possible to identify policy alignment between countries. Whereas France relies on nuclear, Sweden embraces renewables, and Poland does not have plans to phase out carbon plants. Thus, many actors with different visions about energy security and availability make the integration process difficult.

In conclusion renewable energies systems can contribute to modernize energy systems and enhance flexible energy networks across the European countries. On this basis, while energy transition represents an opportunity at the national level, it also represents an opportunity for integration among EU Member States. This feature can ensure the availability of energy in the future by consuming local resources, improving system resilience and reducing prices. This ensures access to energy in the future, reducing current levels of energy poverty and preventing its possible increase.

2.3.3. Reduction of income inequalities

Streimikiene et al. (2020) claim that one of the main energy poverty drivers are low incomes, highlighting that even in high income countries low-income households can face energy deprivation. This argument becomes significant in the EU in a context of higher energy prices due to low-income households allocate more money on energy bills. To address this challenge is necessary mitigate income inequality. Which can be achieved by increasing incomes, employability, and revitalizing local economies.

The renewable energy communities are successful examples of increasing local household incomes. Those initiatives provide to locals the opportunity to receive direct economic benefits from energy trading as Reis et al. (2021) conclude after to study renewable energy communities across Europe. Thus, Gorroño-Albizu et al. (2019) and Süsser & Kannen (2017) show how citizen ownership enhances the participation of communities in the allocation of capital in wind and solar farm projects by becoming investors in them. As a result, most of the local investors have increased their income compared to those who are not part of any energy community. This has led to an improvement in their quality of life, which translates into a significant reduction in the probability of living below the EP threshold.

Furthermore, Ingelsi-Lotz (2016) present low-carbon technologies as an effective measure to increase employment rates, and purchasing capacity measured in more internal consumption. In this line, Llera Sastresa et al. (2010) analyzed the case of Aragon in Spain, concluding that renewable energies create more direct jobs per installed capacity than traditional fossil fuels. Furthermore, Okkonen & Lethonen (2016) found that energy communities in Scotland have generated a positive impact on indirect employment. This has been achieved by the regeneration of local business enhancing internal consumption, and by the diffusion of new technical skills. This last aspect is vital to reduce income inequalities, as renewable energies are developing new commercial activities in addition to energy trading. For example, households can provide technical services to maintain and operate facilities in other communities. With the improvement of job opportunities locally communities can avoid depopulation, but mainly improving locals' access to the economic resources requires to reduce income inequalities avoiding energy deprivation.

The subchapter 2.2. presents the indicators that will be used to measure EP in this research. Additionally, since energy transition is one of the measures suggested in the Commission Recommendation (EU 2023/2407) on energy poverty to eradicate EP, it is possible to put forward two hypotheses:

- **H1: Higher rates of renewable electricity consumption can reduce energy poverty**
- **H2: Higher rates of renewable electricity production can reduce fuel poverty**

Moreover, the mechanisms presented in the subchapter 2.3 suggest that the energy transition presents itself as a tool to confront EP's causes. On this basis is possible to raise three additional hypotheses:

- **H3: The lower the electricity prices, the lower the levels of energy poverty in the EU**
- **H4: The greater the energy security, the lower the levels of energy poverty in the EU**
- **H5: Reducing income inequality in the EU reduces levels of energy poverty**

3. METHODOLOGY

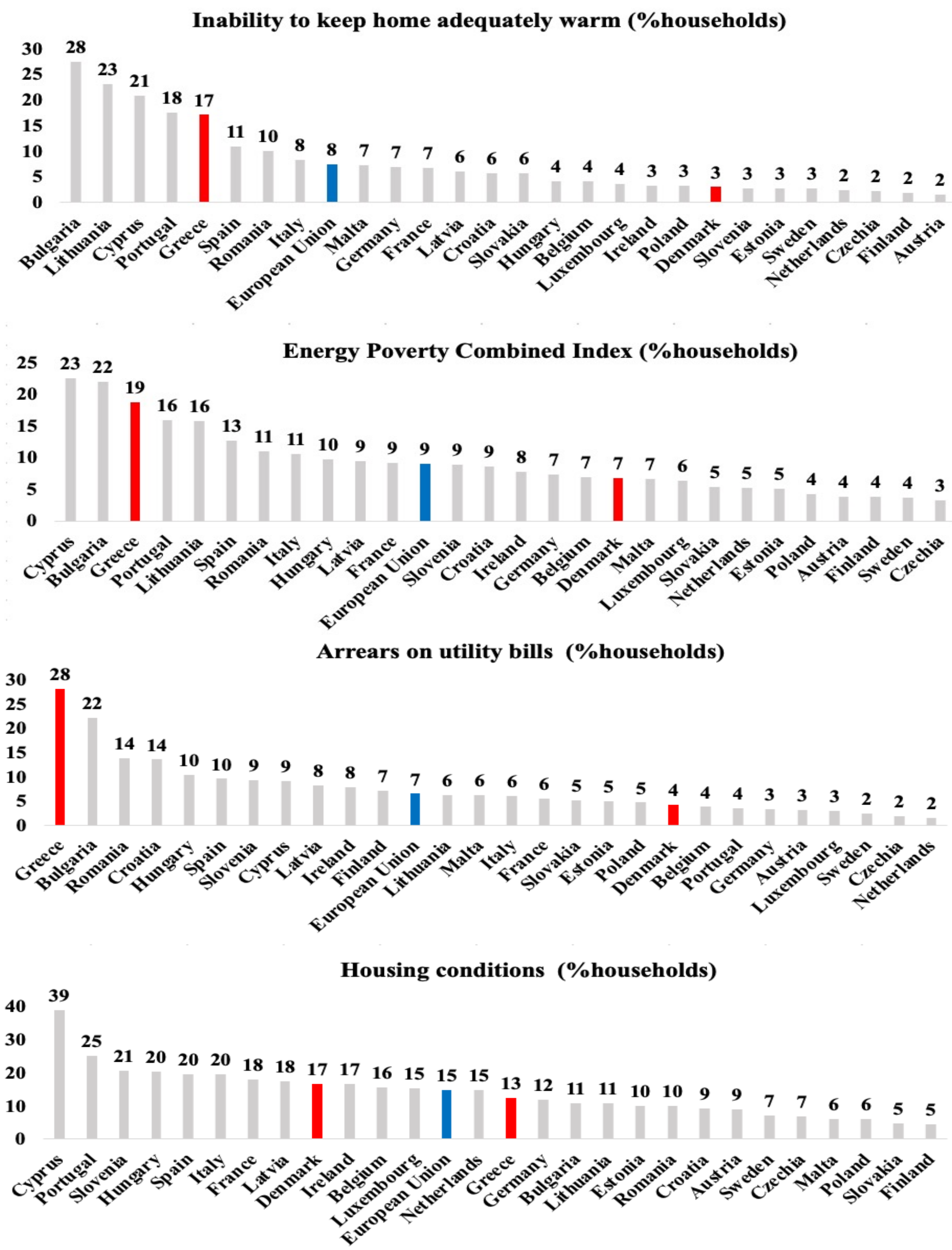
3.1. Case selection

To select the EU Member states to run the study I followed the following criteria:

a) Clustering by level of EP

The Figure 1 shows a ranking of the four EP indicators for the EU in 2020. EU Member States performed differently, although there are two groups of EP levels: while Northern European countries had on average lower EP levels than the EU average, Southern European countries had higher levels.

Figure 1 Energy poverty 2020 indicators ranking (source: own elaboration / data source: EUROSTAT)

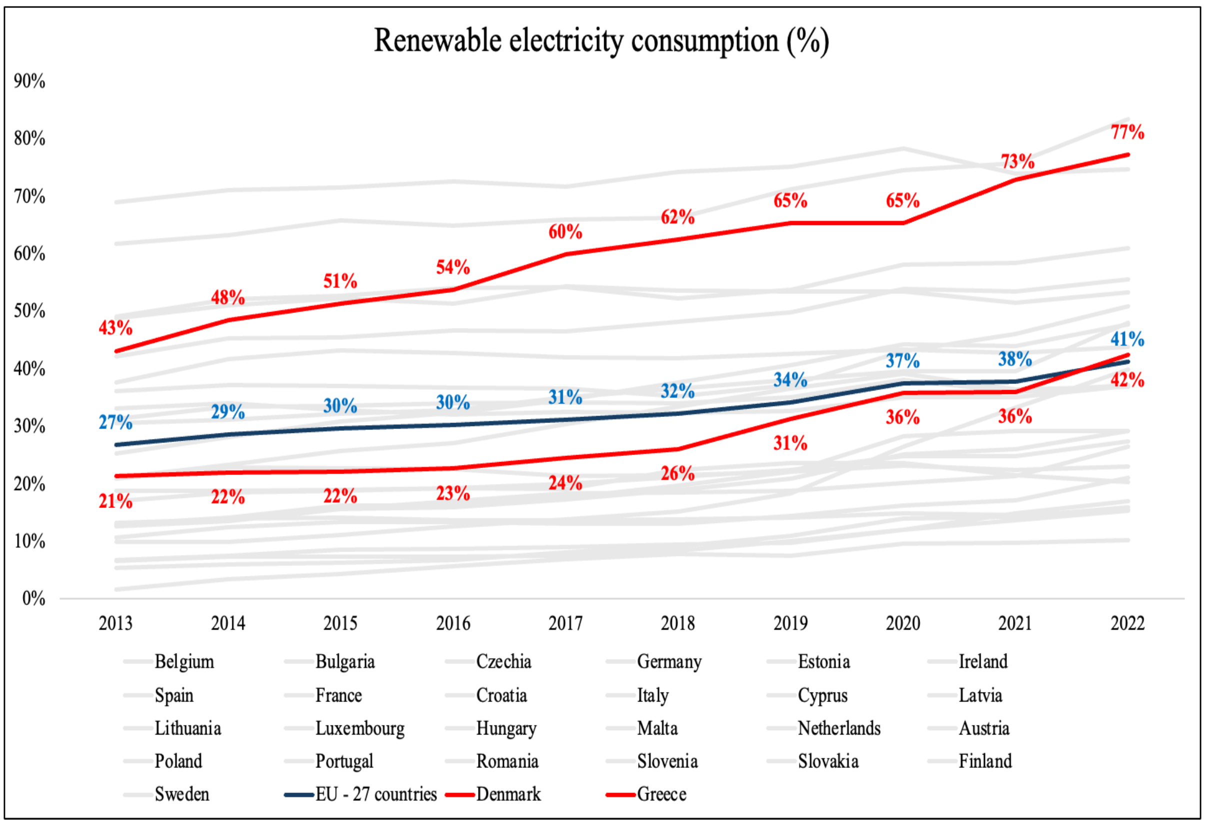


b) Consumption of renewable electricity

The Figure 2 shows the evolution of renewable electricity production in the EU since 2013 until 2022. Over the time the share of renewable electricity increased in all the EU Member States with different rates. The lines in red represents the increase of renewable electricity production in two countries, Denmark and Greece, which following the Figure 1 had one of the lowest and highest levels of EP in 2020 respectively.

Applying both criteria I selected Denmark and Greece to run the research. In addition, the in both figures in blue I presented the indicators of the EU, since one of the subobjective of this research is to evaluate the difference between supranational and national level, the research will include an analysis at EU level.

Figure 2 Share of renewable sources over the total electricity consumption in the EU (source: own elaboration/ data from EUROSTAT)



3.2. Energy poverty empirical model

To address the research and sub-research questions I used:

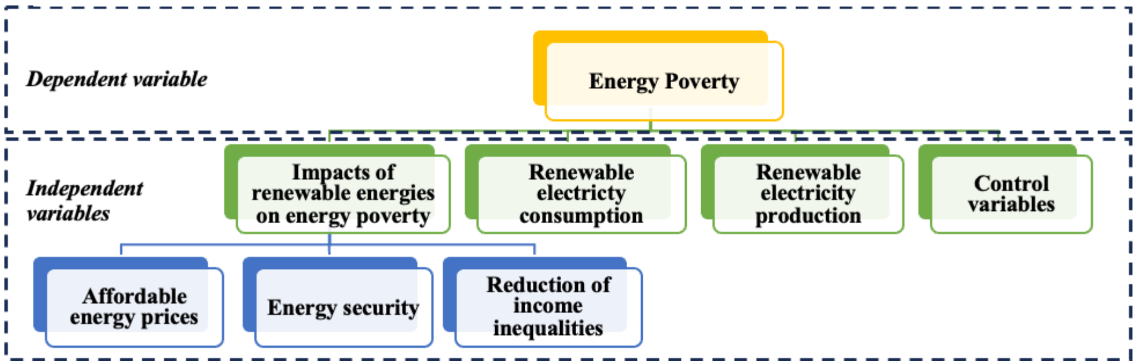
a) Descriptive statistic to analyze the situation of EP in the EU, Denmark and Greece

b) An empirical energy poverty model (EPEC) was used to test the hypotheses presented in the Chapter 2

I designed the EPEC based on Nguyen & Nasir (2021), Zhao et al. (2021) and Kocack et al. (2023), and the literature review. Furthermore, the data source for the variables was EUROSTAT, and its time frame is between 2013 and 2022 with annual data due to its availability.

The Figure 3 shows the EPEC scheme, where energy poverty is a function of four independent variables.

Figure 3 Empirical energy poverty model structure (source: own elaboration)



Where:

a) Consumption of renewable electricity refers to the share of renewable electricity over the total electricity consumption,

b) Production of renewable electricity refers to the share of renewable electricity over the total electricity production,

c) The impacts of the renewable energies on energy poverty refers to the three mechanisms through which renewable energies reduce energy poverty,

d) Control variables refer to variables that are not of interest but help to avoid alternative explanations to the statistic relationship.

To operationalize the variables, I selected some indicators. Not all of them are available as single variables in EUROSTAT, therefore they were calculated by using indicators available on it. In addition, some variables depend on the energy consumption level such as the electricity prices. In this case the band of prices were chosen calculating a consumption per capita.

To determinate the statistical relationship between the variables I decided to use Generalized Linear Models (GLM). GML provides the facility to test different link functions to identify which is the best link between the dependent and independent variables when this is unknown. For this thesis four link functions: identity, log, logit and inverse were used. In addition, GLM can be used for multiple errors distribution, for this thesis I assumed a normal distribution of errors. This will be validated by a normality-test for which p-values of the null hypothesis >0.1 will be considered as acceptable. For more details about GLM read Nelder & Wedderburn (1972), Myers & Montgomery (1997) and Venables & Dichmont (2004). The Appendix 1 shows more information about GLM link function.

3.3.Dependent variables operationalization

I operationalize energy poverty by:

a) using the indicators: inability to keep home adequately warm (IKW), arrears on utility bill (AUB), and housing conditions (HC) separately, the codes of the indicators in EUROSTAT are: ilc_meds01, ilc_mdes07, and ilc_mdho01 respectively and their units are households (%),

b) combining those indicators into an energy poverty combined index (EPCI) created by Rodriguez-Alvarez et al. (2021) presented in the Eq. 1.

$$Energy\ poverty\ combined\ index\ = 0.5 * IKW + 0.25 * AUB + 0.25 * HC\ (Eq.1.)$$

The weighting of the variables used in the Eq.1. were found by the scholars after to test different weighting distributions, for more information read Rodriguez-Alvarez et al. (2021). On this basis I used four ways to operationalize EP within the EPEC, those will be used in the subsequent analysis.

3.4. Depended variable data overview

I miss data for the EP indicator HC in 2021 and 2022. Since those years are particularly significant for the research, I decided to estimate them using IKW and AUB. For this purpose, I employed a GLM since this tool provide four link functions to estimate the best function to fit the data. In this case, HC was the dependent variable, and IKW and AUB were the independent variables as the Eq. 7 shows.

$$g((HC)_{it}) = \beta_0 + \beta_1 IKW_i + \beta_2 AUB_{it} + \varepsilon_{it}\ (Eq.7)$$

The details of these regressions are in the Appendix 2. Regressions with p-values <0.1 were accepted, in the case of the EU and Greece HC is a function of IKW and AUB. Whereas in the case of Denmark, after to run a first GLM, a second one was run only considering HC and IKW getting acceptable results. Additionally, the residuals' normality test validated their normal distribution, and the deviances show values closer to 0. The Table 2 shows these regressions summary.

Table 2 HC indicators GLM regressions details (source: own elaboration)

	EU_27	**Denmark**	**Greece**
Link function	Identity	Identity	Inverse
Independent variables	IKW / AUB	IKW	IKW / AUB
Deviance	1.74E-05	8.60E-05	1.02E-04
Prob(LR statistic)	0.002421*	0.087407***	0.000001*

p<0.01;p**<0.05;p***<0.1*

The Appendix 3 has the dependent variables detail. Moreover, the Table 3 shows the p-values to test a null a hypothesis that assumes normal a distribution of the independent variables. Since the p-values are > 1% I cannot reject the null hypothesis which means the variables have normal distributions. I used this result to supports the assumption that the errors also have normal distribution to run the GLM's regressions.

Table 3 Dependent variables probabilities (source: own elaboration / data source: EUROSTAT)

Dependent variables	Probability (p-values)(b)
EU - 27 IKW(a)	0.6700
EU - 27 AUB (a)	0.5309
EU - 27 – HC (a)	0.6164
EU - 27 EPCI(a)	0.6508
Denmark IKW(a)	0.0515
Denmark AUB	0.7760
Denmark HC	0.7262
Denmark EPCI	0.2631
Greece IKW	0.5942
Greece AUB	0.8120
Greece HC	0.7478
Greece EPCI	0.5826

(a) *IKW: Inability to keep home adequately warm / AUB: Arrears on utility bill / HC: Housing conditions*

(b) *null hypothesis: normal distribution of variables -> p-values>1% -> null hypothesis cannot be rejected.*

3.5.Independent variables operationalization

3.5.1. Renewable electricity consumption by households

To operationalize this variable within the EPEC I considered two variables. The first is **renewable electricity consumption (RREC)** obtained from the indicator Share of renewable energy in gross final energy consumption by sector (EUROSTAT code: sdg_07_40/ nrg_ind_ren). It represents the share of the renewable electricity over the total electricity consumption.

The second variable is **households' electricity consumption (HEC**) which unit is percentage. HEC was obtained from the indicator Supply, transformation, and consumption of electricity indicates total power consumption by sectors (EUROSTAT code: nrg_cb_e). This indicator shows in detail the electricity consumption by free clients, transportation and households. Thus, HEC was obtained dividing households' electricity consumption over the total national consumption as the Eq.2 shows.

$$HEC\ (\%) = \frac{Househdols'electricity\ consumption\ (GWh)}{Total\ electricity\ consumption\ (GWh)}\ (Eq. 2)$$

3.5.2. Renewable electricity production

To operationalize this variable, I used the variable **renewable electricity production (RREP)**. The indicator Production of electricity and derived heat by type of fuel (EUROSTAT code: nrg_bal_peh) shows how much electricity was produced by different type of sources such as oil, nuclear, wind, among others. Thus, RREP was calculated from this indicator dividing the amount of renewable electricity over the total electricity production per country, see the Eq. 3. To identify what are renewable sources I followed the Directive (EU) 2018/2001 on the promotion of the use of energy from renewable sources (recast) to classify the sources as renewables.

$$RREP\ (\%) = \frac{Renewable\ electricity\ production\ (GWh)}{Total\ electricity\ production\ (GWh)}\ (Eq. 3)$$

3.5.3. Affordable energy prices

To operationalize this, I used the prices of electricity. To identify clearly how the prices impact I decided to use two variables. The first was **electricity prices (ELP)** related to power chain excluding taxes and levies. The second was **electricity taxes and levies (TLE)** not considering recoverable taxes.

The indicator Electricity prices - bi-annual data (EUROSTAT code: nrg_pc_204) shows the semestral prices of electricity. For EPEC the annual data was calculated as semester prices average. Electricity prices vary according to consumption in killowatts per hour. In the EU, prices are set in five bands from 0 kW.h to more than 15 kW.h. Depending on the band, prices vary downwards, so that households have on average higher tariffs than large consumer. To identify the price band, I used an electricity consumption per capita which was obtained dividing households' electricity consumption over the total population, see Eq.4. For households' electricity consumption I used the indicator Supply, transformation, and consumption of electricity (EUROSTAT code: nrg_bal_peh). While for the total population I used the indicator Population on 1 January (EUROSTAT code tps00001).

$$Electricy\ band = \frac{Househdols'electricity\ consumption\ (kWh)}{Total\ popilation}\ (Eq. 4)$$

3.5.4. Energy security

This variable was operationalized through the indicator **Energy import dependency by products (EID)** (EUROSTAT code: sdg_07_50). EID provides how much energy requirements a country imports to meet its energy needs. In detail for values closer to 1 the country has a high energy import dependency, whereas values closer to 0 has a higher energy import independency.

3.5.5. Reduction of income inequality

To operationalize this variable the indicator **Gini coefficient of equivalized disposable income (GC)** (EUROSTAT code: ilc_di12) was used. This indicator considers disposable income including social transfers and pensions, values close to 0 indicate a lower income inequality.

3.5.6. Control variable

Monetary poverty vulnerability was considered as a control variable. Thus, I used the variable **At-risk-of-poverty rate (ARP).** ARP was obtained from the indicator At-risk-of-poverty rate by poverty threshold and household type (EUROSTAT code: ilc_li03). ARP shows the proportion of the population with low incomes, which may influence their levels of energy poverty.

In the Appendix 3 there are tables with the details and the summary of the independent variables . On this basis, the EPEC can be presented in the Eq. 5.

$$EP = f(RREC, HEC, RREP, ELP, TLE, EID, GC, ARP)\ (Eq. 5)$$

To estimate the relationship between the variables I employed a Generalized Linear Models. The Eq. 5 can be transformed into the Eq.6 where g() is the link function, u the dependent variables, β (0) is a constant, and β (1-6) are coefficients. Additionally, t refers the period, i the geographic unit, and ε the error. The statist tool used to run the GLMs was Eviews 12.

$$g((u)_{it}) = \beta_0 + \beta_1 RREH_i + \beta_2 ELP_{it} + \beta_3 TLE_{it} + \beta_4 EID_{it} + \beta_5 CG_{it} + \beta_6 ARP_{it} + \varepsilon_{it} \ (Eq. 6)$$

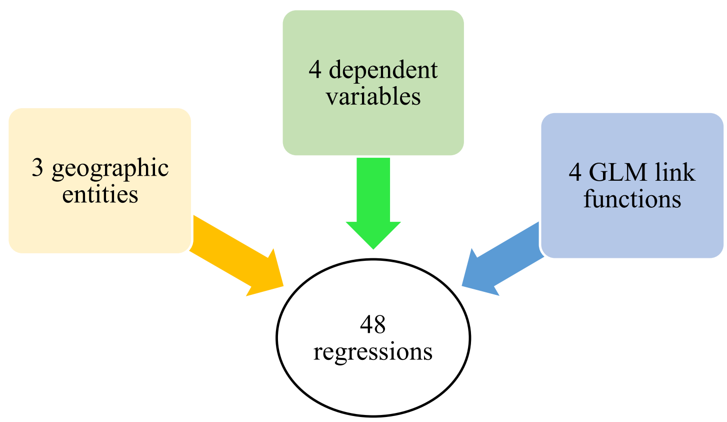
The Appendix 4 shows the descriptive statistics of each independent variable per each geographic entity. As is shown in this, there is not data missing for the period of evaluation.

3.6. Energy poverty generalized linear models

3.6.1. Models' selection criteria

As I explained before the link function between the dependent and independent variables is unknown. To determinate the best link function I tested 4 link functions: linear, log, logic and inverse, per each dependent variable at each geographic entity. In total 48 regressions were tested, the Figure 4 shows how this amount was obtained.

Figure 4 Energy poverty GLMs (source: own elaboration)



In addition, I selected the best regression per each dependent variable at each geographic unit. Thus 12 GLM were selected according to the following criteria:

a) Deviance: values closer to 0 means better fit data,

b) Prob. (LR statistic): 3 different p-values p*<0.01, p**<0.05, p***<0.1 were considered as acceptable,

c) Pearson statistic: values different from 0 mean independent and dependent variables correlation,

d) Akaike info criterion: the lower value of this indicates a better fit of the link function to the dependent variable.

As I explained before a normal distribution of the errors was assumed following the results presented in Table 3. To validate this, a normality test will be performed for each regression, considering p-values greater than 0.05 in order not to deny the null hypothesis of normal distribution. Finally, the Appendix 5 has the 48 regressions and their normality tests' details.

3.6.2. Energy poverty generalized linear models

I named the 12 selected models using the EP indicators abbreviations. The Table 4, Table 5, and Table 6 show the energy poverty models selected by applying the criteria of the former section. As is shown in the case of the EU and Greece all the models got accepted p-values, however, in the case of Denmark only one model got a relevant p-value. In addition, the tables show the link function between the dependent and independent variables selected per each model. In the next sections the results and discussions will be based on those models.

Table 4 EU GLM regressions details (source: own elaboration)

	IKW	**AUB**	**HC**	**EPCI**
Error distribution (Random component)	Normal distribution	Normal distribution	Normal distribution	Normal distribution
Link function	Inverse	Inverse	Inverse	Inverse
Deviance	9.45E-06	8.00E-06	1.13E-08	4.54E-06
Prob. (LR statistic)	0.0000*	0.0000*	0.0000*	0.0000*
Pearson statistic	9.45E-06	8.00E-06	1.13E-08	4.54E-06

p<0.01;p**<0.05;p***<0.1*

Table 5 Denmark GLM regressions detail (source: own elaboration)

	IKW	**AUB**	**HC**	**EPCI**
Error distribution (Random component)	Normal distribution	Normal distribution	Normal distribution	Normal distribution
Link function	Identity	Identity	Inverse	Inverse
Deviance	3.54E-06	1.81E-04	1.11E-04	4.88E-05
Prob. (LR statistic)	0.0000*	0.9831	0.5291	0.6111
Pearson statistic	3.54E-06	1.81E-04	1.11E-04	4.88E-05

p<0.01;p**<0.05;p***<0.1*

Table 6 Greece GLM regressions detail (source: own elaboration)

	IKW	**AUB**	**HC**	**EPCI**
Error distribution (Random component)	Normal distribution	Normal distribution	Normal distribution	Normal distribution
Link function	Inverse	Identity	Inverse	Inverse
Deviance	5.81E-05	2.47E-05	4.99E-07	1.39E-04
Prob. (LR statistic)	0.0000*	0.0000*	0.0000*	0.0000*
Pearson statistic	5.81E-05	2.47E-05	4.99E-07	1.39E-04

p<0.01;p**<0.05;p***<0.1*

4. RESULTS

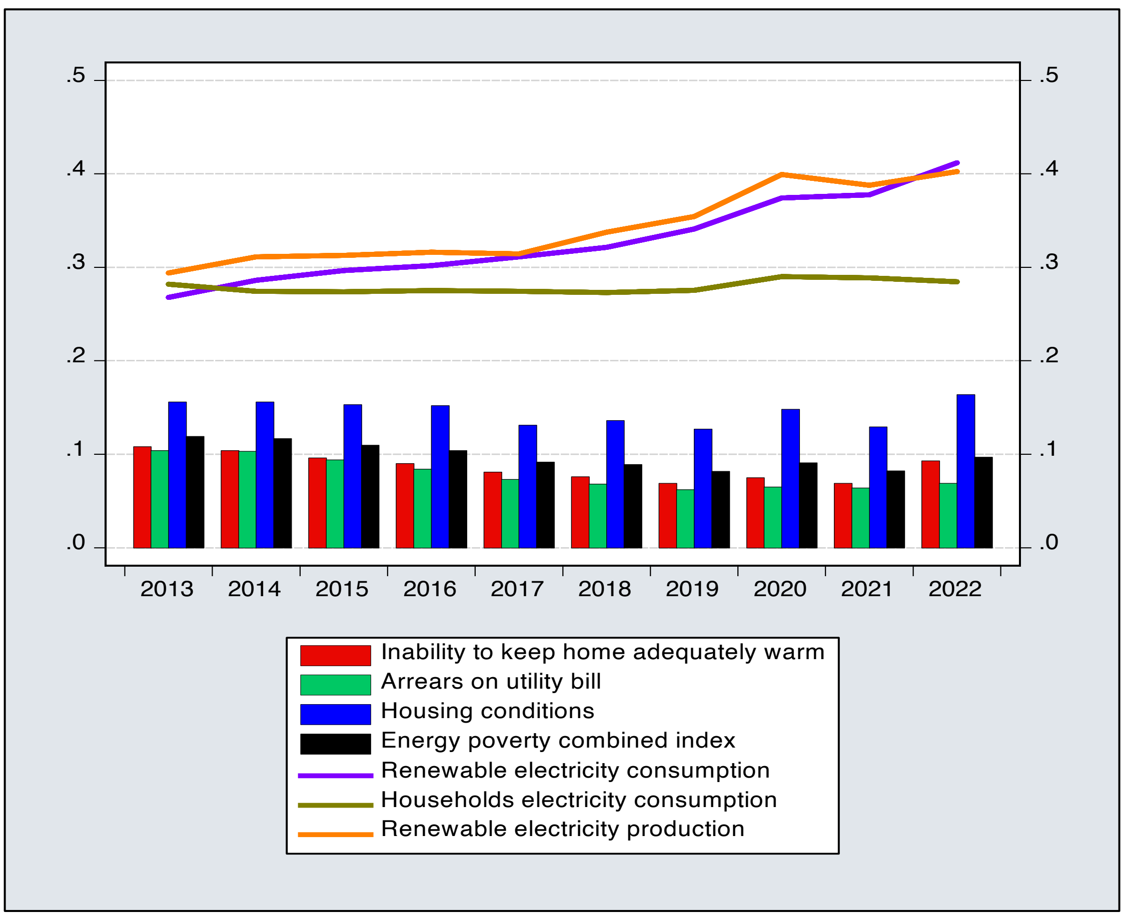
Before to review the results, is necessary to provide some guidelines about how to read them. The results will be shown in two tables. The first will elucidates general information such as the link function selected. The second table will show the regression coefficients and the p-value for each independent variable. In inverse regressions, a positive coefficient means that when the independent variable increases the dependent variable decreases. A negative coefficient means that when the independent variable increases, the dependent variable also increases. For identity regressions, the relationship is direct, positive coefficients mean that an increase in the independent variable generates an increase in the dependent variable. For negative coefficients the effect is the opposite.

4.1.Energy poverty in the EU

4.1.1. Energy poverty situation in the EU

The Figure 5 shows a comparison between the EP indicators and the evolution of the consumption and production of renewable electricity in the EU between 2013 and 2022. Since 2013 until 2017 the production and consumption of renewable electricity remained constant at around 30%. However, after 2018 they have increased by 10%. Also, the households' electricity consumption has not seen any significant change over the same period.

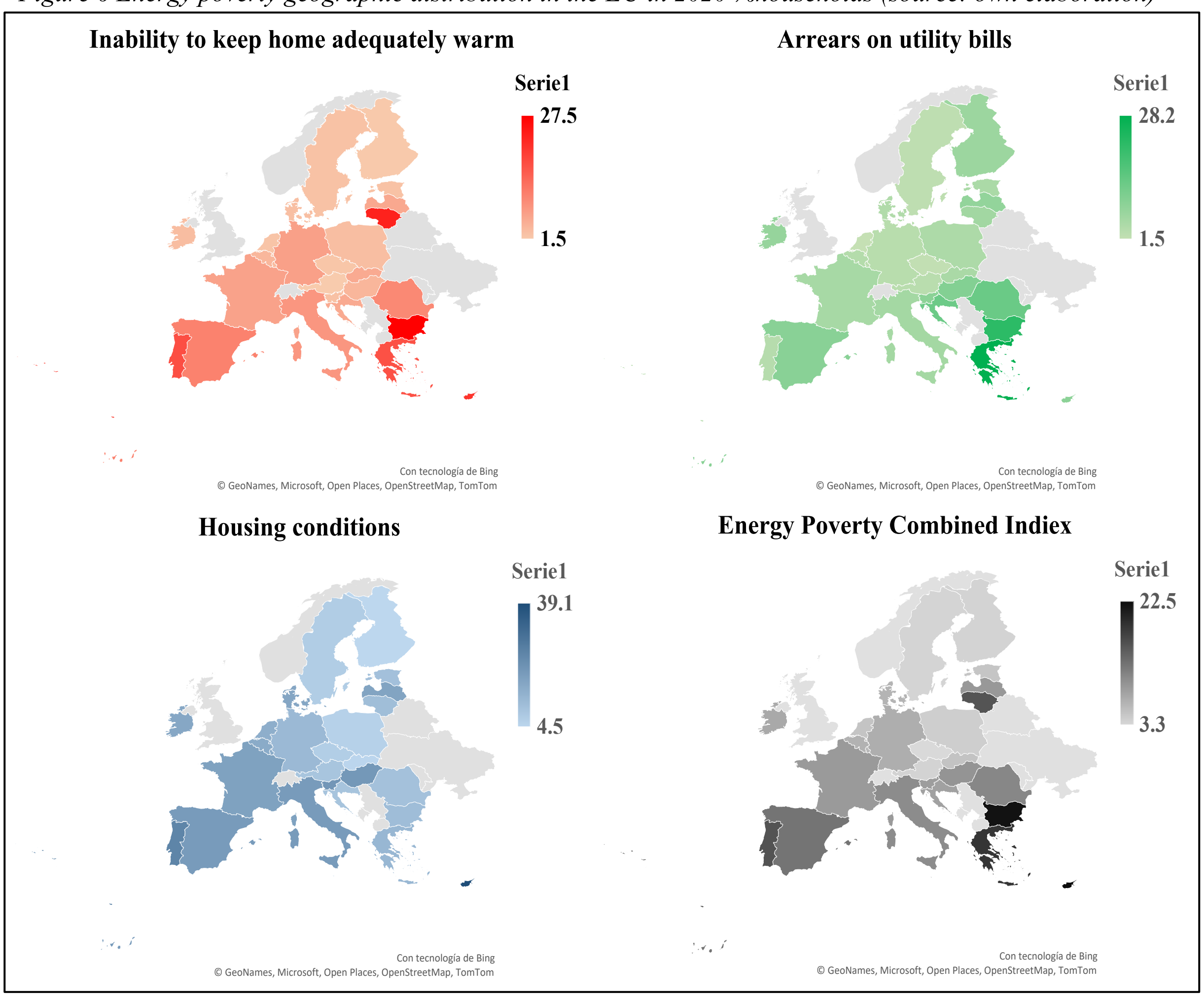
Figure 5 Energy poverty vs renewable consumption and production in the EU in % (source: own elaboration)



In terms of energy poverty from 2013 until 2019 there was a clear reduction trend, however from 2020 the trend reversed to an increase of all the indicators with different rates. Regarding to the EP indicators, HC had values higher than IKW and AUB. On average HC was 14.5% of total households, which means that a significant portion of Europeans live in homes with inappropriate physical conditions. Moreover, IKW was 9% which in terms of population according to the Commission Recommendation (EU) 2023/2407 on energy poverty represents 40 million Europeans. It is possible to underline that although since 2020 the consumption and production of renewable electricity had a significant increase, the EP levels increased. The reasons behind this are related to inflation and the energy crisis produced by the Covid-19 pandemic and the Ukrainian innovation.

Moreover, the Figure 6 elucidates a geographic distribution of EP indicators in the EU in 2020. It is possible to identify a trend: while northern and central European countries had low levels of EP, southeastern countries had the highest levels. Contrasting the Figure 5 and the Figure 6 it can be seen that between EU and national EP levels differ substantially. For example, in 2020 AUB in the EU was less than 13% of households, while in Greece it was slightly above 28% and in Denmark it hovered around 4%. This reinforces the need to compare supra-national and national level analyses to determine whether energy poverty policies are achieving their objectives. On this basis, it is possible to state that energy poverty represents a major challenge for the EU and its Member States. This requires each country to adapt the EC recommendations to its national context, as stated by Bouzarovski et al. (2021).

Figure 6 Energy poverty geographic distribution in the EU in 2020 %households (source: own elaboration)



4.1.2. EU energy poverty model results

The EU regressions models' results are presented in the Table 7, in brackets I show the link function between the dependent and independent variables per each model.

Table 7 EU GLM regressions independent vs dependent variables detail (source: own elaboration)

Dependent / Independent Variables	Hypotheses	IKW (inverse)		AUB (inverse)		HC (inverse)		EPCI (inverse)	
		Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
RREC	**H1**	-84.3768	0.3560	65.3278	0.2634	19.6057	0.0000*	-38.7415	0.4190
HEC	**H1**	-55.3607	0.6181	-130.7122	0.2655	-50.5975	0.0000*	-7.6943	0.2175
RREP	**H2**	40.1859	0.4618	-101.0979	0.3087	-26.0866	0.0000*	11.2567	0.6969
ELP	**H3**	187.3600	0.1033	180.4648	0.1568	33.4431	0.0000*	127.2689	0.0307**
TLE	**H3**	409.4366	0.0217**	380.4332	0.0541***	94.1189	0.0000*	268.9017	0.0032*
EID	**H4**	-9.5995	0.7564	-11.3333	0.7316	-17.9191	0.0000*	-15.1866	0.3410
GC	**H5**	328.2189	0.2276	-667.8567	0.0181**	-36.2478	0.0000*	-265.7743	0.0616***
ARP	**Control variable**	113.7690	0.5139	141.0866	0.4508	-84.6426	0.0000*	33.6896	0.7106

p<0.01;p**<0.05;p***<0.1*

4.1.2.1.Inability to keep home adequately warm (IKW)

The p-values presented in the Table 7 show the consumption and production of renewable electricity, and the share of households in electricity consumption did not have impact on the dependent variable. On the other hand, the p-value of TLE was < 0.01 showing taxes influenced on IKW levels. It is important to highlight that TLE only includes taxes and levies related to operation of the infrastructure, environmental performance and promotion of renewable energies. TLE got a positive coefficient, which means that an increase of TLE led to a decrease of IKW. This result is not in line with the theory that lower taxes should reduce EP. Liobikienė et al. (2019) highlight that energy taxes have produced an increase of electricity prices, and even when their aims were to foster renewable energies' consumption those have had the opposite effect. Thus, the result shown can be influenced by the mix of electricity market systems with different characteristics, pricing, taxation and subsidies schemes. The lack of a standardized EU-wide electricity pricing system makes the use of price variables for supranational regression models invalid. Thus, the results of grouping different systems are variables with trends that differ from the trends observed in each EU Member State, producing erroneous conclusions. My results are in line with Primc & Slabe-Erker (2020), who concluded that this characteristic leads to make wrong conclusions from a supranational level.

4.1.2.2. Arrears on utility bill (AUB)

The results in the Table 4 show that the inverse regression got a p-value of <1%, which validates it use for estimating AUB. Regarding to the independent variables, the Table 7 shows that the taxes and levies, and the Gini coefficient had an influence on AUB. The coefficient of TLE was positive which means that an increase of it led to a decrease of AUB, contradicting the assumption that lower energy prices reduce EP. Again, it validates that the use of variables that mixed different electricity systems lead to make wrong conclusions in empirical analysis.

Moreover, CG got a negative coefficient, which means that a reduction of income inequality led to reduce the levels of AUB. It is in line with the literature review presented in the chapter 2. Regarding to the other variables their p-values elucidate they did not impact on AUB.

4.1.2.3. Housing conditions (HC)

The Table 4 shows that the inverse regression has a p-value of <1% which validates use of the regression for estimating HC. Furthermore, the Table 7 shows that all the independent variables can explain HC having p-values <1%. On this basis, renewable electricity had different impacts in this EP indicator. The coefficients show that an increase in RREC caused a decrease in HC. While for the same period an increase in RREP and HEC produced an increase in HC.

Moreover, ELP and TLE have positive coefficients showing that higher prices of renewable electricity reduced HC. It contradicts the literature review about energy affordability. This shows that the combination of different electricity pricing and taxes systems into a single variable distort the models' results, as was explained before. Regarding CG and ARP got negative coefficients. This means the lower the risk of monetary poverty and income inequality, the lower the levels of HC. Also, EID has also a negative coefficient underling that lower levels of energy dependency decreased HC.

4.1.2.4. Energy poverty combined index (EPCI)

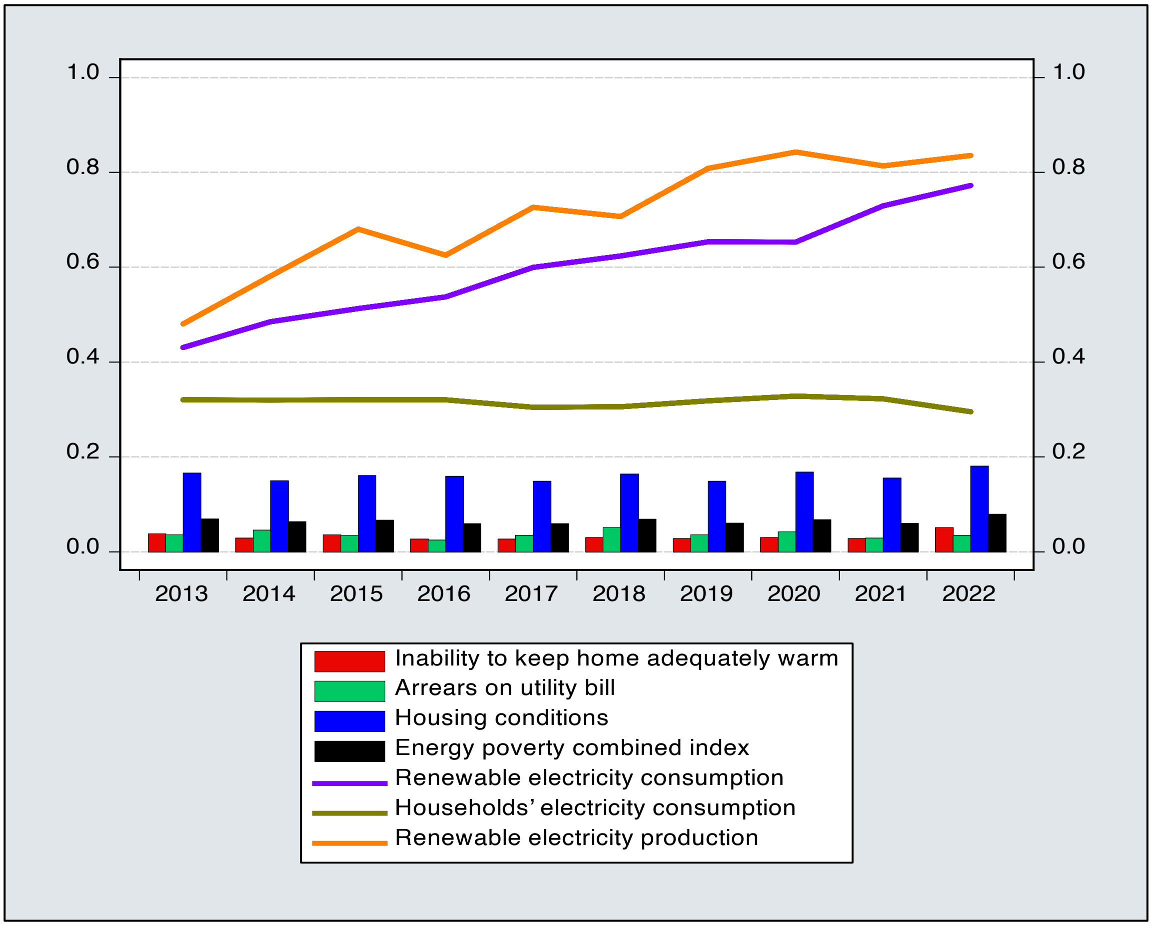
The results in the Table 4 show that the GLM inverse regression has a p-value of <1%, which means the model can be used to estimate EPCI. The Table 7 shows that only ELP, TLE and CG got significant p-values. On one hand, the coefficients elucidate that higher prices and taxes on electricity reduced EPCI. These results are in line with previous explanations about the use of variables that gather different electricity pricing systems. On the other hand, the coefficients also show that lower levels of income inequality led to lower EPCI.

4.2.Energy poverty in Denmark

4.2.1. Energy poverty situation in Denmark

The Figure 7 shows the evolution of renewable electricity consumption, production and households sharing versus the EP indicators in Denmark between 2013 and 2022. While RREC and RREP increased by 50%, EP indicators have not seen any significant change. In contrast, even though maximum values of RREC and RREP were reached in the last 3 years, EP values increased following the EU trend. Within the EP indicators, since 2020 there has been an upward trend. By 2022 IKW, AUB and HC, reached 5%, 4%, and 18% of total households respectively. Moreover, Denmark has one of the lowest energy poverty levels in the EU. However, Denmark's HC levels was worse than the EU average, representing almost 16% of households.

Figure 7 Energy poverty vs renewable consumption and production in Denmark in % (source: own elaboration)



4.2.2. Energy poverty model results

The Table 8 shows that the only regression which p-value is significant is for IKW, while for the other regressions cannot be used. Furthermore, the Table 8 indicates that the independent variables only had a statistically influence on IKW, while for AUB, HC and EPCI they did not. This result shows how difficult it is to try to represent EP through a single economic model, highlighting the complexity of this challenge. Thus, analyzing the validity of the GLM regressions for predicting the dependent variables, the results show great variability. The causes behind this could be related to the data quality, the amount of observation, or even the use of other statistics methods. The strengths of the models I have used are based on the ability to analyze different link functions to find the one that best fits the data. However, statistical models such as those used by Kocack et al. (2023), and Rodriguez-Alvarez et al. (2021) may have higher capabilities for determining statistical significance in cases where the value of the dependent variable at an earlier time may affect its value at a future time. This development leads to claim that the complexity of EP cannot be capture in an only model. Moreover, its statistical relationship with the energy transition requires more research. However, the results obtained in the present thesis can be used to test the hypotheses raised at the end of the chapter 2. Also, they can be employed to bridge the differences between a supranational analysis and a member state level analysis.

Table 8 Denmark GLM regressions independent vs dependent variables detail (source: own elaboration)

Dependent / Independent variables	Hypotheses	IKW (identity)		AUB (identity)		HC (inverse)		EPCI (inverse)	
		Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
RREC	**H1**	-0.0793	0.0010*	-0.0778	0.6515	-0.4928	0.9270	12.9128	0.5979
HEC	**H1**	-0.0713	0.7070	0.0330	0.9806	18.2658	0.6882	28.8338	0.8767
RREP	**H2**	0.0149	0.5252	-0.0080	0.9616	4.3230	0.4182	5.9509	0.7841
ELP	**H3**	0.1863	0.0000*	-0.0313	0.8884	-5.2462	0.4528	-26.3206	0.3451
TLE	**H3**	0.3850	0.0063*	-0.3421	0.7339	-47.0545	0.1634	-97.8056	0.4617
EID	**H4**	0.0334	0.0459**	0.0279	0.8155	-6.0376	0.1290	-14.9689	0.3531
GC	**H5**	1.1895	0.0001*	1.0742	0.6287	79.4301	0.2887	187.4093	0.5145
ARP	**Control variable**	0.8077	0.1406	2.1835	0.5768	-1.6987	0.9891	-241.5915	0.6343

p<0.01;p**<0.05;p***<0.1*

4.2.2.1.Inability to keep home adequately warm (IKW)

The Table 8 presents that between RREC, REEP and HEC, only the former had a significant influence on IKW. Its coefficient was positive which means that the higher the consumption of renewable electricity, the lower IKW. Furthermore, ELP and TLE got p-values <1% with positive coefficients. This shows that as electricity prices rose, the level of energy poverty increased. Moreover, EID got a significant p-value with a positive coefficient. This means that the greater the dependence on external resources, the higher the EP levels were. Finally, the Gini coefficient got a p-value <0.01 with a negative coefficient. This result means that an increase of income inequality led to a decrease of IKW.

4.3.Energy poverty in Greece

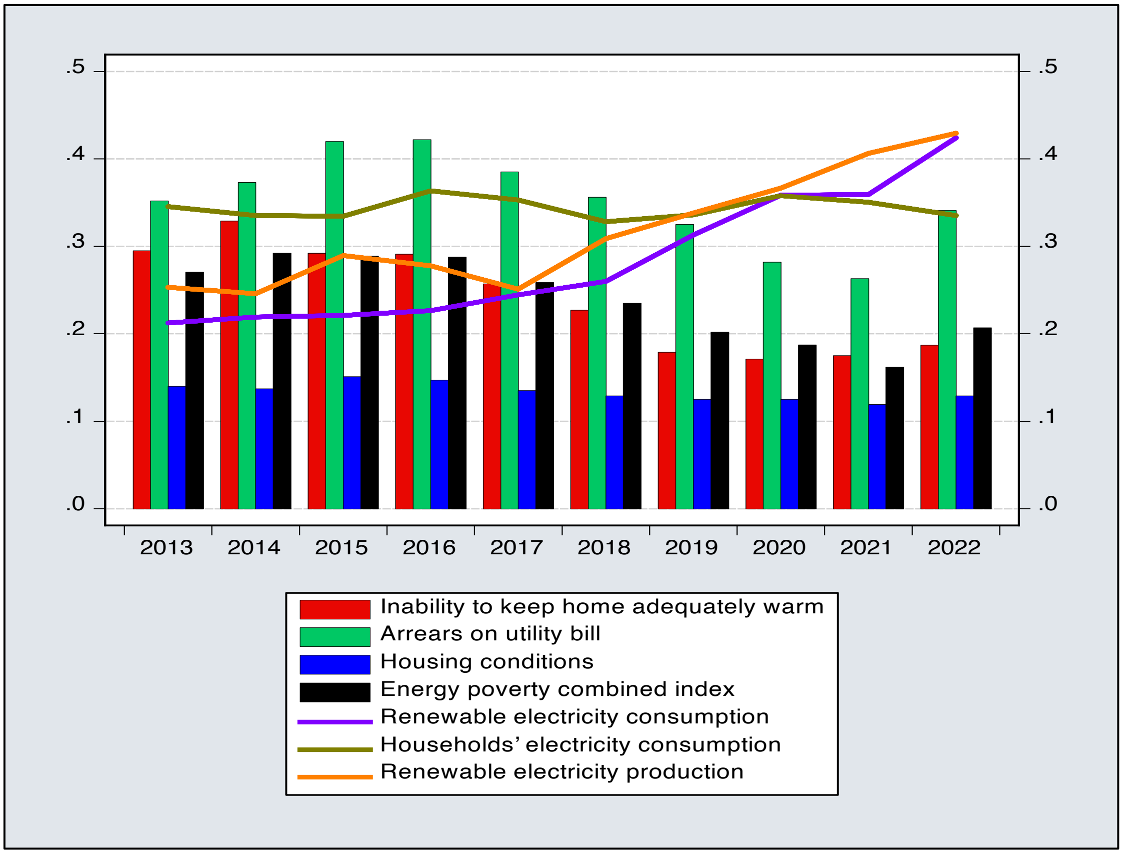
4.3.1. Energy poverty situation in Greece

The Figure 8 shows a comparison between the energy poverty indicators and the production and consumption of renewable electricity, and households' share in the market in Greece from 2013 until 2022. Both consumption and production of renewable electricity did not have any important change until 2016. However, from 2017 both increased by on average 23% reaching the EU's levels by 2022. This follows the European trend to increase the share of renewable energies. Regarding households' electricity consumption, this fluctuated around 35% remaining steady.

Whitin the EP indicators, AUB reached values over 40% of total households in 2015 and 2016. In comparison with the EU, Greeks households performed better in terms of HC. But regarding the other indicators their performance was by far over the European's performance classifying it as high energy poor country. However, since 2016 until 2021 the level of EP dropped significantly by 15% on average. Moreover, following the EU's trend from 2021 EP increased reaching the levels recorded in

2018. By 2022 almost 35% of total households could not pay their energy bills on time, and 20% could not keep their homes warm in the same year.

Figure 8 Energy poverty vs renewable consumption and production in Greece in % (source: own elaboration)



4.3.2. Energy poverty model results

The Table 9 summarized the regression results for the case of Greece. In this case, the results only show a relevant statistical influence of the independent variables on IKW, AUB and HC, so the explanation of results will only be made on these three independent variables.

Table 9 Greece GLM regressions dependent variable vs independent variable (source: own elaboration)

Dependent / Independent variables	Hypotheses	IKW (inverse)		AUB (identity)		HC (inverse)		EPCI (inverse)	
		Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
RREC	**H1**	-1.4552	0.8588	-2.5138	0.0000*	16.9628	0.0000*	5.6178	0.6288
HEC	**H1**	14.0647	0.2065	1.2687	0.0002*	5.5295	0.0424**	17.9287	0.2760
RREP	**H2**	4.4393	0.0852***	-0.0114	0.9214	-4.2908	0.0000*	4.9344	0.2238
ELP	**H3**	17.2303	0.5089	3.7194	0.0000*	3.2019	0.5857	25.6706	0.4912
TLE	**H3**	26.5856	0.3876	3.6753	0.0000*	7.9467	0.2563	39.2294	0.3771
EID	**H4**	-0.0618	0.9880	0.4568	0.0001*	-12.9433	0.0000*	-8.8648	0.1414
GC	**H5**	-121.6853	0.0493**	7.6804	0.0000*	-29.7600	0.0452**	-67.9682	0.4404
ARP	**Control variable**	38.6237	0.1215	2.3640	0.0033*	-38.8882	0.0000*	17.1514	0.6345

p<0.01;p**<0.05;p***<0.1*

4.3.2.1. Inability to keep home adequately warm (IKW)

The Table 9 elucidates that the only variables which significant p-values were RREP, and GC. The production of renewable electricity got a positive coefficient. It means that higher production of renewable electricity led to reduce EP. Also, the GC has a negative coefficient validating the premise that the lower income inequality, the lower energy poverty.

4.3.2.2. Arrears on utility bill (AUB)

The Table 9 shows that the only independent variable with a p-value > 10% was the production of renewable electricity. RREC got a negative coefficient showing that an increase of renewable electricity consumption led a decrease of AUB. Whereas the share of households on electricity consumption got a positive coefficient, which means that it had a negative impact on AUB.

Moreover, the electricity prices and taxes got a positive coefficient validating the literature review about the impacts of affordable energy in the mitigation of EP. In this line, CG obtained a positive coefficient, which show that an increase on income inequality led to an increase of AUB. Finally, EID also got a positive coefficient elucidating that an increase in energy security led to a reduction in EP.

4.3.2.3. Housing conditions (HC)

The Table 9 shows that the only independent variables with a p-value > 0.1 were electricity prices, and taxes and levies. RREC, and HEC got a positive coefficient elucidating that an increase of those variables led a decrease of EP. In contrast the production of renewable electricity showed a negative coefficient having a negative impact in the reduction of HC.

Furthermore, EID and ARP got a negative coefficient showing that an increase of energy insecurity and risk to poverty led to an increase of HC. The Gini coefficient got a negative coefficient meaning that the higher income inequality, the higher levels of HC.

A general comparison of the results shows a greater impact of socioeconomic variables on EP indicators than renewable electricity penetration. In none of the geographic units were statistical correlations found for all hypotheses 1 and 2. This shows that the penetration levels of renewable electricity have not had a strong impact on the reduction of EP. Furthermore, at the EU level the use of variables that bring together different electricity pricing and taxation systems distort the trends leading to erroneous conclusions. On the other hand, when comparing Greece and Denmark, I have found that socio-economic variables have had a greater impact on the former. The reason for this evolution can be found in the EP driver. In this regard, Bouzarovski & Tirado Herrero (2017) identified different drivers across Europe. The scholars found that the drivers of PE in northern countries are related to energy prices and inequalities in energy access. In contrast, in southern countries they are related to income inequalities, lack of energy access and economic poverty. Thus, it can be deduced that the reduction of EP would be more related to socioeconomic factors than to the penetration levels of renewable energies. This can be clearly seen in Denmark. Despite the high levels of renewable electricity, the apparent success in reducing PE is based on its levels of social protection.

5. RESULTS DISCUSSIONS

The analysis I have conducted has found three key messages: first, measuring energy poverty levels remains complex. Second, I have not found a strong correlation between renewable electricity production and consumption and EP reduction. And third, EP has been more affected by socioeconomic variables such as income inequality or electricity prices. These will be explained in detail below.

5.1. Energy poverty measurement

Thomson et al. (2017) stress the multidimensional nature of EP. This shows that EP can be affected by social gaps, geographic location, access to education, economic poverty, among others. This complex context cannot be capture in a single indicator as Castaño-Rosa et al. (2019) indicate, for which the use of more than one indicator is more appropriate. Furthermore, the most extended data source for EP in the EU is the EU-SILC survey published by EUROSTAT, and it has a consensual approach. Among its criticisms, its subjectivity is underlined, leaving it to the interpretation of the households to recognize themselves as energy poor. Another criticism is that the survey is not intended to measure EP, as Petrova et al. (2013) highlight.

Other weakness of energy poverty studies is the lack of information. In this research I had to deal with this. For the years 2021 and 2022 HC is not available in EUROSTAT. However, it was estimated through GLM regressions to bridge this gap. Therefore, is relevant that The EU must ensure the continuity of the indicators and avoid the previous year's data become obsolete. The discontinuity of data represents significant challenges for EP policymakers when it comes to analyze the policies' results. Whitin the recommendations to improve EP measurement, Thomson et al. (2017) recommend to implementing a separate survey for EP. With this, the scholars claim would be possible to get more details about the causes, and aspects that influence EP. Moreover, some indicators such as IKW should adjusted introducing the option of cooling. This recommendation is becoming relevant in the face of heat waves in southern Europe as Thomson et al. (2017) stress. Despite the EU-SLIC survey's weaknesses, currently it is the most reliable data source in the EU. This has been supported by Thomson & Snell (2013), Petrova et al. (2013), and Rodriguez-Alvarez et al. (2021). On this basis, four indicators were used to measure and elucidate the context of energy poverty in the EU and in two Member States. When comparing the geographic distribution of the EP indicators I could establish a trend. It shows that northern European countries performed on average better than southern countries, but not for all the EP indicators. These results are in line with the argument that it is not possible to capture in a single indicator all the factors that influence household EP conditions. In this way, analyzing these indicators separately without a complementary approach may lead to erroneous conclusions.

Additionally, I found that indicators subjectivity may influence on households' answers as was introduced before. This argument can be appreciated in the level of EP in 2020 and 2021. I expected that because of the economic impact of the Covid-19 pandemic energy poverty would increase, as also stated by Bouzarovski et al. (2020). However, in Greece the downward trend that began in 2016 did not stop, while in Denmark the increase was not significant. At the EU level, the numbers show an increase of in 2020 but in 2021 these dropped to 2019's levels. On one hand, these results could be related to Member States' efforts to provide financial support to cover high energy prices. This may distort conclusions about the effects of the increase in renewable electricity in those years. On the other hand, this trend can be related to subjectivity of the survey. This highlights the role of data reliability in analyzing policy outcomes. This in turn reinforces the need for tools focused on measuring EP, both directly and indirectly.

In general, the use of more than one indicator to measure EP provided a clear picture about its multidimensional aspects such as location, economy, genre, energy policies, among others. For instance, the geographic location influence in the cooling or warming needs of households. The economy influences in their possibility to face energy prices. Income inequality makes women more vulnerable to ended up under EP, and energy policies pave the way to mitigate or increase EP. This characteristic can only be collected when using more than one indicator. On this basis, this complexity is already capture in European Commission energy poverty definition. Thus, policymakers should propose mitigation strategies and performance measures according to the situation of each EU Member State. Finally, despite the weaknesses of the EU-SILC survey, this tool offers the possibility of determining whether EP policies are achieving their objectives. This calls for studies to be carried out at the local level. This calls for studies at the local level, considering the diversity of socio-economic contexts among EU countries. This is to avoid inappropriate generalizations.

5.2. The effects of renewable electricity on energy poverty

My results do not show a strong correlation between renewable electricity and PE reduction. What I have found is an impact that varies partially depending on the geographic unit of analysis. For the EU renewable electricity only had impact on HC showing positive outcomes for its consumption, but negative for its production. For case of Denmark and Greece, the results can be compared by indicator. Therefore, for the case of IKW the consumption of renewable electricity had positive impacts in Denmark, while in Greece the positive impact come from its production. Moreover, in the case of AUB, both production and consumption of renewable electricity had impacts only in Greece, which was positive. For the case of HC there were only impacts in Greece, where renewable electricity consumption had positive outcomes, while its production impacted negatively. Thus, the results do not show a clear trend of positive or negative impacts on all EP indicators at EU and Member States levels. However, renewable electricity consumption has shown positive results on at least one indicator per geographical unit, while production shows mixed results. Thus, it elucidates that the increased consumption of renewable electricity has had to some extent a positive impact on the reduction of EP. On the other hand, Swain & Karimu (2020) claim that higher demand for renewable electricity has led to higher prices in the EU, which should have increased EP. These opposing conclusions can be explained through the role of state subsidies to mitigate rising energy costs, or to encourage renewable self-generation. In this way, Pye et al. (2015) highlight that financial support measures for the payment of energy bills are in place in all EU Member States. These measures have obtained positive results in the short term, but it is crucial to deploy tools to address EP drivers in the long term. As for renewable electricity production, the variability of the results does not allow us to identify a pattern. However, it can be stated that its impact is more visible through electricity prices, and the liberalization of the electricity markets.

The last paragraph leads to conclude that European policies to foster more renewable energies has generated different impacts between the EU and the Member States. Thus, is clear that the EU energy transition is aimed to replace the existing energy carriers, and the level of EP has been reduced. However, is also clear that this development is increasing economic burdens on households, for which EU Member States have had to provide economic support to cope with them. Moreover, coscript the analysis of the role of renewable electricity in the mitigation of EP only at EU level can generate wrong conclusions. In addition, the variability of results between Greece and Denmark, countries with different EP levels, leads to conclude that renewable electricity's impacts should be analyzed in relation to their socioeconomic context. Which can be related with the implementation of specific policies, and how the transition is being addressed.

On one hand Bouzarovski et al. (2021) underline that the technical and economic gaps between EU Member States to mitigate EP led to obtain different results. Thus, societies with better economies and lower inequalities, such as Denmark, have maintained lower energy poverty than societies with higher monetary poverty and inequalities, such as Greece. This result was also found by Rodriguez-Alvarez et al. (2021). The scholars underline the role of social assistances in the mitigation of EP is crucial and has got positive results in countries with higher economic resources. This leads to supply social protection to vulnerable households and enhance subsidies schemes. Thus, in these countries, it has been possible to mitigate the negative effects of the liberalization of the electricity market and the introduction of renewable sources in it. However, Bouzarovski et al. (2021) found that in most of them the approach about EP has been packaged as part of the monetary poverty like the case of Denmark. Which has generated that strategies are focused on provide economic support than in eradicate energy poverty's drivers. This statement can be corroborated by analyzing the EP performance in Denmark. While IKW and AUB, indicators related to direct subsidies from the government, were by far under the EU average, indicators not related to subsidies such as HC got levels over the European's average. Moreover, these strategies lead to almost unchanged EP levels over time. However, their sustainability depends on how long governments can continue to provide financial assistance to households, as stated by Bouzarovski et al. (2021). In addition, some countries with high levels of EP have specific policies to cope with it, developing their own definition, indicators and strategies. Thus, the approach has been focused on eradicate EP drivers as is the case of Greece, where energy poverty was significantly reduced between 2015 and 2021. This has been possible thanks to three types of policies such as Streimikiene et al. (2021) state. The first focused on giving tax incentives to the renovation of homes with the aim of increasing energy efficiency. As well as information campaigns on the best use of energy and to a lesser extent economic support through social rates. The impacts of these policies can be observed in Greece's HC levels showing lower levels than those obtained in Denmark. However, the economic repercussions of the Covid-19 pandemic and the 2022 energy crisis undermined the results of these policies, causing energy poverty to rise sharply again. On the other hand, all the results elucidate the impacts of electricity prices on the levels of EP, which can be related to the way the energy transition is being addressed. Hiteva (2013), and Muhammad et al. (2023) stress two reason of this, the liberalization of energy markets fostered by the EU since 1990s, and the incorporation renewable energies in the power mix. Thus, the privatization of energy companies together with the vertical integration has increased the prices. Moreover, the goals to achieve carbon neutrality and energy independency have transferred the burden of carbon externalities to electricity prices, as Primc & Slabe-Erker (2020) state. As a result of this, households in countries with highest level of economic poverty are facing more difficulties to pay their utility bills on time like the Greece's numbers show.

In addition, in general my results across the three geographic entities stress more impacts of socioeconomic variables on EP levels than the consumption and production of renewable electricity. Thus, the effects of the energy dependency index on EP show that higher dependency on external energy resources impact negatively on EP. This is supported by the lack of capacity of energy resource-importing countries to control prices. For example, the restriction of natural gas supply to Europe generated a crisis, which in turn increased EP in all EU Member States in 2022. Kuzemko et al. (2022) highlight that the consequences of this crisis have enhanced the need to achieve energy security through participation of renewables in the market. As proof of this, The European Commission launched the REPowerEU plan to catalyze the net-zero goal by 2050. To achieve this the EU is going to deploy more capitals into renewables to accelerate its penetration However, scholar such as Muhammad et al. (2023) claim that in capital-intensive stages renewables energies can increase price. This side effect may translate into more difficulties for households to meet their energy needs, generating a possible further increase in EP. Moreover, in all the geographic units, the electricity prices, taxes and levies, as well as income inequality, at risk of poverty and energy security have had negative outcomes on EP indicators. These results clearly show the socioeconomic face of energy poverty. On this basis, although the models' results show partially positive effects of renewable electricity consumption on some EP indicators, the intervention of the states to control their side effects has been crucial. The literature used in this subchapter shows that electricity prices have increased due to the increase of renewable energies in the electricity market. This has shifted economic burdens to households and has led to governments having to implement subsidy schemes. Therefore, it can be concluded that the trend to produce and consume more renewable electricity has neither mitigated nor eradicated energy poverty in the EU. Rather, the reduction of EP observed in the EU or in countries such as Greece is based on economic subsidies and the reduction of monetary poverty and income inequality.

Finally, with respect to the hypotheses raised in the literature review it is noticeable that the reduction of EP relays more in socio-economic aspects (H3/H4/H5) than in the rate of renewable electricity production or consumption (H1/H2). On one hand, northern European countries with better economic performance and less inequalities have more possibilities to increase the penetration of renewable electricity and control its negative effects. Which is based on their higher capacities to financially support the most disadvantaged households. This is why, despite the increase in electricity prices, their energy poverty levels have remained almost unchanged. On the other hand, mediterranean countries with worse economic performance are facing more difficulties to cope with the impacts of the energy transition. These difficulties have made it possible to deploy policies focused on reducing energy poverty, with positive results, as in the case of Greece. However, their weak capacity to cope with economic and energy crises produces rebound effects. This is easy to appreciate in the Greek case, where after reducing EP by almost 15% between 2015 and 2021, in the year 2022 EP levels increased by an average of 9%. On this basis, it can be concluded that the mitigation of EP is related to the government's capacity to cope with higher energy prices, with the countries' economic performance, and less inequalities than with more penetration of renewable energies.

6. CONCLUSIONS AND RECOMMENDATIONS

6.1.Conclusions

Although the definition of energy poverty is still a work in progress, the European Commission has endeavored to develop its own definition. The aim of this is to recognize energy poverty as a substantial challenge for EU Member States. The impact of which was felt in the deprivation of keeping the homes of 40 million European citizens warm in 2022, as shown by EUROSTAT data. Also, institutions whose main task is to measure and combat fuel poverty in the EU have been created, such as the Energy Poverty Advisory Hub. Among the ways to measure EP the EU-SILC survey is the tool with the highest approval among scholars and the European Commission. However, it has disadvantages such as its subjective approach, and its lack of specific focus on energy poverty, which can lead to measurement errors. The first conclusion of this thesis is that since EP is a problem with complex socio-economic characteristics, improvements in its measurement strategies are required. These improvements come from the development of a specific survey focused exclusively on energy poverty. In addition to incorporating new weather patterns, such as the lack of cooling, and looking for more direct ways to measure deprivation on energy access, rather than just focusing on its consequences.

The European Commission has urged the EU Member States to enhance the energy transition as a tool to eradicate EP. In addition, this institution has identified mechanisms through which the energy transition could mitigate EP. This development led to two types of hypotheses. The first type (H1/H2) stated that countries with higher rate of increase in consumption and production of renewable electricity performed better in the reduction of EP. While the second type were focused on the mechanisms (H3/H4/H5). The results obtained do not show that the penetration of renewable electricity has had an impact on the reduction of EP. This leads to answer the research question by stating that based on the results obtained, renewable energies have not had a positive impact on the reduction of EP. On the contrary, the results validate the hypotheses 3,4, and 5. In this way EP reduction is more linked to socio-economic aspects such as electricity prices or income inequality. Therefore, success in reducing EP should focus on reduce energy prices, reduce income inequality and improve energy security. For which each EU Member State should develop policies to cope with EP based on their socio-economic context.

In this way, each EU Member States have created their own strategies to cope with EP. These have depended largely on their economic capacities to provide direct financial support to their citizens and the way that energy poverty is being addressed. Thus, countries with better economic performance have integrated EP as part of monetary poverty. While countries with weaker economies have deployed policies focused on combating its drivers. The results of the different strategies have varied among the countries. On the one hand, countries such as Denmark have maintained almost unchanged levels of energy poverty, while Greece has made progress in reducing it. Which leads to the conclusion that the reduction of EP is related to the governments' abilities to react against the causes of EP such as the increase of energy prices. In addition, even when renewable electricity is reaching records in consumption and production in the EU, a poor capacity to manage economic and energy crises is leading to an increase in EP. Thus, it is concluded that reducing energy poverty requires the deployment of policies focused on accelerate the necessary energy transition that leave no one behind ensuring affordable prices, enhancing energy security and reducing social gaps.

6.2. Recommendations

Since EP is socio-economic challenge which definition and measurement strategies that are still in progress, the first recommendation for further research is to study way to improve its measurement. In addition, will be relevant examine the effectiveness of the indicators suggested by Thomson & Snell (2013), Petrova et al. (2013), and Rodriguez-Alvarez et al. (2021). Regarding the energy transition, I recommend conducting research about it impacts in the electricity prices increase considering the policies focused on market liberalization and the European net zero-carbon goals. Moreover, it would be relevant to further research investigate the impact of approaches and policies against energy poverty implemented by EU Member States. As well as to study the impacts of the energy transition on energy poverty at the local level in each country.

REFERENCES

Awerbuch, S., (2006). Portfolio-based electricity generation planning: policy implications for renewables and energy security. *Mitigation and Adaptation Strategies for Global Change*, *11*, 693 – 710. DOI: 10.1007/s11027-006-4754-4

Bouzarovski, S., & Tirado Herrero, S. (2017). The energy divide: Integrating energy transitions, regional inequalities and poverty trends in the European Union. *European Urban and Regional Studies*, *24*(1), 69-86. DOI: 10.1177/0969776415596449

Bonatz, N., Guo, R., Wu, W., & Liu, L. (2019). A comparative study of the interlinkages between energy poverty and low carbon development in China and Germany by developing an energy poverty index. Energy & Buildings, 183, 817 – 831. https://doi.org/10.1016/j.enbuild.2018.09.042

Bouzarovski, S., Thomson, H., & Cornelis, M. (2021). Confronting energy poverty in Europe: A research and policy agenda. *Energies*, *14*(4), 858. https://doi.org/10.3390/en14040858

Bouzarovski, S, Thomson, H., Cornelis, M., Varo, A. & Guyet R. (2020). Towards an inclusive energy transition in the European Union: Confronting energy poverty amidst a global crisis. *European Commission: Brussels, Belgium*. doi: 10.2833/103649

Castaño-Rosa, R., Solís-Guzmán, J., Rubio-Bellido, C., & Marrero, M. (2019). Towards a multiple-indicator approach to energy poverty in the European Union: A review. *Energy & Buildings*, *193*, 36-48. https://doi.org/10.1016/j.enbuild.2019.03.039

Connolly, D., Lund., H., & Mathiensen, B.,V., (2016). Smart Energy Europe: The technical and economic impact of one potential 100% renewable energy scenario for the European Union. *Renewable and Sustainable Energy Reviews*, *60*, 1634 – 1633.

European Commission. (2020). Commission Recommendation (EU) 2020/1563 of 14 October 2020 on Energy Poverty. ELI: http://data.europa.eu/eli/reco/2020/1563/oj

European Commission. (2023). Commission Recommendation (EU) 2023/2407 of 20 October 2023 on energy poverty. ELI: http://data.europa.eu/eli/reco/2023/2407/oj

Child, M., Kemfert, C., Bogdanov, D., & Breyer, C.(2019). Flexible electricity generation, grid exchange and storage for the transition to a 100% renewable energy system in Europe. *Renewable Energy*, *139*, 80 – 101. https://doi.org/10.1016/j.renene.2019.02.077

Churchill S.A., & Smyth R. (2021). Energy poverty and health: Panel data evidence from Australia. *Energy Economics, 27*, 105219. https://doi.org/10.1016/j.eneco.2021.105219.

Directive 2009/72*. Directive (EU) 2009/72/EC of the European Parliament and of the Council of 13 July 2009 concerning common rules for the internal market in electricity and repealing Directive 2003/54/EC.* http://data.europa.eu/eli/dir/2009/72/oj

Directive 2009/73 *.Directive (EU) 2009/73/EC of the European Parliament and of the Council of 13 July 2009 concerning common rules for the internal market in natural gas and repealing Directive 2003/55/EC.* ELI: http://data.europa.eu/eli/dir/2009/73/2022-06-23.

Directive 2018/2001. *Directive (EU) 2018/2001 of the European parliament and of the Council of 11 December 2018 on the promotion of the use of energy from renewable sources.* *http://data.europa.eu/eli/dir/2018/2001/oj*

Directive 2019/944. *Directive (EU) 2019/944 of the European Parliament and of the Council of 5 June 2019 on common rules for the internal market for electricity and amending Directive 2012/27/EU (recast).* http://data.europa.eu/eli/dir/2019/944/oj

Directive 2023/179. *Directive (EU) 2023/1791 of the European Parliament and of the Council of 13 September 2023 on energy efficiency and amending Regulation (EU) 2023/955 (recast*). http://data.europa.eu/eli/dir/2023/1791/oj

Dong, K., Ren, X., & Zhao, J. (2021). How does low-carbon energy transition alleviate energy poverty in China? A nonparametric panel causality analysis. *Energy Economics*, *103*, 105620. https://doi.org/10.1016/j.eneco.2021.105620

Heshmati, A., & Abolhosseini, S. (2017). 15 European Energy Security: Challenges and Green Opportunities. In Arent, D., Arndt C., Miller, M., Tarp, F., & Zinaman, O. (Eds), *The Political Economy of Clean Energy Transitions* (pp 292 – 310). Oxford University Press. https://doi.org/10.1093/oso/9780198802242.001.0001

Hiteva, R. P. (2013). Fuel poverty and vulnerability in the EU low-carbon transition: the case of renewable electricity. *Local Environment*, *18*(4), 487-505. https://doi.org/10.1080/13549839.2012.752800

Inglesi-Lotz, R. (2016). The impact of renewable energy consumption to economic growth: a panel data application. *Energy Economics*, 53, 58 – 63. https://doi.org/10.1016/j.eneco.2015.01.003

International Energy Agency. (2014). *Energy Supply Security: Emergency Response of IEA Countries 2014*. https://iea.blob.core.windows.net/assets/73908149-4d6e-4f10-b626-d55c60ab3bd7/ENERGYSUPPLYSECURITY2014.pdf

International Renewable Energy Agency. (2017). *Electricity Storage and Renewables: Costs and Markets to 2030*. https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2017/Oct/IRENA_Electricity_Storage_Costs_2017.pdf

International Renewable Energy Agency. (2022). *Renewable Power Generation Costs in 2021.* https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2022/Jul/IRENA_Power_Generation_Costs_2021.pdf?rev=34c22a4b244d434da0accde7de7c73d8

Gorroño-Albizu, L., Sperling, K., & Djørup, S. (2019). The past, present and uncertain future of community energy in Denmark: Critically reviewing and conceptualising citizen ownership. *Energy Research & Social Science, 54*, 101231. https://doi.org/10.1016/j.erss.2019.101231

Kocak, E., Ulug, E., E., & Oralhan, B. (2023). The impact of electricity from renewable and non-renewable sources on energy poverty and greenhouse gas emissions (GHGs): Empirical evidence and policy implications. *Energy, 272*, 127125. https://doi.org/10.1016/j.energy.2023.127125

Kyprianou, I., Serghides, D. K., Varo, A., Gouveia, J. P., Kopeva, D., & Murauskaite, L. (2019). Energy poverty policies and measures in 5 EU countries: A comparative study. *Energy and Buildings*, *196*, 46-60. https://doi.org/10.1016/j.renene.2023.03.090

Kuzemko, C., Blondeel, M., Dupont, C., & Brisbois, M. C. (2022). Russia's war on Ukraine, European energy policy responses & implications for sustainable transformations. *Energy Research & Social Science*, *93*, 102842. https://doi.org/10.1016/j.erss.2022.102842

Li, X. (2005). Diversification and localization of energy systems for sustainable development and energy security. *Energy Policy*, *33*(17), 2237 – 2243. doi:10.1016/j.enpol.2004.05.002

Liobikienė, G., Butkus, M., & Matuzevičiūtė, K. (2019). The contribution of energy taxes to climate change policy in the European Union (EU). *Resources*, *8*(2), 63. https://doi.org/10.3390/resources8020063

Llera Sastresa, E., Aranda Usón, A., Zabalza Bribián, I., & Scarpellini, S. (2010). Local impact of renewables on employment: Assessment methodology and case study. *Renewable and Sustainable Energy Reviews, 14*(2), 679 – 690. doi:10.1016/j.rser.2009.10.017

Myers, R. H., & Montgomery, D. C. (1997). A Tutorial on Generalized Linear Models. *Journal of Quality Technology, 29(3),* 274–291. https://doi.org/10.1080/00224065.1997.11979769

Muhammad, S., Pan, Y., Ke, X., Agha, M. H., Borah, P. S., & Akhtar, M. (2023). European transition toward climate neutrality: Is renewable energy fueling energy poverty across Europe?. *Renewable Energy*, *208*, 181-190. https://doi.org/10.1016/j.renene.2023.03.090

Nelder, J. A., & Wedderburn, R. W. M. (1972). Generalized Linear Models. *Journal of the Royal Statistical Society. Series A (General)*, *135*(3), 370–384. https://doi.org/10.2307/2344614

Nguyen, C., P., & Nasir, M., A. (2021). An inquiry into the nexus between energy poverty and income inequality in the light of global evidence. *Energy Economics*, *99*, 105289. https://doi.org/10.1016/j.eneco.2021.105289

Okkonen, L., & Lehtonen, O. (2016). Socio-economic impacts of community wind power projects in Northern Scotland. *Renewable Energy*, *85*, 826 – 833. https://doi.org/10.1016/j.renene.2015.07.047

Papaefthymiou, G., & Dragoon, K. (2016). Towards 100% renewable energy systems: Uncapping power system flexibility. *Energy Policy*, *92*, 69 – 82. https://doi.org/10.1016/j.enpol.2016.01.025

Petrova, S., Gentile, M., Mäkinen, IH., & Bouzarovski, S. (2013). Perceptions of Thermal Comfort and Housing Quality: Exploring the Microgeographies of Energy Poverty in Stakhanov, Ukraine. *Environment and Planning A: Economy and Space*, *45*(5), 1240-1257. https://doi.org/10.1068/a45132

Primc, K., & Slabe-Erker, R. (2020). Social policy or energy policy? Time to reconsider energy poverty policies. *Energy for Sustainable Development*, *55*, 32-36. https://doi.org/10.1016/j.esd.2020.01.001

Pye, S., Dobbins, A., Baffert, C., Brajković, J., Deane, P., & De Miglio, R. (2015). Addressing energy poverty and vulnerable consumers in the energy sector across the EU. *L'Europe en formation*, (4), 64-89. https://doi.org/10.3917/eufor.378.0064

Reis, F., G., I., Gonçalves, I., Lopes, A., R., M., Antunes, H., C. (2021). Business models for energy communities: A review of key issues and trends. Renewable and Sustainable Energy Reviews, *144*, 111013. https://doi.org/10.1016/j.rser.2021.111013

Regulation 2023/955. *Regulation (EU) 2023/955 of the European Parliament and of the Council of 10 May 2023 establishing a Social Climate Fund and amending Regulation (EU) 2021/1060.* ELI: http://data.europa.eu/eli/reg/2023/955/oj

Rodriguez-Alvarez, A., Llorca, M., & Jamasb, T. (2021). Alleviating energy poverty in Europe: Front-runners and laggards. *Energy Economics, 103*, 105575. https://doi.org/10.1016/j.eneco.2021.105575

Spiecker, S., & Weber, C. (2014). The future of the European electricity system and the impact of fluctuating renewable energy – A scenario analysis. *Energy policy*, *65*, 185 – 197. https://doi.org/10.1016/j.enpol.2013.10.032

Streimikiene, D., Kyriakopoulos, G. L., Lekavicius, V., & Siksnelyte-Butkiene, I. (2021). Energy poverty and low carbon just energy transition: comparative study in Lithuania and Greece. *Social Indicators Research*, *158*(1), 319-371. https://doi.org/10.1007/s11205-021-02685-9

Streimikiene, D., Lekavicius, V., Baležentis, T., Kyriakopoulos, G., L., & Abrhám, J. (2020). Climate Change Mitigation Policies Targeting Households and Addressing Energy poverty in European Union. *Energies, 13*(13), 3389. doi:10.3390/en13133389

Süsser, D., & Kannen, A. (2017). 'Renewables? Yes, please!': perceptions and assessment of community transition induced by renewable-energy projects in North Frisia. *Sustain Sci*, *12*, 563 – 578. DOI 10.1007/s11625-017-0433-5

Swain, R. B., & Karimu, A. (2020). Renewable electricity and sustainable development goals in the EU. *World Development*, *125*, 104693. https://doi.org/10.1016/j.worlddev.2019.104693

Thomson, H., & Snell, C. (2013). Quantifying the prevalence of fuel poverty across the European Union. *Energy Policy*, *52*, 563 – 572. http://dx.doi.org/10.1016/j.enpol.2012.10.009

Thomson, H., Bouzarovski S., & Snell ,C. (2017). Rethinking the measurement of energy poverty in Europe: A critical analysis of indicators and data. *Indoor and Built Environment*, *26*(7), 879–90. DOI:10.1177/1420326X17699260

Tobin, I., Greuell, W., Jerez, S., Ludwing, F., Vautard, R., Van Vliet, M., T., H., & Breón F-M. (2018). Vulnerabilities and resilience of European power generation to 1.5 ◦C, 2 ◦C and 3 ◦C warming. *Environmental Research Letters*, *13*(4), 044024. https://doi.org/10.1088/1748-9326/aab211

Umbach, F. (2010). Global energy security and the implications for the EU. *Energy Policy*, *38(3)*, 1229 – 1240. doi:10.1016/j.enpol.2009.01.010

Venables, W. N., & Dichmont, C. M. (2004). GLMs, GAMs and GLMMs: an overview of theory for applications in fisheries research. *Fisheries research*, *70*(2-3), 319-337. https://doi.org/10.1016/j.fishres.2004.08.011

Zapata, W., Junginger, M., & Van den Broek, M. (2019). Is a 100% renewable European power system feasible by 2050?. *Applied Energy*, *233*, 10227-1050. https://doi.org/10.1016/j.apenergy.2018.08.109

Zhao, J., Dong, K., Jiang, Q., & Shahbaz, M. (2021). Does low-carbon energy transition mitigate energy poverty ? The case of natural gas for China. *Energy Economics*, *99*, 105324.. https://doi.org/10.1016/j.eneco.2021.105324

APPENDIX 1

Generalized Linear Models

GLM is a statistic regression model where the dependent variable can have different types of distributions, and this can link with the independent variable through a link function. GLM requires to identify three aspects:

A) The systematic component: represents the independent variables combination in the model
B) The random component: represents the distribution of the dependent variable. For the distribution GLM offers different types of distribution from normal, Poison, gamma, negative binomial, and beta.
C) Link function: represents how the systematic component, and the random component are linked. GLM offers different types of link functions, identity, logit, log, and inverse.

GLM can be represented generally through the following development:

$$y = \alpha + \beta_1 x_i + \beta_2 x_i \ldots + \beta_k x_k \ (Eq. 1)$$

$$y = g(\mu_i) \ (Eq. 2)$$

Where y represents the dependent variable, and x the explanatory variables, and y can be estimated as a function (g) of μ. Eq.1 and 2 represents the link function and the Table 1 shows a summary of different types of link functions. Based on the nature of EP some random components can be ruled out since EPCI is not binary variable. Therefore, binominal distribution will not be considered, however we can combine a random component with a different link function.

Table 1. Link function for GLM (own elaboration)

Link function	$y = g(\mu_i)$	Random component
Identity	μ_i	normal
Logit	$log_e \frac{\mu_i}{1-\mu_i}$	binomial
Log	$log_e \mu_i$	poison
Inverse	${\mu_i}^{-1}$	gamma

APPENDIX 2

HC estimation applying GLM

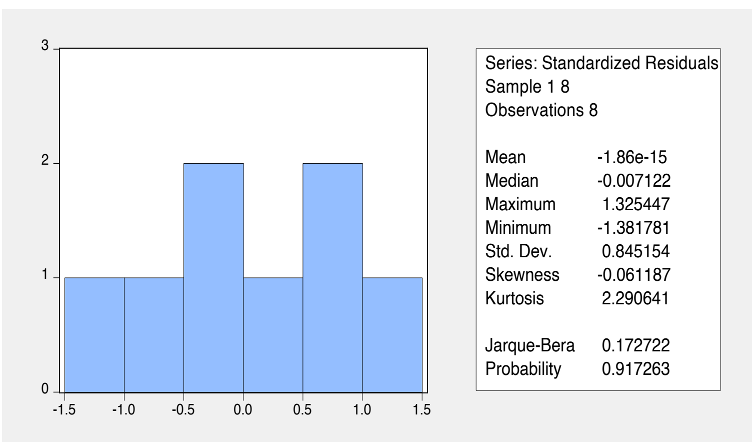
1. EU

Dependent Variable: EU___27___HC
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/10/24   Time: 12:09
Sample: 1 8
Included observations: 8
Family: Normal
Link: Identity
Dispersion computed using Pearson Chi-Square
Convergence achieved after 1 iteration
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
EU___27_IKW	1.608597	1.911302	0.841624	0.4000
EU___27_AUB	-0.785545	1.608812	-0.488277	0.6254
C	0.068444	0.038938	1.757778	0.0788

Mean dependent var	0.144875	S.D. dependent var	0.011740
Sum squared resid	0.000283	Root MSE	0.005948
Log likelihood	29.26652	Akaike info criterion	-6.566630
Schwarz criterion	-6.536839	Hannan-Quinn criter.	-6.767555
Deviance	0.000283	Deviance statistic	5.66E-05
Restr. deviance	0.000965	LR statistic	12.04736
Prob(LR statistic)	* 0.002421	Pearson SSR	0.000283
Pearson statistic	5.66E-05	Dispersion	5.66E-05

p<0.01;p**<0.05;p***<0.1*



EU_27 HC equation:
$g(HC)_t$ = 1.6085971955* IKW - 0.785545183179* AUB + 0.0684439456202
$g(HC)_t = HC_t$

2. Denmark

Dependent Variable: DENMARK_HC
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/13/24 Time: 09:18
Sample (adjusted): 2013 2020
Included observations: 8 after adjustments
Family: Normal
Link: Inverse
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
DENMARK_IKW	-44.63542	31.95743	-1.396715	0.1625
DENMARK_AUB	3.316241	20.85246	0.159034	0.8736
C	7.582128	0.836988	9.058829	0.0000

Mean dependent var	0.158250	S.D. dependent var	0.007888
Sum squared resid	0.000294	Root MSE	0.006061
Log likelihood	29.11607	Akaike info criterion	-6.529018
Schwarz criterion	-6.499228	Hannan-Quinn criter.	-6.729944
Deviance	0.000294	Deviance statistic	5.88E-05
Restr. deviance	0.000436	LR statistic	2.410363
Prob(LR statistic)	0.299638	Pearson SSR	0.000294
Pearson statistic	5.88E-05	Dispersion	5.88E-05

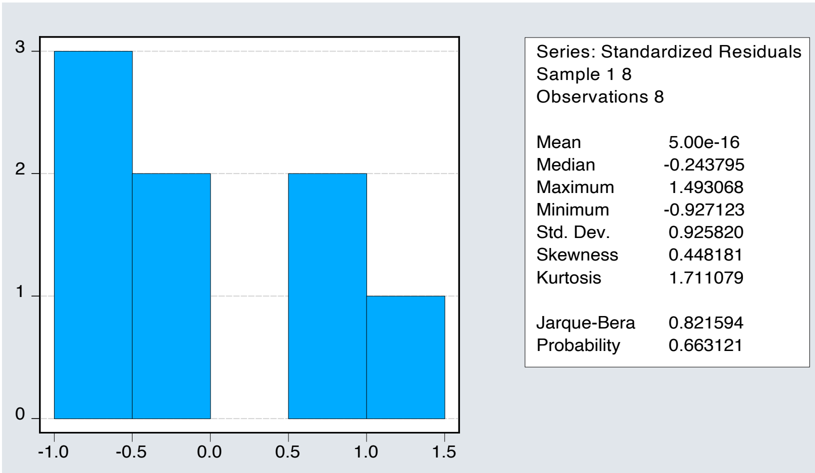
p<0.01;p**<0.05;p***<0.1*

Dependent Variable: DENMARK_HC
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 09:10
Sample: 1 8
Included observations: 8
Family: Normal
Link: Identity
Dispersion computed using Pearson Chi-Square
Convergence achieved after 0 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
DENMARK_IKW	1.090719	0.638133	1.709236	0.0874
C	0.124847	0.019698	6.337938	0.0000

Mean dependent var	0.158250	S.D. dependent var	0.007888
Sum squared resid	0.000293	Root MSE	0.006051
Log likelihood	29.35840	Akaike info criterion	-6.839601
Schwarz criterion	-6.819741	Hannan-Quinn criter.	-6.973552
Deviance	0.000293	Deviance statistic	4.88E-05
Restr. deviance	0.000436	LR statistic	2.921486
Prob(LR statistic)	0.087407	Pearson SSR	0.000293
Pearson statistic	4.88E-05	Dispersion	4.88E-05

p<0.01;p**<0.05;p***<0.1*



Denmark_ HC equation:

$g(HC)_t =$ 1.09071949948*IKW

$g(HC)_t = HC_t$

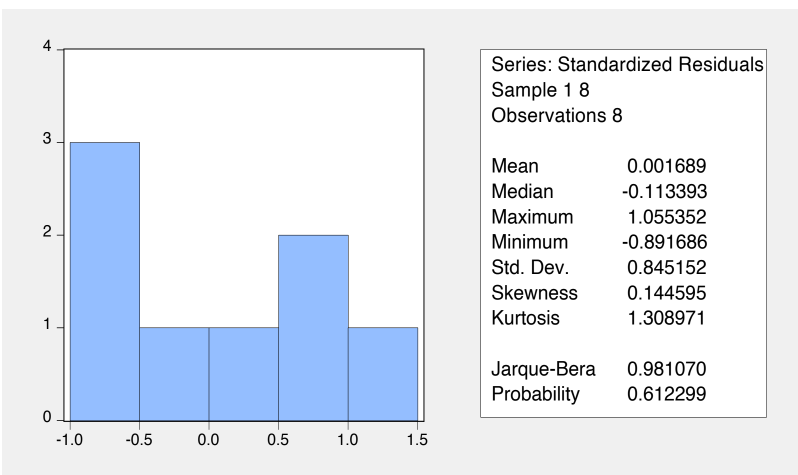
3. Greece

Dependent Variable: GREECE_HC
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/10/24 Time: 11:50
Sample: 1 8
Included observations: 8
Family: Normal
Link: Inverse
Dispersion computed using Pearson Chi-Square
Convergence achieved after 4 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
GREECE_IKW	-2.953270	2.397850	-1.231632	0.2181
GREECE_AUB	-7.710255	2.923656	-2.637196	0.0084
C	10.93869	0.801268	13.65173	0.0000

Mean dependent var	0.136125	S.D. dependent var	0.009672
Sum squared resid	0.000102	Root MSE	0.003565
Log likelihood	33.36112	Akaike info criterion	-7.590280
Schwarz criterion	-7.560490	Hannan-Quinn criter.	-7.791206
Deviance	0.000102	Deviance statistic	2.03E-05
Restr. deviance	0.000655	LR statistic	27.20402
Prob(LR statistic)	* 0.000001	Pearson SSR	0.000102
Pearson statistic	2.03E-05	Dispersion	2.03E-05

p<0.01;p**<0.05;p***<0.1*



Greece HC equation:

$g(HC)_t$ = -2.95327003137*IKW - 7.71025472632*AUB + 10.938692457

$g(HC)_t = 1/HC_t$

APPENDIX 3

Dependent variables detail
(a)Calculated based on Appendix 2.
(b)Calculated based on Eq.1.

EU-27	EPCI[b]	IKW	AUB	HC
2013	0.119	0.108	0.14	0.156
2014	0.11675	0.104	0.137	0.156
2015	0.10975	0.096	0.151	0.153
2016	0.104	0.09	0.147	0.152
2017	0.0915	0.081	0.135	0.131
2018	0.089	0.076	0.129	0.136
2019	0.08175	0.069	0.125	0.127
2020	0.09075	0.075	0.125	0.148
2021	0.082313	0.069	0.119132	0.1291623[a]
2022	0.096813	0.093	0.128912	0.1638409[a]
Denmark	**EPCI[b]**	**IKW**	**AUB**	**HC**
2013	0.0695	0.038	0.036	0.166
2014	0.0635	0.029	0.046	0.15
2015	0.06675	0.036	0.034	0.161
2016	0.0595	0.027	0.025	0.159
2017	0.0595	0.027	0.035	0.149
2018	0.06875	0.03	0.051	0.164
2019	0.06025	0.028	0.036	0.149
2020	0.0675	0.03	0.042	0.168
2021	0.060097	0.028	0.029	0.1553869[a]
2022	0.079368	0.051	0.035	0.1804734[a]
Greece	**EPCI[a]**	**IKW**	**AUB**	**HC**
2013	0.2705	0.295	0.352	0.14
2014	0.292	0.329	0.373	0.137
2015	0.28875	0.292	0.42	0.151
2016	0.28775	0.291	0.422	0.147

Greece	EPCI[(a)]	IKW	AUB	HC
2017	0.2585	0.257	0.385	0.135
2018	0.23475	0.227	0.356	0.129
2019	0.202	0.179	0.325	0.125
2020	0.18725	0.171	0.282	0.125
2021	0.161938	0.175	0.263	0.1191317[(a)]
2022	0.206938	0.187	0.341	0.1289119[(a)]

Independent variables detail

EU	RREC	HEC	RREP	ELP	TLE	EID	GC	ARP
2013	0.26769	0.2819854	0.2940007	0.1498	0.0352	0.53905	0.306	0.168
2014	0.28601	0.2743059	0.3111601	0.1496	0.0387	0.54397	0.309	0.173
2015	0.29655	0.2737872	0.3128285	0.14905	0.04145	0.55849	0.308	0.174
2016	0.30172	0.2750222	0.3161802	0.1466	0.04385	0.56057	0.306	0.175
2017	0.31104	0.2742212	0.3143874	0.1498	0.04705	0.57394	0.303	0.169
2018	0.32134	0.2731251	0.3374352	0.15675	0.04575	0.57951	0.304	0.168
2019	0.34086	0.2753374	0.3542246	0.15325	0.0548	0.60475	0.302	0.164
2020	0.37408	0.2899581	0.3993223	0.15365	0.0524	0.57464	0.3	0.167
2021	0.37754	0.2885615	0.3878025	0.16835	0.05095	0.55521	0.302	0.168
2022	0.41174	0.2844229	0.402438	0.24735	0.0085	0.62522	0.296	0.165
Denmark	**RREC**	**HEC**	**RREP**	**ELP**	**TLE**	**EID**	**GC**	**ARP**
2013	0.43084	0.320571	0.4801798	0.1276	0.1332	0.12312	0.268	0.119
2014	0.48493	0.3200608	0.5812853	0.12485	0.1407	0.12225	0.277	0.121
2015	0.51292	0.3205291	0.6803138	0.109	0.15755	0.13077	0.274	0.122
2016	0.53717	0.3205126	0.6252571	0.1096	0.1577	0.13568	0.277	0.119
2017	0.5994	0.3045675	0.7259516	0.1121	0.1493	0.11343	0.276	0.124
2018	0.62394	0.3055597	0.7067491	0.12535	0.14495	0.22697	0.278	0.127

Denmark	RREC	HEC	RREP	ELP	TLE	EID	GC	ARP
2019	0.65347	0.318316	0.8084131	0.1261	0.13	0.38868	0.275	0.125
2020	0.65323	0.3284075	0.8430577	0.1132	0.13315	0.44892	0.273	0.121
2021	0.72916	0.3223889	0.8136716	0.1452	0.12765	0.32297	0.27	0.123
2022	0.7722	0.2950888	0.8355727	0.31885	0.11685	0.42867	0.277	0.124
Greece	**RREC**	**HEC**	**RREP**	**ELP**	**TLE**	**EID**	**GC**	**ARP**
2013	0.21241	0.345479	0.2532264	0.11165	0.0242	0.6175	0.344	0.231
2014	0.21923	0.3350786	0.2458189	0.11855	0.0341	0.65455	0.345	0.221
2015	0.22089	0.3344075	0.2894376	0.1274	0.0325	0.71047	0.342	0.213
2016	0.22657	0.3633572	0.277783	0.121	0.0334	0.72911	0.343	0.211
2017	0.24464	0.3529273	0.2511178	0.11855	0.03195	0.71282	0.334	0.202
2018	0.26001	0.3280601	0.3088652	0.11785	0.0329	0.70681	0.323	0.184
2019	0.31295	0.3358933	0.3380398	0.1213	0.027	0.74103	0.31	0.177
2020	0.35856	0.3579763	0.3666413	0.1338	0.0268	0.81415	0.314	0.176
2021	0.35934	0.3504927	0.4064073	0.14965	0.02695	0.73819	0.324	0.195
2022	0.42408	0.3351488	0.4293828	0.38895	-0.16805	0.79601	0.314	0.188

Independent variables detail

Variable name and abbreviation	Type of variable(*)	Indicator(s) name in EUROSTAT	EUROSTAT code	Unit
Renewable electricity consumption (RREC)	Single	Share of renewable energy in gross final energy consumption by sector	sdg_07_40/ nrg_ind_ren	Percentage
Households' electricity consumption (HEC)	Calculated from multiple EUROSTAT variables	Supply, transformation, and consumption of electricity	nrg_cb_e	Percentage
Renewable electricity production (RREP)	Calculated	Production of electricity and derived heat by type of fuel	nrg_bal_peh	Percentage
Electricity prices (ELP) **Electricity taxes and levies (TLE)**	Single	Electricity prices for household consumers - bi-annual data (from 2007 onwards)	nrg_pc_204	Euros/kWh
Energy import dependency by products (EID)	Single	Energy import dependency by products	sdg_07_50	Percentage
Gini coefficient (GC)	Single	Gini coefficient of equivalized disposable income - EU-SILC survey	ilc_di12	Scale 0 – 1
At-risk-of-poverty rate (ARP)	Single	At-risk-of-poverty rate by poverty threshold and household type - EU-SILC and ECHP surveys	ilc_li03	Percentage

(*) a) Single variable: available directly from EUROSTAT
b)Calculated variable: estimated based on indicators available in EUROSTAT

APPENDIX 4

Dependent variables descriptive statistics

Indicator / Descrip. Stat.	Mean	Median	Maximum	Minimum	Std. Dev.	Jarque-Bera	Probability	Obs.
EU - 27 IKW	0.0861	0.085	0.108	0.069	0.0141	0.0801	0.6700*	10
EU - 27 AUB	0.0786	0.071	0.104	0.062	0.0164	1.2664	0.5309*	10
EU - 27 - HC	0.1452	0.15	0.1638	0.127	0.0132	0.9677	0.6164*	10
EU - 27 EPCI	0.099	0.0978	0.119	0.0818	0.0136	0.8592	0.6508*	10
Denmark IKW	0.0324	0.0295	0.051	0.027	0.0075	5.9337	0.0515*	10
Denmark AUB	0.034	0.0345	0.042	0.022	0.0066	0.5072	0.7760*	10
Denmark HC	0.1602	0.16	0.1805	0.149	0.01	0.6398	0.7262*	10
Denmark EPCI	0.0658	0.0651	0.0811	0.0595	0.0066	2.6707	0.2631*	10
Greece IKW	0.2403	0.242	0.329	0.171	0.0598	1.041	0.5942*	10
Greece AUB	0.3519	0.354	0.422	0.263	0.0524	0.4165	0.8120*	10
Greece HC	0.1337	0.132	0.151	0.1191	0.0102	0.5813	0.7478*	10
Greece EPCI	0.2416	0.2466	0.292	0.183	0.0434	1.0806	0.5826*	10

p<0.01;p**<0.05;p***<0.1*

Independent variables descriptive statistics EU

EU	Mean	Median	Maximum	Minimum	Std. Dev.	Jarque-Bera	Probability	Obs.
REC	0.328857	0.31619	0.41174	0.26769	0.04614	0.759336	0.684089	10
HEC	0.279073	0.27518	0.289958	0.273125	0.006545	1.376311	0.502502	10
RREP	0.342978	0.326808	0.402438	0.294001	0.040459	1.13398	0.56723	10
ELP	0.16242	0.151525	0.24735	0.1466	0.030466	18.624290*	0.00009	10
TLE	0.041865	0.0448	0.0548	0.00085	0.013227	6.718374*	0.034766	10
EID	0.571535	0.567255	0.62522	0.53905	0.026742	1.066148	5.71535	10
GC	0.3036	0.3035	0.309	0.296	0.003893	0.400442	0.81844	10
ARP	0.1691	0.168	0.175	0.164	0.003725	0.721847	0.697032	10

p<0.01;p**<0.05;p***<0.1*

Independent variables descriptive statistics in Denmark

Denmark	Mean	Median	Maximum	Minimum	Std. Dev.	Jarque-Bera	Probability	Obs.
REC	0.599726	0.61167	0.7722	0.43084	0.108519	0.422481	0.809579	10
HEC	0.3156	0.320287	0.328408	0.29089	0.010294	1.339879	0.511739	10
RREP	0.710045	0.71635	0.843058	0.48018	0.120931	0.767518	0.681296	10
ELP	0.141185	0.1251	0.31885	0.109	0.06334	19.561810*	0.000057	10
TLE	0.13905	0.13695	0.1577	0.11685	0.01336	0.407108	0.815826	10
EID	0.244146	0.181325	0.44892	0.11343	0.13928	1.301613	0.521625	10
GC	0.2745	0.2755	0.278	0.268	0.003308	1.413426	0.493263	10
ARP	0.1225	0.1225	0.127	0.118	0.002593	0.368701	0.831644	10

p<0.01;p**<0.05;p***<0.1*

Independent variable descriptive statistics in Greece

Greece	Mean	Median	Maximum	Minimum	Std. Dev.	Jarque-Bera	Probability	Obs.
REC	0.283868	0.252325	0.42408	0.21241	0.074849	1.169051	0.55737	10
HEC	0.343882	0.340686	0.363357	0.32806	0.011849	0.827977	0.661009	10
RREP	0.316672	0.299151	0.429383	0.245819	0.066138	0.972315	0.614985	10
ELP	0.15087	0.12115	0.38895	0.11165	0.084334	21.016780*	0.000027	10
TLE	0.010175	0.029475	0.0341	-0.16805	0.062719	22.397790*	0.000014	10
EID	0.733064	0.720965	0.81415	0.6175	0.058273	0.1078	0.947527	10
GC	0.3293	0.239	0.345	0.31	0.013913	1.116745	0.572139	10
ARP	0.1998	0.1985	0.231	0.176	0.018931	0.682276	0.310961	10

p<0.01;p**<0.05;p***<0.1*

APPENDIX 5

1. The EU

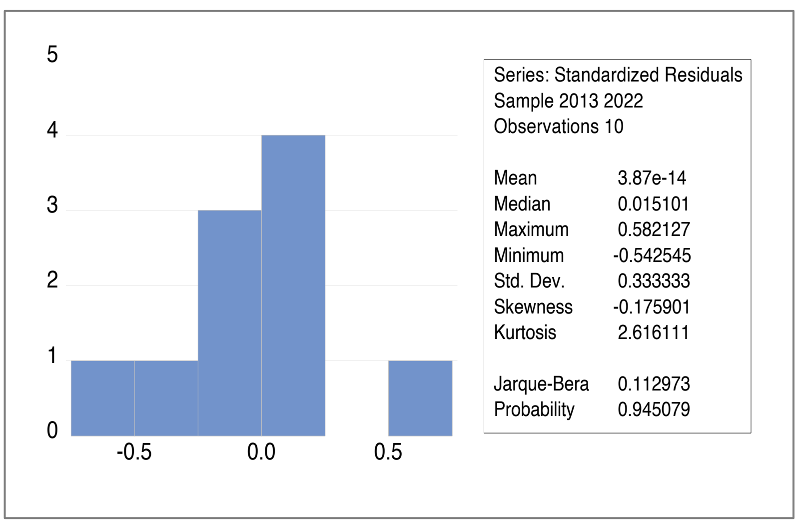
1.1. EPCI

Dependent Variable: EPCI
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/13/24 Time: 19:11
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Identity
Dispersion computed using Pearson Chi-Square
Convergence achieved after 0 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	0.357304	0.644989	0.553969	0.5796
HEC	1.238049	0.743854	1.664372***	0.0960
RREP	-0.187240	0.385410	-0.485819	0.6271
ELP	-1.055604	0.753645	-1.400666	0.1613
TLE	-2.284787	1.160177	-1.969343	**0.0489
EID	0.248117	0.191293	1.297053	0.1946
GC	3.806405	2.011008	1.892784	**0.0584
ARP	-0.602107	1.279047	-0.470746	0.6378
C	-1.229138	0.715609	-1.717612	0.0859

Mean dependent var	0.098163	S.D. dependent var	0.013555
Sum squared resid	8.62E-06	Root MSE	0.000929
Log likelihood	48.61495	Akaike info criterion	-7.922991
Schwarz criterion	-7.650664	Hannan-Quinn criter.	-8.221732
Deviance	8.62E-06	Deviance statistic	8.62E-06
Restr. deviance	0.001654	LR statistic	190.7427
Prob(LR statistic)	*0.000000	Pearson SSR	8.62E-06
Pearson statistic	8.62E-06	Dispersion	8.62E-06

p<0.01;p**<0.05;p***<0.1*

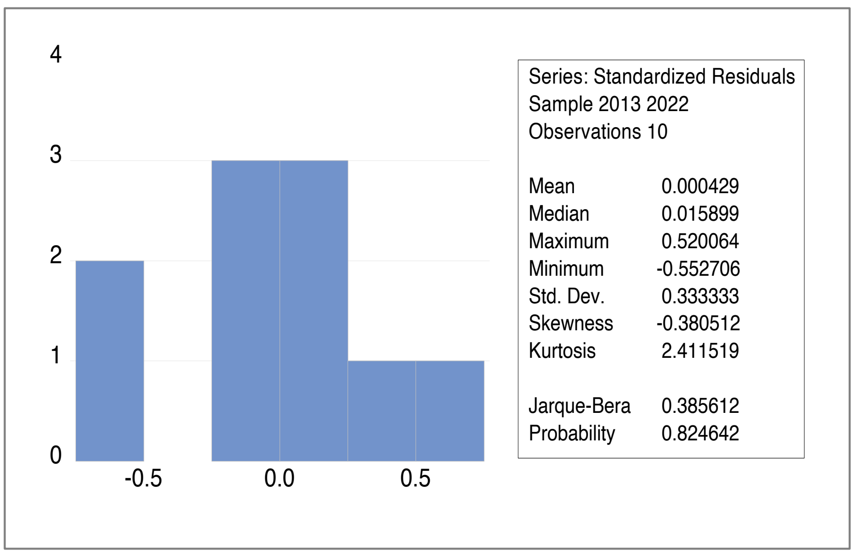


Dependent Variable: EPCI
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/13/24 Time: 19:17
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Log
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	3.622321	5.699505	0.635550	0.5251
HEC	9.686857	6.799022	1.424743	0.1542
RREP	-1.430871	3.443457	-0.415533	0.6778
ELP	-11.47886	6.805307	-1.686751	***0.0917
TLE	-24.59741	10.48723	-2.345463	**0.0190
EID	1.985047	1.804206	1.100233	0.2712
GC	32.17822	17.40628	1.848656	***0.0645
ARP	-4.586956	11.07211	-0.414280	0.6787
C	-12.96740	6.607680	-1.962474	0.0497

Mean dependent var	0.098163	S.D. dependent var	0.013555
Sum squared resid	6.65E-06	Root MSE	0.000816
Log likelihood	49.91290	Akaike info criterion	-8.182580
Schwarz criterion	-7.910253	Hannan-Quinn criter.	-8.481322
Deviance	6.65E-06	Deviance statistic	6.65E-06
Restr. deviance	0.001654	LR statistic	247.5747
Prob(LR statistic)	*0.000000	Pearson SSR	6.65E-06
Pearson statistic	6.65E-06	Dispersion	6.65E-06

p<0.01;p**<0.05;p***<0.1*

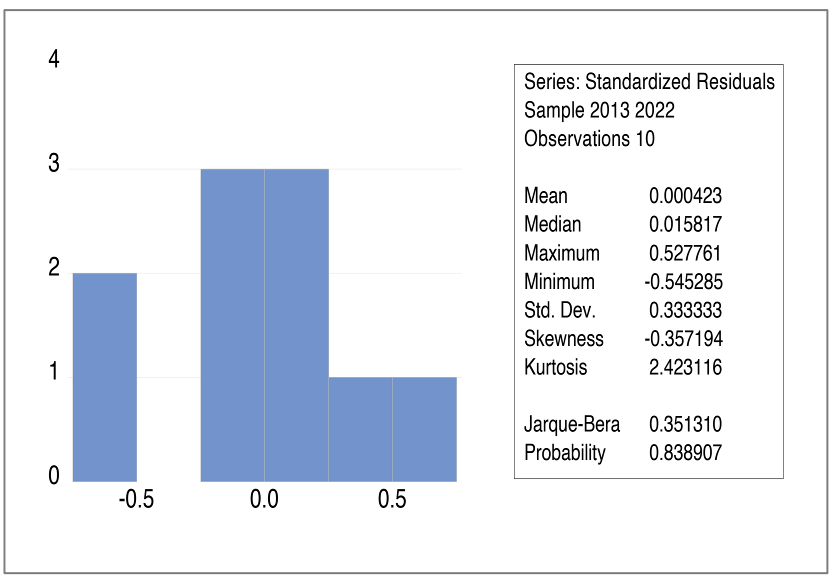


Dependent Variable: EPCI
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/13/24 Time: 19:18
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Logit
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	4.014311	6.431997	0.624116	0.5326
HEC	11.07767	7.655178	1.447082	0.1479
RREP	-1.638316	3.883775	-0.421836	0.6731
ELP	-12.64007	7.660090	-1.650121***	0.0989
TLE	-27.11748	11.80239	-2.297626 **	0.0216
EID	2.262429	2.024578	1.117482	0.2638
GC	36.45269	19.69856	1.850525 **	0.0642
ARP	-5.274694	12.52391	-0.421170	0.6736
C	-14.35574	7.429147	-1.932353	0.0533

Mean dependent var	0.098163	S.D. dependent var	0.013555
Sum squared resid	6.87E-06	Root MSE	0.000829
Log likelihood	49.74976	Akaike info criterion	-8.149952
Schwarz criterion	-7.877625	Hannan-Quinn criter.	-8.448693
Deviance	6.87E-06	Deviance statistic	6.87E-06
Restr. deviance	0.001654	LR statistic	239.5950
Prob(LR statistic)	*0.000000	Pearson SSR	6.87E-06
Pearson statistic	6.87E-06	Dispersion	6.87E-06

p<0.01;p**<0.05;p***<0.1*

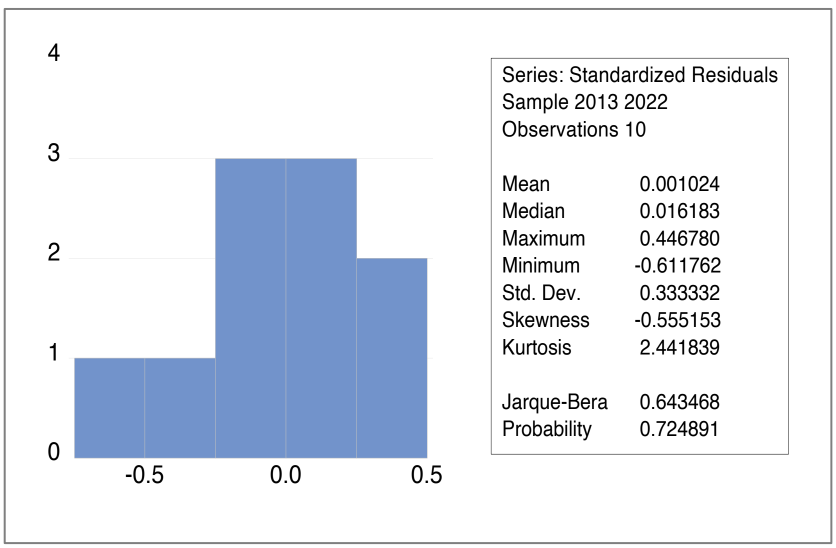


Dependent Variable: EPCI
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/13/24 Time: 19:20
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Inverse
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-38.74152	47.93753	-0.808167	0.4190
HEC	-71.69431	58.13435	-1.233252	0.2175
RREP	11.25668	28.90455	0.389443	0.6969
ELP	127.2689	58.89163	2.161069	** 0.0307
TLE	268.9017	91.07440	2.952549	* 0.0032
EID	-15.18655	15.94755	-0.952281	0.3410
GC	-265.7743	142.1863	-1.869198	***0.0616
ARP	33.68961	90.80124	0.371026	0.7106
C	90.99078	57.33236	1.587075	0.1125

Mean dependent var	0.098163	S.D. dependent var	0.013555
Sum squared resid	4.54E-06	Root MSE	0.000674
Log likelihood	51.82654	Akaike info criterion	-8.565307
Schwarz criterion	-8.292981	Hannan-Quinn criter.	-8.864049
Deviance	4.54E-06	Deviance statistic	4.54E-06
Restr. deviance	0.001654	LR statistic	363.4797
Prob(LR statistic)	* 0.000000	Pearson SSR	4.54E-06
Pearson statistic	4.54E-06	Dispersion	4.54E-06

p<0.01;p**<0.05;p***<0.1*



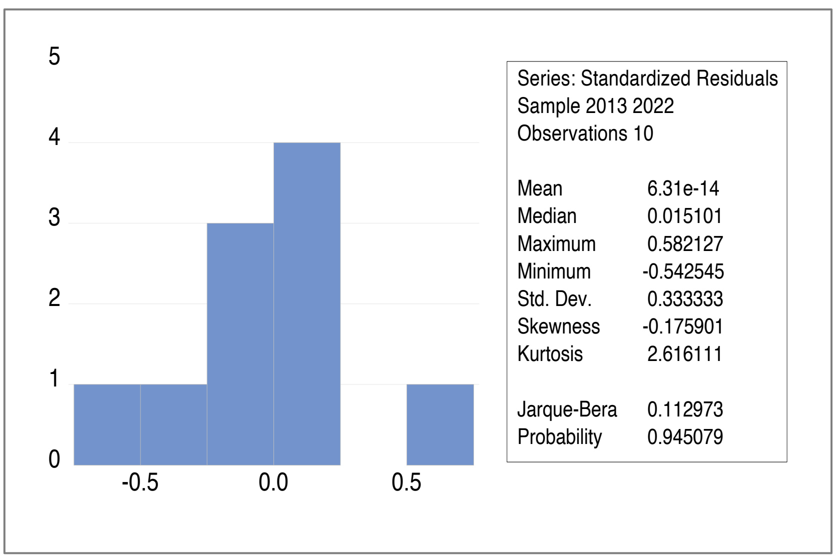
1.2. IKW

Dependent Variable: IKW
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 08:15
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Identity
Dispersion computed using Pearson Chi-Square
Convergence achieved after 1 iteration
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	0.561616	0.859321	0.653558	0.5134
HEC	1.188281	0.991039	1.199026	0.2305
RREP	-0.375565	0.513483	-0.731406	0.4645
ELP	-1.132924	1.004083	-1.128317	0.2592
TLE	-2.570783	1.545707	-1.663176***	0.0963
EID	0.221518	0.254860	0.869177	0.3848
GC	3.927389	2.679272	1.465842	0.1427
ARP	-1.118440	1.704078	-0.656331	0.5116
C	-1.139595	0.953407	-1.195287	0.2320

Mean dependent var	0.086100	S.D. dependent var	0.014130
Sum squared resid	1.53E-05	Root MSE	0.001237
Log likelihood	45.74586	Akaike info criterion	-7.349173
Schwarz criterion	-7.076846	Hannan-Quinn criter.	-7.647915
Deviance	1.53E-05	Deviance statistic	1.53E-05
Restr. deviance	0.001797	LR statistic	116.3731
Prob(LR statistic)	*0.000000	Pearson SSR	1.53E-05
Pearson statistic	1.53E-05	Dispersion	1.53E-05

p<0.01;p**<0.05;p***<0.1*

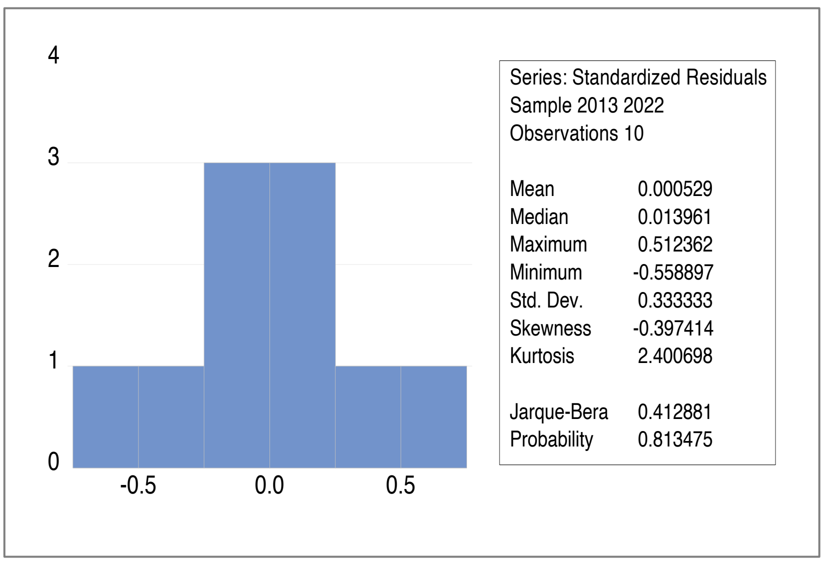


Dependent Variable: IKW
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 08:16
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Log
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	6.765286	9.050675	0.747490	0.4548
HEC	9.149794	10.82750	0.845052	0.3981
RREP	-3.813916	5.450892	-0.699687	0.4841
ELP	-14.43297	10.91657	-1.322116	0.1861
TLE	-32.18592	16.84487	-1.910726***	0.0560
EID	1.689442	2.893996	0.583775	0.5594
GC	36.83384	27.69777	1.329848	0.1836
ARP	-11.24392	17.66712	-0.636432	0.5245
C	-12.48984	10.55061	-1.183803	0.2365

Mean dependent var	0.086100	S.D. dependent var	0.014130
Sum squared resid	1.27E-05	Root MSE	0.001129
Log likelihood	46.66536	Akaike info criterion	-7.533072
Schwarz criterion	-7.260746	Hannan-Quinn criter.	-7.831814
Deviance	1.27E-05	Deviance statistic	1.27E-05
Restr. deviance	0.001797	LR statistic	140.0701
Prob(LR statistic)	* 0.000000	Pearson SSR	1.27E-05
Pearson statistic	1.27E-05	Dispersion	1.27E-05

p<0.01;p**<0.05;p***<0.1*

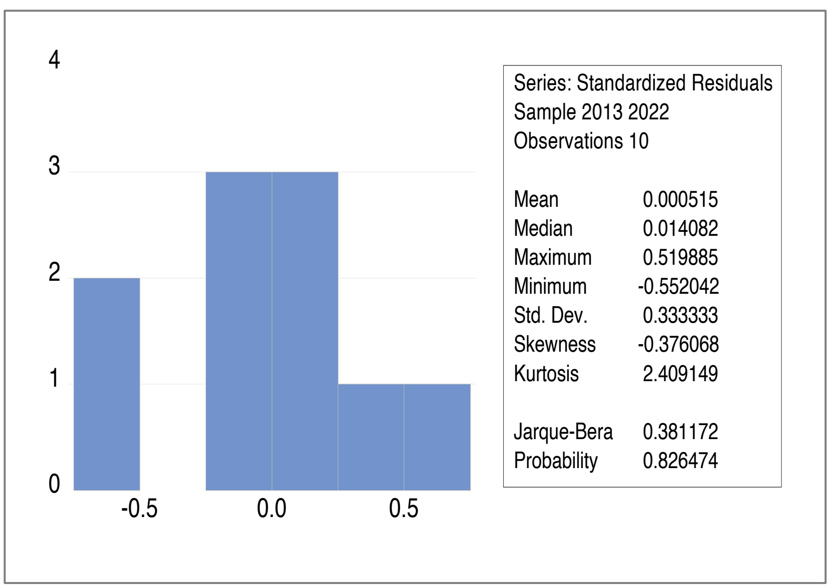


Dependent Variable: IKW
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 08:17
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Logit
Dispersion computed using Pearson Chi-Square
Convergence achieved after 4 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	7.373073	10.00787	0.736728	0.4613
HEC	10.47544	11.95077	0.876549	0.3807
RREP	-4.223939	6.026970	-0.700840	0.4834
ELP	-15.66048	12.03232	-1.301535	0.1931
TLE	-34.98024	18.56144	-1.884565***	0.0595
EID	1.936026	3.182873	0.608264	0.5430
GC	41.18764	30.69909	1.341657	0.1797
ARP	-12.48640	19.56643	-0.638155	0.5234
C	-13.76518	11.62689	-1.183909	0.2364

Mean dependent var	0.086100	S.D. dependent var	0.014130
Sum squared resid	1.30E-05	Root MSE	0.001140
Log likelihood	46.56425	Akaike info criterion	-7.512851
Schwarz criterion	-7.240524	Hannan-Quinn criter.	-7.811592
Deviance	1.30E-05	Deviance statistic	1.30E-05
Restr. deviance	0.001797	LR statistic	137.2461
Prob(LR statistic)	*0.000000	Pearson SSR	1.30E-05
Pearson statistic	1.30E-05	Dispersion	1.30E-05

p<0.01;p**<0.05;p***<0.1*

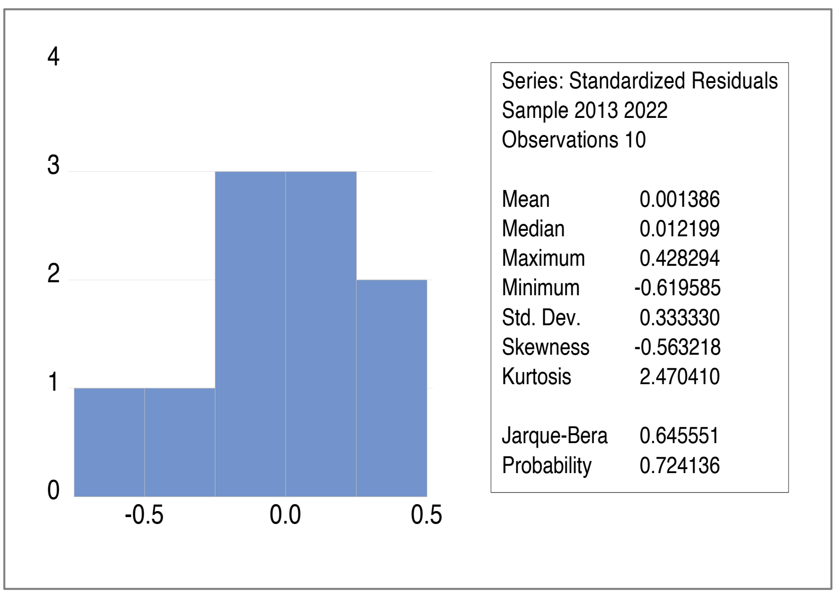


Dependent Variable: IKW
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 08:18
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Inverse
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-84.37683	91.42279	-0.922930	0.3560
HEC	-55.36072	111.0340	-0.498593	0.6181
RREP	40.18591	54.61290	0.735832	0.4618
ELP	187.3600	115.0179	1.628964	0.1033
TLE	409.4366	178.4020	2.295023	**0.0217
EID	-9.599478	30.94297	-0.310231	0.7564
GC	-328.2189	271.9987	-1.206693	0.2276
ARP	113.7690	174.2872	0.652767	0.5139
C	79.63801	110.2939	0.722053	0.4703

Mean dependent var	0.086100	S.D. dependent var	0.014130
Sum squared resid	9.45E-06	Root MSE	0.000972
Log likelihood	48.15655	Akaike info criterion	-7.831311
Schwarz criterion	-7.558984	Hannan-Quinn criter.	-8.130052
Deviance	9.45E-06	Deviance statistic	9.45E-06
Restr. deviance	0.001797	LR statistic	189.0896
Prob(LR statistic)	*0.000000	Pearson SSR	9.45E-06
Pearson statistic	9.45E-06	Dispersion	9.45E-06

p<0.01;p**<0.05;p***<0.1*



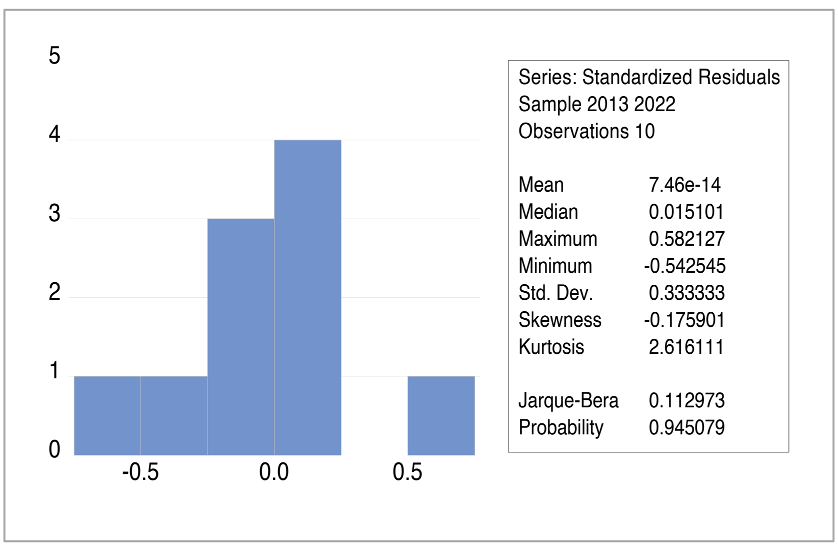
1.3. AUB

Dependent Variable: AUB
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/16/24 Time: 08:25
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Identity
Dispersion computed using Pearson Chi-Square
Convergence achieved after 0 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREP	-0.552287	0.542289	-1.018436	0.3085
HEC	1.603440	1.046634	1.531997	0.1255
RREC	0.762843	0.907527	0.840573	0.4006
ELP	-1.200960	1.060410	-1.132543	0.2574
TLE	-2.464862	1.632419	-1.509945	0.1311
EID	0.247293	0.269157	0.918769	0.3582
GC	6.452589	2.829574	2.280410	** 0.0226
ARP	-1.660063	1.799674	-0.922424	0.3563
C	-1.951695	1.006892	-1.938337	0.0526

Mean dependent var	0.078600	S.D. dependent var	0.016386
Sum squared resid	1.71E-05	Root MSE	0.001307
Log likelihood	45.20005	Akaike info criterion	-7.240011
Schwarz criterion	-6.967684	Hannan-Quinn criter.	-7.538752
Deviance	1.71E-05	Deviance statistic	1.71E-05
Restr. deviance	0.002416	LR statistic	140.5158
Prob(LR statistic)	* 0.000000	Pearson SSR	1.71E-05
Pearson statistic	1.71E-05	Dispersion	1.71E-05

p<0.01;p**<0.05;p***<0.1*

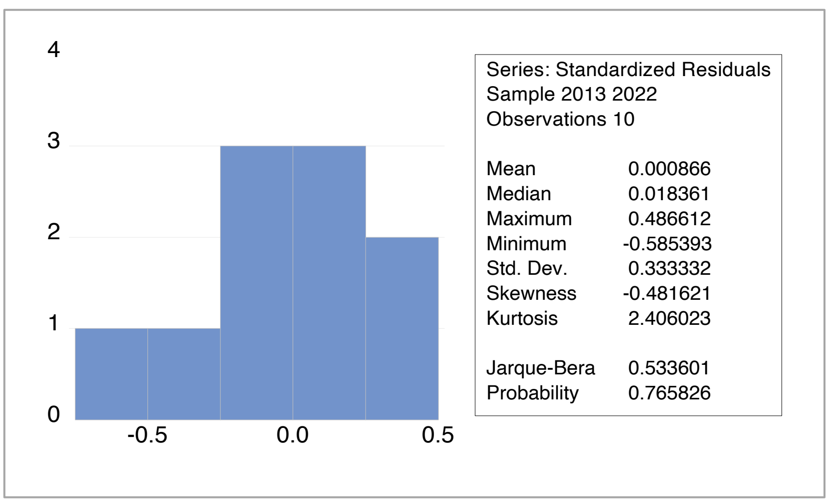


Dependent Variable: AUB
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/16/24 Time: 08:27
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Log
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREP	-5.799466	5.889687	-0.984681	0.3248
HEC	14.76310	11.67980	1.263986	0.2062
RREC	8.511108	9.804490	0.868083	0.3853
ELP	-14.40161	11.92404	-1.207780	0.2271
TLE	-30.10009	18.38602	-1.637118	0.1016
EID	1.922175	3.135378	0.613060	0.5398
GC	66.07195	29.51725	2.238418	**0.0252
ARP	-15.68878	19.05087	-0.823520	0.4102
C	-22.39768	11.40308	-1.964179	0.0495

Mean dependent var	0.078600	S.D. dependent var	0.016386
Sum squared resid	1.28E-05	Root MSE	0.001130
Log likelihood	46.65280	Akaike info criterion	-7.530560
Schwarz criterion	-7.258233	Hannan-Quinn criter.	-7.829301
Deviance	1.28E-05	Deviance statistic	1.28E-05
Restr. deviance	0.002416	LR statistic	188.2294
Prob(LR statistic)	*0.000000	Pearson SSR	1.28E-05
Pearson statistic	1.28E-05	Dispersion	1.28E-05

p<0.01;p**<0.05;p***<0.1*

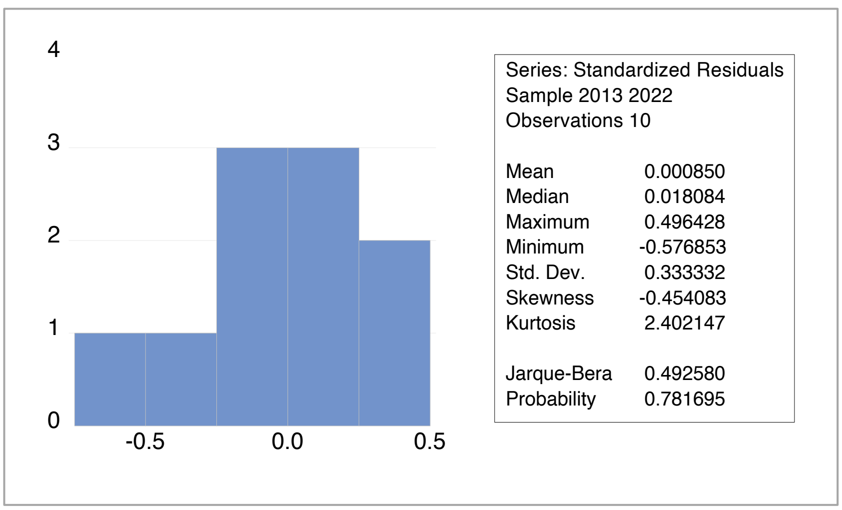


Dependent Variable: AUB
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/16/24 Time: 08:29
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Logit
Dispersion computed using Pearson Chi-Square
Convergence achieved after 4 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREP	-6.394192	6.505807	-0.982844	0.3257
HEC	16.50529	12.89072	1.280401	0.2004
RREC	9.337035	10.82283	0.862716	0.3883
ELP	-15.70742	13.11252	-1.197895	0.2310
TLE	-32.78551	20.21415	-1.621910	0.1048
EID	2.189669	3.447599	0.635129	0.5253
GC	73.14127	32.71611	2.235635	**0.0254
ARP	-17.53660	21.06777	-0.832390	0.4052
C	-24.53165	12.56165	-1.952901	0.0508

Mean dependent var	0.078600	S.D. dependent var	0.016386
Sum squared resid	1.32E-05	Root MSE	0.001148
Log likelihood	46.49700	Akaike info criterion	-7.499401
Schwarz criterion	-7.227074	Hannan-Quinn criter.	-7.798142
Deviance	1.32E-05	Deviance statistic	1.32E-05
Restr. deviance	0.002416	LR statistic	182.4241
Prob(LR statistic)	*0.000000	Pearson SSR	1.32E-05
Pearson statistic	1.32E-05	Dispersion	1.32E-05

p<0.01;p**<0.05;p***<0.1*

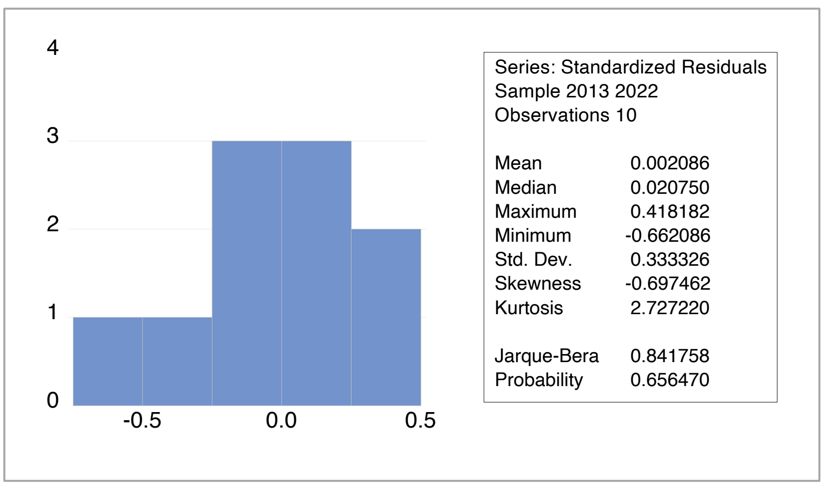


Dependent Variable: AUB
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/16/24 Time: 08:30
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Inverse
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREP	65.32775	58.41470	1.118344	0.2634
HEC	-130.7122	117.3981	-1.113409	0.2655
RREC	-101.0979	99.32164	-1.017884	0.3087
ELP	180.4648	127.4652	1.415796	0.1568
TLE	380.4332	197.5193	1.926056	***0.0541
EID	-11.33325	33.03901	-0.343026	0.7316
GC	-667.8567	282.6550	-2.362798	**0.0181
ARP	141.0866	187.1146	0.754011	0.4508
C	200.6565	117.4647	1.708228	0.0876

Mean dependent var	0.078600	S.D. dependent var	0.016386
Sum squared resid	8.00E-06	Root MSE	0.000894
Log likelihood	48.99301	Akaike info criterion	-7.998602
Schwarz criterion	-7.726276	Hannan-Quinn criter.	-8.297344
Deviance	8.00E-06	Deviance statistic	8.00E-06
Restr. deviance	0.002416	LR statistic	301.1740
Prob(LR statistic)	*0.000000	Pearson SSR	8.00E-06
Pearson statistic	8.00E-06	Dispersion	8.00E-06

p<0.01;p**<0.05;p***<0.1*



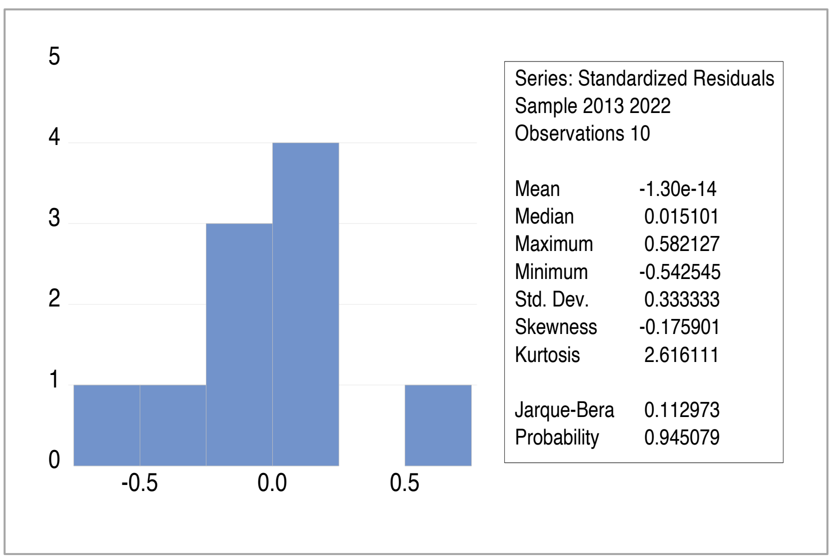
1.4. HC

Dependent Variable: HC
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 15:14
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Identity
Dispersion computed using Pearson Chi-Square
Convergence achieved after 1 iteration
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic		Prob.
RREC	-0.362718	0.188272	-1.926564	***	0.0540
HEC	1.223153	0.217131	5.633261	*	0.0000
RREP	0.466513	0.112501	4.146743	*	0.0000
ELP	-0.627622	0.219989	-2.852976	*	0.0043
TLE	-1.843926	0.338655	-5.444848	*	0.0000
EID	0.409271	0.055838	7.329596	*	0.0000
GC	1.201070	0.587012	2.046072	**	0.0407
ARP	1.627396	0.373353	4.358865	*	0.0000
C	-0.931486	0.208886	-4.459307		0.0000

Mean dependent var	0.145200	S.D. dependent var	0.013209
Sum squared resid	7.35E-07	Root MSE	0.000271
Log likelihood	60.92841	Akaike info criterion	-10.38568
Schwarz criterion	-10.11336	Hannan-Quinn criter.	-10.68442
Deviance	7.35E-07	Deviance statistic	7.35E-07
Restr. deviance	0.001570	LR statistic	2135.963
Prob(LR statistic)	* 0.000000	Pearson SSR	7.35E-07
Pearson statistic	7.35E-07	Dispersion	7.35E-07

p<0.01;p**<0.05;p***<0.1*

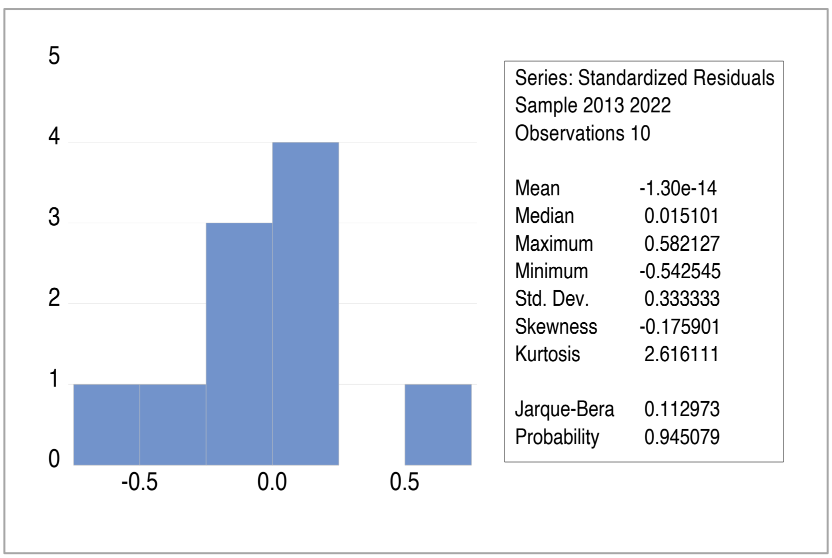


Dependent Variable: HC
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 15:15
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Log
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-2.701033	0.757816	-3.564232	* 0.0004
HEC	7.836695	0.897518	8.731516	* 0.0000
RREP	3.521342	0.459129	7.669613	* 0.0000
ELP	-4.550584	0.887946	-5.124846	* 0.0000
TLE	-13.11892	1.365569	-9.606926	* 0.0000
EID	2.696374	0.234958	11.47597	* 0.0000
GC	6.670712	2.319833	2.875515	* 0.0040
ARP	11.76818	1.463652	8.040290	* 0.0000
C	-8.707901	0.867663	-10.03604	0.0000

Mean dependent var	0.145200	S.D. dependent var	0.013209
Sum squared resid	2.46E-07	Root MSE	0.000157
Log likelihood	66.39826	Akaike info criterion	-11.47965
Schwarz criterion	-11.20733	Hannan-Quinn criter.	-11.77839
Deviance	2.46E-07	Deviance statistic	2.46E-07
Restr. deviance	0.001570	LR statistic	6380.198
Prob(LR statistic)	* 0.000000	Pearson SSR	2.46E-07
Pearson statistic	2.46E-07	Dispersion	2.46E-07

p<0.01;p**<0.05;p***<0.1*

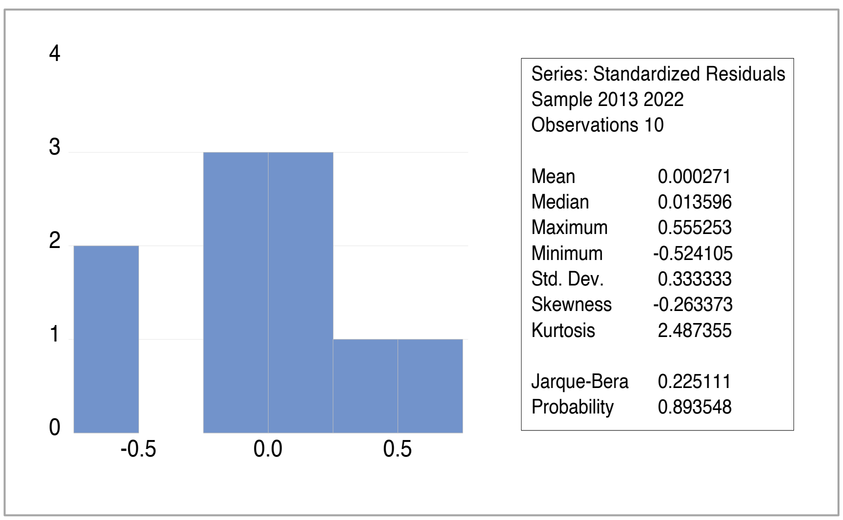


Dependent Variable: HC
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 15:15
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Logit
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-3.124711	0.995030	-3.140318	* 0.0017
HEC	9.272689	1.173823	7.899565	* 0.0000
RREP	4.063649	0.601647	6.754211	* 0.0000
ELP	-5.275439	1.165218	-4.527427	* 0.0000
TLE	-15.26251	1.792207	-8.516042	* 0.0000
EID	3.175745	0.306411	10.36433	* 0.0000
GC	8.096787	3.056084	2.649399	* 0.0081
ARP	13.66172	1.930452	7.076951	* 0.0000
C	-9.817981	1.133728	-8.659909	0.0000

Mean dependent var	0.145200	S.D. dependent var	0.013209
Sum squared resid	3.11E-07	Root MSE	0.000176
Log likelihood	65.22697	Akaike info criterion	-11.24539
Schwarz criterion	-10.97307	Hannan-Quinn criter.	-11.54414
Deviance	3.11E-07	Deviance statistic	3.11E-07
Restr. deviance	0.001570	LR statistic	5047.532
Prob(LR statistic)	* 0.000000	Pearson SSR	3.11E-07
Pearson statistic	3.11E-07	Dispersion	3.11E-07

p<0.01;p**<0.05;p***<0.1*

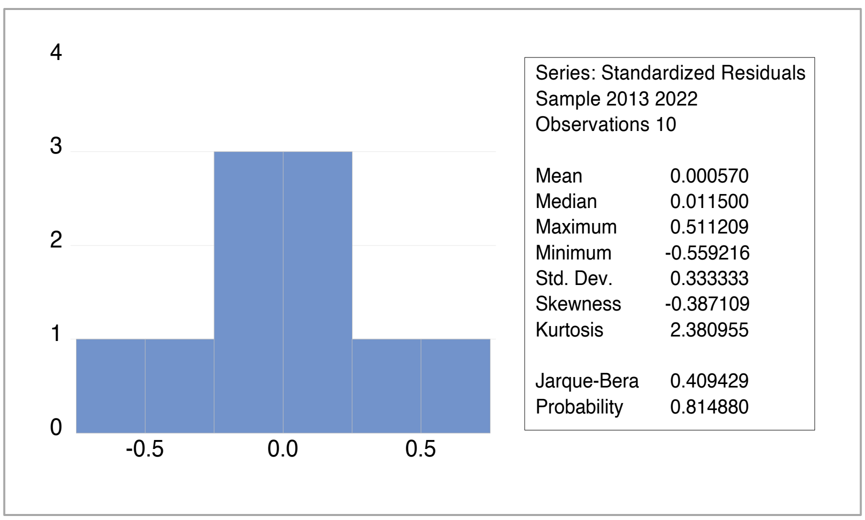


Dependent Variable: HC
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 15:17
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Inverse
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	19.60569	1.135573	17.26502	* 0.0000
HEC	-50.59745	1.372714	-36.85943	* 0.0000
RREP	-26.08658	0.693947	-37.59160	* 0.0000
ELP	33.44309	1.337197	25.00984	* 0.0000
TLE	94.11892	2.056575	45.76490	* 0.0000
EID	-17.91911	0.365968	-48.96365	* 0.0000
GC	-36.24784	3.397361	-10.66941	* 0.0000
ARP	-84.64260	2.132983	-39.68274	* 0.0000
C	49.74707	1.335400	37.25257	0.0000

Mean dependent var	0.145200	S.D. dependent var	0.013209
Sum squared resid	1.13E-08	Root MSE	3.35E-05
Log likelihood	81.82331	Akaike info criterion	-14.56466
Schwarz criterion	-14.29233	Hannan-Quinn criter.	-14.86340
Deviance	1.13E-08	Deviance statistic	1.13E-08
Restr. deviance	* 0.001570	LR statistic	139541.0
Prob(LR statistic)	0.000000	Pearson SSR	1.13E-08
Pearson statistic	1.13E-08	Dispersion	1.13E-08

p<0.01;p**<0.05;p***<0.1*



2. DENMARK

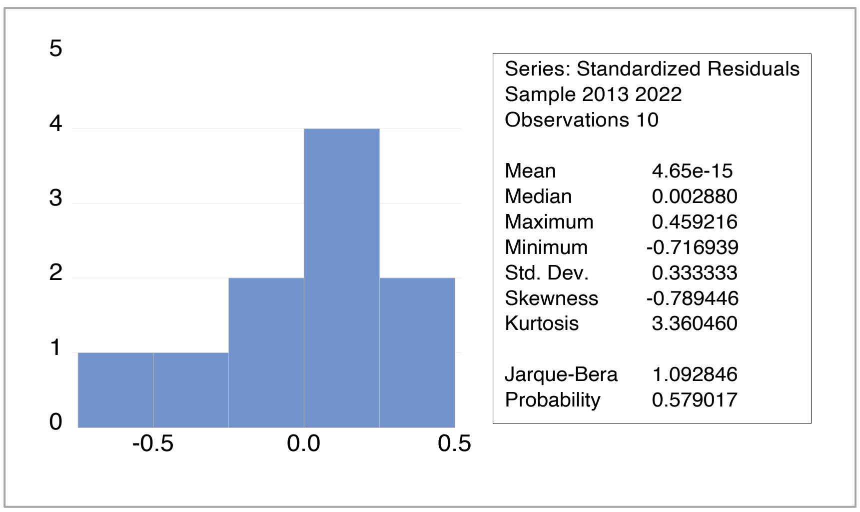
2.1. EPCI

Dependent Variable: EPCI
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 10:17
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Identity
Dispersion computed using Pearson Chi-Square
Convergence achieved after 0 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-0.057109	0.089607	-0.637330	0.5239
HEC	-0.143355	0.704469	-0.203494	0.8387
RREP	-0.020160	0.087033	-0.231639	0.8168
ELP	0.120969	0.115912	1.043626	0.2967
TLE	0.388766	0.523627	0.742448	0.4578
EID	0.060020	0.062195	0.965037	0.3345
GC	-0.795180	1.155628	-0.688094	0.4914
ARP	0.927630	2.035797	0.455659	0.6486
C	0.178109	0.537624	0.331290	0.7404

Mean dependent var	0.065472	S.D. dependent var	0.006300
Sum squared resid	4.89E-05	Root MSE	0.002211
Log likelihood	39.94275	Akaike info criterion	-6.188550
Schwarz criterion	-5.916224	Hannan-Quinn criter.	-6.487292
Deviance	4.89E-05	Deviance statistic	4.89E-05
Restr. deviance	0.000357	LR statistic	6.309900
Prob(LR statistic)	0.612562	Pearson SSR	4.89E-05
Pearson statistic	4.89E-05	Dispersion	4.89E-05

p<0.01;p**<0.05;p***<0.1*

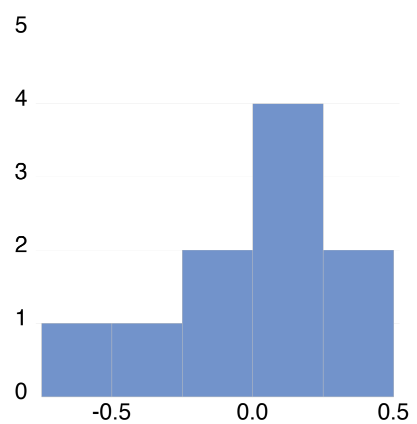


Dependent Variable: EPCI
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 10:18
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Log
Dispersion computed using Pearson Chi-Square
Convergence achieved after 2 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-0.857259	1.421351	-0.603129	0.5464
HEC	-2.023603	11.40891	-0.177370	0.8592
RREP	-0.348287	1.373534	-0.253570	0.7998
ELP	1.779400	1.788364	0.994988	0.3197
TLE	6.154668	8.328939	0.738950	0.4599
EID	0.945919	0.999037	0.946831	0.3437
GC	-12.19174	18.15825	-0.671416	0.5020
ARP	15.00642	32.10011	0.467488	0.6402
C	-1.159414	8.572450	-0.135249	0.8924

Mean dependent var	0.065472	S.D. dependent var	0.006300
Sum squared resid	4.88E-05	Root MSE	0.002210
Log likelihood	39.94497	Akaike info criterion	-6.188994
Schwarz criterion	-5.916667	Hannan-Quinn criter.	-6.487735
Deviance	4.88E-05	Deviance statistic	4.88E-05
Restr. deviance	0.000357	LR statistic	6.313141
Prob(LR statistic)	0.612200	Pearson SSR	4.88E-05
Pearson statistic	4.88E-05	Dispersion	4.88E-05

p<0.01;p**<0.05;p***<0.1*



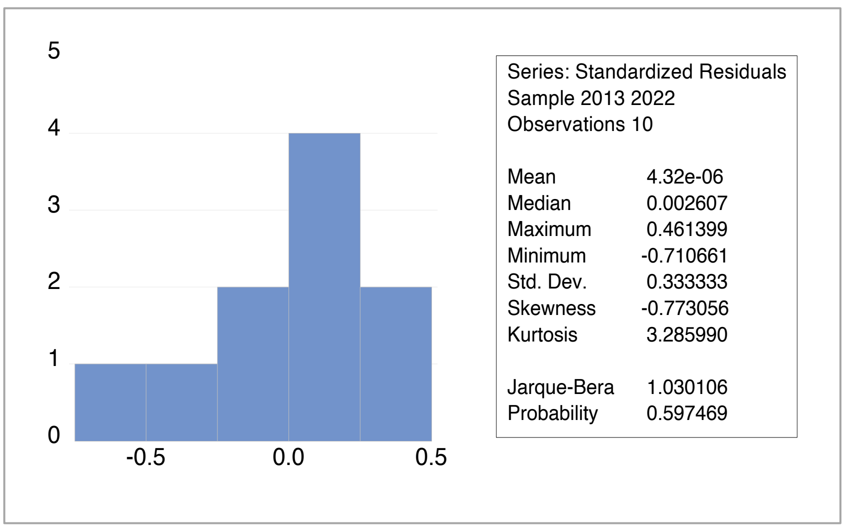
Series: Standardized Residuals	
Sample 2013 2022	
Observations 10	
Mean	4.62e-06
Median	0.002586
Maximum	0.461556
Minimum	-0.710212
Std. Dev.	0.333333
Skewness	-0.771943
Kurtosis	3.280819
Jarque-Bera	1.026018
Probability	0.598691

Dependent Variable: EPCI
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 10:19
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Logit
Dispersion computed using Pearson Chi-Square
Convergence achieved after 2 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-0.918454	1.516977	-0.605450	0.5449
HEC	-2.177603	12.15865	-0.179099	0.8579
RREP	-0.369644	1.466466	-0.252065	0.8010
ELP	1.909286	1.912026	0.998567	0.3180
TLE	6.569531	8.887449	0.739192	0.4598
EID	1.009981	1.065281	0.948089	0.3431
GC	-13.04188	19.38986	-0.672614	0.5012
ARP	15.99470	34.27264	0.466690	0.6407
C	-0.970602	9.144895	-0.106136	0.9155

Mean dependent var	0.065472	S.D. dependent var	0.006300
Sum squared resid	4.88E-05	Root MSE	0.002210
Log likelihood	39.94467	Akaike info criterion	-6.188933
Schwarz criterion	-5.916607	Hannan-Quinn criter.	-6.487675
Deviance	4.88E-05	Deviance statistic	4.88E-05
Restr. deviance	0.000357	LR statistic	6.312699
Prob(LR statistic)	0.612249	Pearson SSR	4.88E-05
Pearson statistic	4.88E-05	Dispersion	4.88E-05

p<0.01;p**<0.05;p***<0.1*

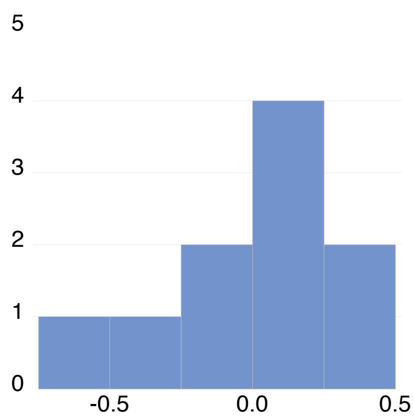


Dependent Variable: EPCI
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 10:20
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Inverse
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	12.91275	22.60729	0.571176	0.5679
HEC	28.83382	185.8227	0.155168	0.8767
RREP	5.950912	21.72181	0.273960	0.7841
ELP	-26.32061	27.88079	-0.944041	0.3451
TLE	-97.80564	132.8774	-0.736059	0.4617
EID	-14.96891	16.11855	-0.928676	0.3531
GC	187.4093	287.4874	0.651887	0.5145
ARP	-241.5915	507.8317	-0.475731	0.6343
C	-6.568166	137.7304	-0.047689	0.9620

Mean dependent var	0.065472	S.D. dependent var	0.006300
Sum squared resid	4.88E-05	Root MSE	0.002209
Log likelihood	39.95159	Akaike info criterion	-6.190318
Schwarz criterion	-5.917992	Hannan-Quinn criter.	-6.489060
Deviance	4.88E-05	Deviance statistic	4.88E-05
Restr. deviance	0.000357	LR statistic	6.322835
Prob(LR statistic)	0.611118	Pearson SSR	4.88E-05
Pearson statistic	4.88E-05	Dispersion	4.88E-05

p<0.01;p**<0.05;p***<0.1*



Series: Standardized Residuals
Sample 2013 2022
Observations 10

Mean	1.93e-05
Median	0.002336
Maximum	0.463464
Minimum	-0.703686
Std. Dev.	0.333333
Skewness	-0.756791
Kurtosis	3.207506
Jarque-Bera	0.972497
Probability	0.614929

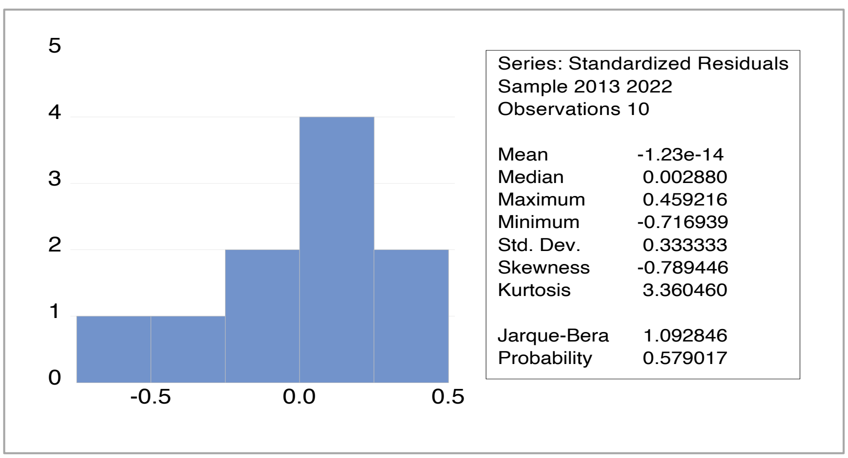
2.2. IKW

Dependent Variable: IKW
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 08:24
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Identity
Dispersion computed using Pearson Chi-Square
Convergence achieved after 0 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-0.079281	0.024122	-3.286726	* 0.0010
HEC	-0.071279	0.189637	-0.375872	0.7070
RREP	0.014887	0.023428	0.635405	0.5252
ELP	0.186310	0.031203	5.970979	* 0.0000
TLE	0.384964	0.140956	2.731095	* 0.0063
EID	0.033422	0.016742	1.996262	* 0.0459
GC	1.189478	0.311086	-3.823636	* 0.0001
ARP	0.807560	0.548020	1.473596	0.1406
C	0.231443	0.144724	1.599206	0.1098

Mean dependent var	0.032400	S.D. dependent var	0.007531
Sum squared resid	3.54E-06	Root MSE	0.000595
Log likelihood	53.06606	Akaike info criterion	-8.813212
Schwarz criterion	-8.540886	Hannan-Quinn criter.	-9.111954
Deviance	3.54E-06	Deviance statistic	3.54E-06
Restr. deviance	0.000510	LR statistic	143.1383
Prob(LR statistic)	* 0.000000	Pearson SSR	3.54E-06
Pearson statistic	3.54E-06	Dispersion	3.54E-06

p<0.01;p**<0.05;p***<0.1*

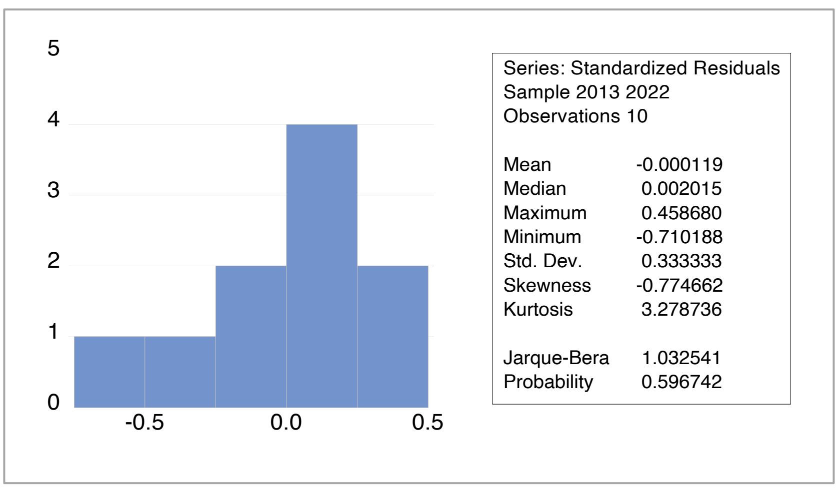


Dependent Variable: IKW
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24   Time: 08:25
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Log
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-2.368085	0.834443	-2.837922	* 0.0045
HEC	-0.867083	6.634946	-0.130684	0.8960
RREP	0.372288	0.820172	0.453915	0.6499
ELP	5.284641	0.985863	5.360419	* 0.0000
TLE	11.75247	4.885566	2.405550	* 0.0161
EID	1.017451	0.593140	1.715364	* 0.0863
GC	36.40311	10.30179	-3.533670	* 0.0004
ARP	28.98856	18.86451	1.536672	0.1244
C	1.792088	4.983306	0.359618	0.7191

Mean dependent var	0.032400	S.D. dependent var	0.007531
Sum squared resid	3.68E-06	Root MSE	0.000607
Log likelihood	52.87270	Akaike info criterion	-8.774541
Schwarz criterion	-8.502214	Hannan-Quinn criter.	-9.073282
Deviance	3.68E-06	Deviance statistic	3.68E-06
Restr. deviance	0.000510	LR statistic	137.6707
Prob(LR statistic)	* 0.000000	Pearson SSR	3.68E-06
Pearson statistic	3.68E-06	Dispersion	3.68E-06

p<0.01;p**<0.05;p***<0.1*

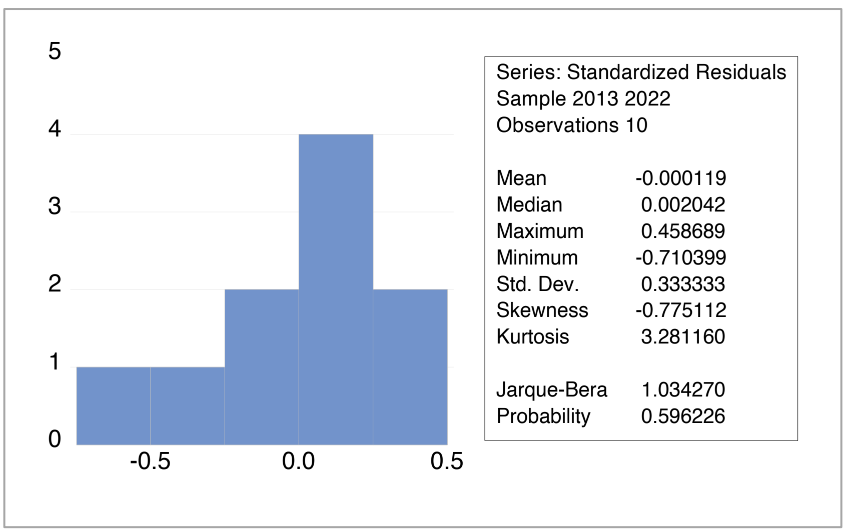


Dependent Variable: IKW
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 08:27
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Logit
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-2.450185	0.859194	-2.851725	* 0.0043
HEC	-0.942417	6.828923	-0.138004	0.8902
RREP	0.387821	0.844197	0.459396	0.6459
ELP	5.478007	1.017698	5.382744	* 0.0000
TLE	12.15065	5.030142	2.415568	* 0.0157
EID	1.052026	0.610312	1.723751	* 0.0848
GC	37.63273	10.62042	-3.543432	* 0.0004
ARP	29.81836	19.42624	1.534953	0.1248
C	2.031783	5.131311	0.395958	0.6921

Mean dependent var	0.032400	S.D. dependent var	0.007531
Sum squared resid	3.68E-06	Root MSE	0.000606
Log likelihood	52.87838	Akaike info criterion	-8.775677
Schwarz criterion	-8.503350	Hannan-Quinn criter.	-9.074418
Deviance	3.68E-06	Deviance statistic	3.68E-06
Restr. deviance	0.000510	LR statistic	137.8283
Prob(LR statistic)	* 0.000000	Pearson SSR	3.68E-06
Pearson statistic	3.68E-06	Dispersion	3.68E-06

p<0.01;p**<0.05;p***<0.1*

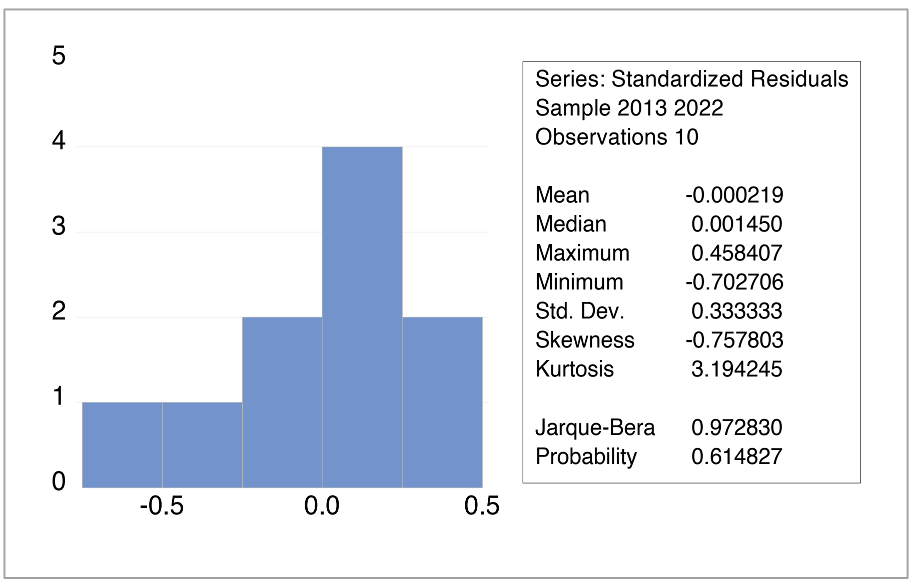


Dependent Variable: IKW
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 08:33
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Inverse
Dispersion computed using Pearson Chi-Square
Convergence achieved after 4 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	71.86383	29.26009	2.456036	** 0.0140
HEC	-8.581473	236.9849	-0.036211	0.9711
RREP	-9.157536	29.08020	-0.314906	0.7528
ELP	-154.1065	32.78836	-4.700036	* 0.0000
TLE	-364.8975	171.7268	-2.124872	* 0.0336
EID	-31.73042	21.19124	-1.497337	0.1343
GC	-1121.009	350.5432	3.197920	* 0.0014
ARP	-1012.189	661.0584	-1.531165	0.1257
C	-105.3317	175.7738	-0.599246	0.5490

Mean dependent var	0.032400	S.D. dependent var	0.007531
Sum squared resid	3.81E-06	Root MSE	0.000618
Log likelihood	52.69584	Akaike info criterion	-8.739167
Schwarz criterion	-8.466840	Hannan-Quinn criter.	-9.037909
Deviance	3.81E-06	Deviance statistic	3.81E-06
Restr. deviance	0.000510	LR statistic	132.8511
Prob(LR statistic)	* 0.000000	Pearson SSR	3.81E-06
Pearson statistic	3.81E-06	Dispersion	3.81E-06

p<0.01;p**<0.05;p***<0.1*



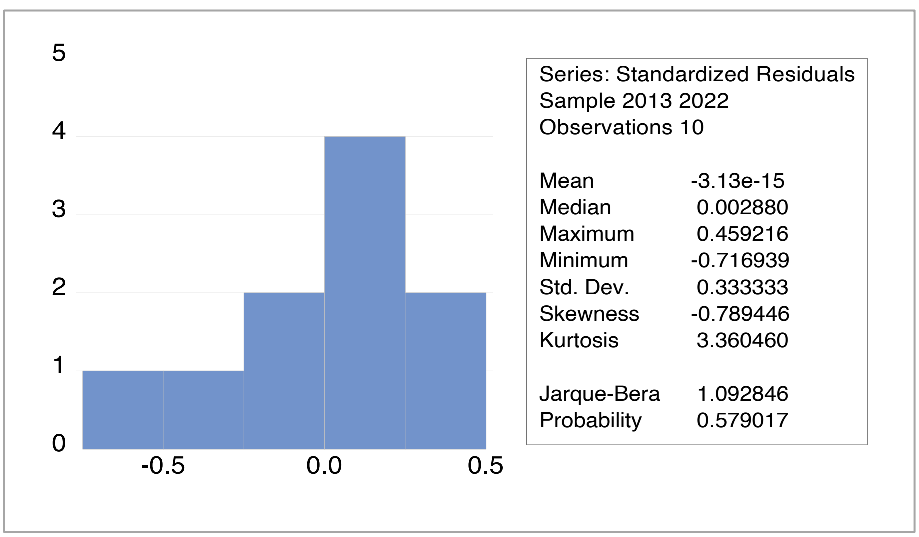
2.3. AUB

Dependent Variable: AUB
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 11:09
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Identity
Dispersion computed using Pearson Chi-Square
Convergence achieved after 0 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-0.077782	0.172231	-0.451611	0.6515
HEC	0.033007	1.354038	0.024377	0.9806
RREP	-0.008043	0.167283	-0.048083	0.9616
ELP	-0.031271	0.222791	-0.140359	0.8884
TLE	-0.342134	1.006448	-0.339942	0.7339
EID	0.027897	0.119543	0.233366	0.8155
GC	1.074154	2.221198	0.483592	0.6287
ARP	2.183481	3.912945	0.558015	0.5768
C	-0.438294	1.033351	-0.424148	0.6715

Mean dependent var	0.036900	S.D. dependent var	0.007666
Sum squared resid	0.000181	Root MSE	0.004249
Log likelihood	33.40872	Akaike info criterion	-4.881745
Schwarz criterion	-4.609418	Hannan-Quinn criter.	-5.180486
Deviance	0.000181	Deviance statistic	0.000181
Restr. deviance	0.000529	LR statistic	1.929731
Prob(LR statistic)	0.983091	Pearson SSR	0.000181
Pearson statistic	0.000181	Dispersion	0.000181

p<0.01;p**<0.05;p***<0.1*

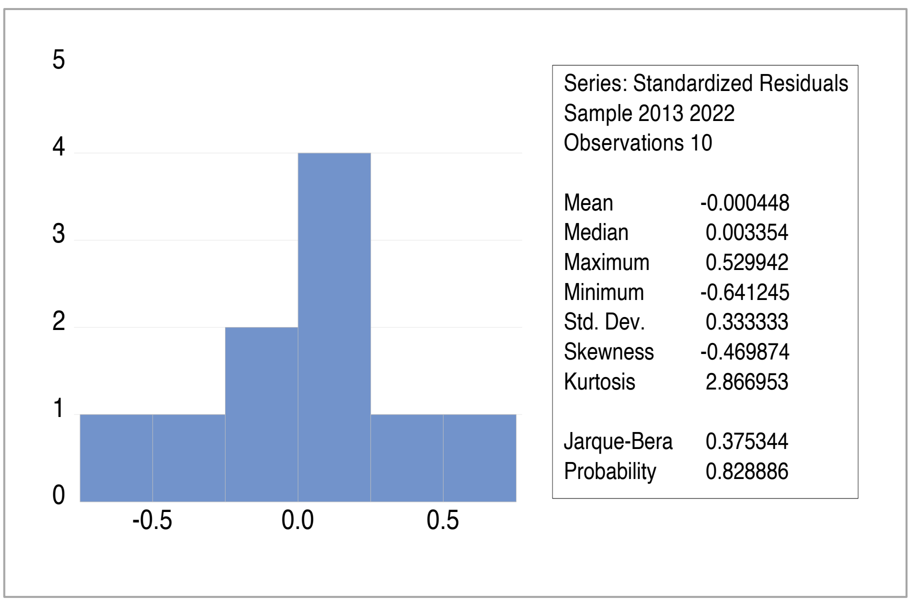


Dependent Variable: AUB
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 11:17
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Log
Dispersion computed using Pearson Chi-Square
Convergence achieved after 4 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-2.047078	5.292959	-0.386755	0.6989
HEC	-0.742400	40.64070	-0.018267	0.9854
RREP	-0.330205	4.576309	-0.072155	0.9425
ELP	-0.810883	6.644229	-0.122043	0.9029
TLE	-8.010509	27.03807	-0.296268	0.7670
EID	0.815905	3.418622	0.238665	0.8114
GC	29.07408	59.32664	0.490068	0.6241
ARP	53.15386	113.5184	0.468240	0.6396
C	-15.07762	28.59559	-0.527271	0.5980

Mean dependent var	0.036900	S.D. dependent var	0.007666
Sum squared resid	0.000188	Root MSE	0.004341
Log likelihood	33.19355	Akaike info criterion	-4.838709
Schwarz criterion	-4.566383	Hannan-Quinn criter.	-5.137451
Deviance	0.000188	Deviance statistic	0.000188
Restr. deviance	0.000529	LR statistic	1.806324
Prob(LR statistic)	0.986385	Pearson SSR	0.000188
Pearson statistic	0.000188	Dispersion	0.000188

p<0.01;p**<0.05;p***<0.1*

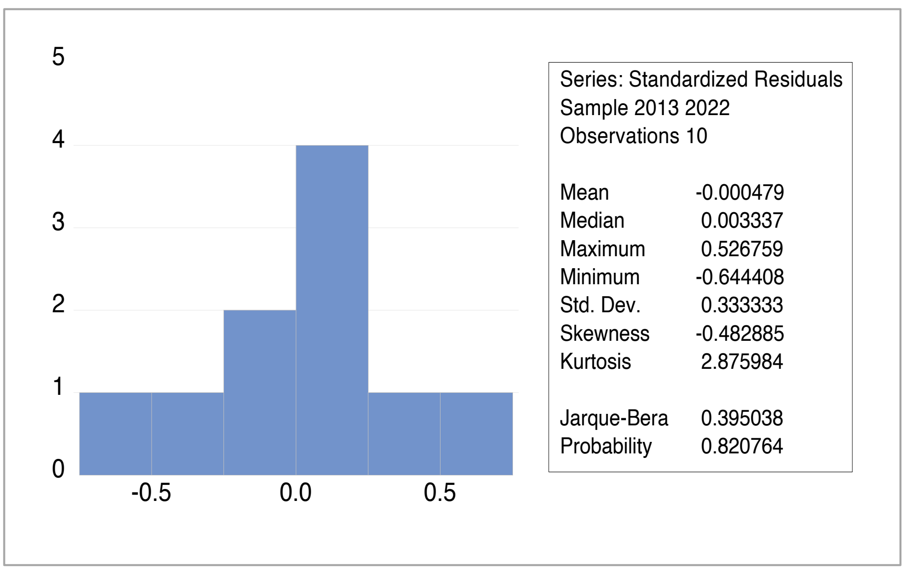


Dependent Variable: AUB
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 11:18
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Logit
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-2.128122	5.473287	-0.388820	0.6974
HEC	-0.712322	42.03563	-0.016946	0.9865
RREP	-0.337770	4.754842	-0.071037	0.9434
ELP	-0.844436	6.875969	-0.122810	0.9023
TLE	-8.366355	28.10288	-0.297705	0.7659
EID	0.845313	3.541571	0.238683	0.8114
GC	30.17674	61.66006	0.489405	0.6246
ARP	55.39635	117.5710	0.471174	0.6375
C	-15.52584	29.66983	-0.523287	0.6008

Mean dependent var	0.036900	S.D. dependent var	0.007666
Sum squared resid	0.000188	Root MSE	0.004339
Log likelihood	33.19772	Akaike info criterion	-4.839545
Schwarz criterion	-4.567218	Hannan-Quinn criter.	-5.138287
Deviance	0.000188	Deviance statistic	0.000188
Restr. deviance	0.000529	LR statistic	1.808669
Prob(LR statistic)	0.986326	Pearson SSR	0.000188
Pearson statistic	0.000188	Dispersion	0.000188

p<0.01;p**<0.05;p***<0.1*

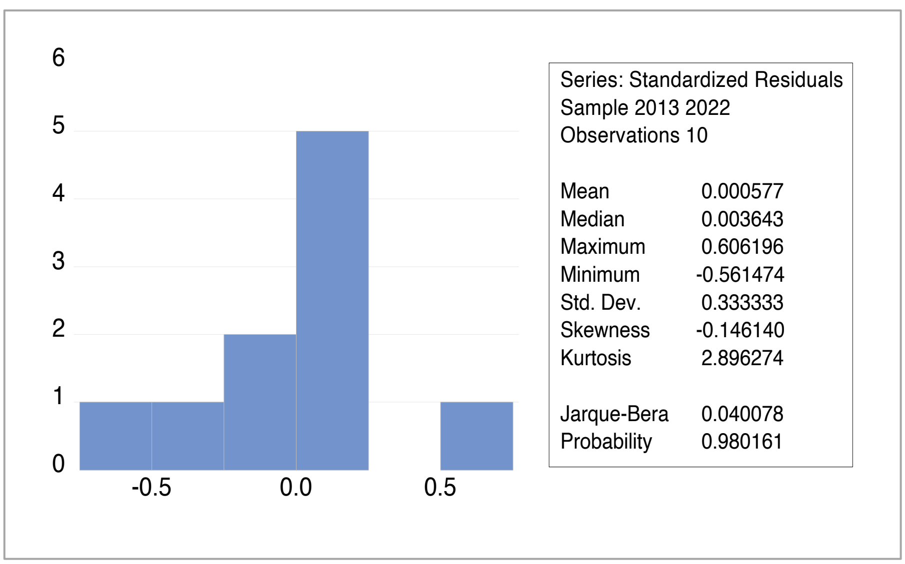


Dependent Variable: AUB
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24   Time: 11:20
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Inverse
Dispersion computed using Pearson Chi-Square
Convergence achieved after 5 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	57.31810	166.4264	0.344405	0.7305
HEC	66.76912	1252.461	0.053310	0.9575
RREP	10.67348	122.3166	0.087261	0.9305
ELP	20.59324	196.3369	0.104887	0.9165
TLE	191.6228	716.7099	0.267364	0.7892
EID	-23.91108	103.1052	-0.231910	0.8166
GC	-811.9639	1573.702	-0.515958	0.6059
ARP	-1318.109	3338.995	-0.394762	0.6930
C	325.3773	798.2343	0.407621	0.6836

Mean dependent var	0.036900	S.D. dependent var	0.007666
Sum squared resid	0.000189	Root MSE	0.004345
Log likelihood	33.18497	Akaike info criterion	-4.836994
Schwarz criterion	-4.564667	Hannan-Quinn criter.	-5.135735
Deviance	0.000189	Deviance statistic	0.000189
Restr. deviance	0.000529	LR statistic	1.801513
Prob(LR statistic)	0.986504	Pearson SSR	0.000189
Pearson statistic	0.000189	Dispersion	0.000189

p<0.01;p**<0.05;p***<0.1*



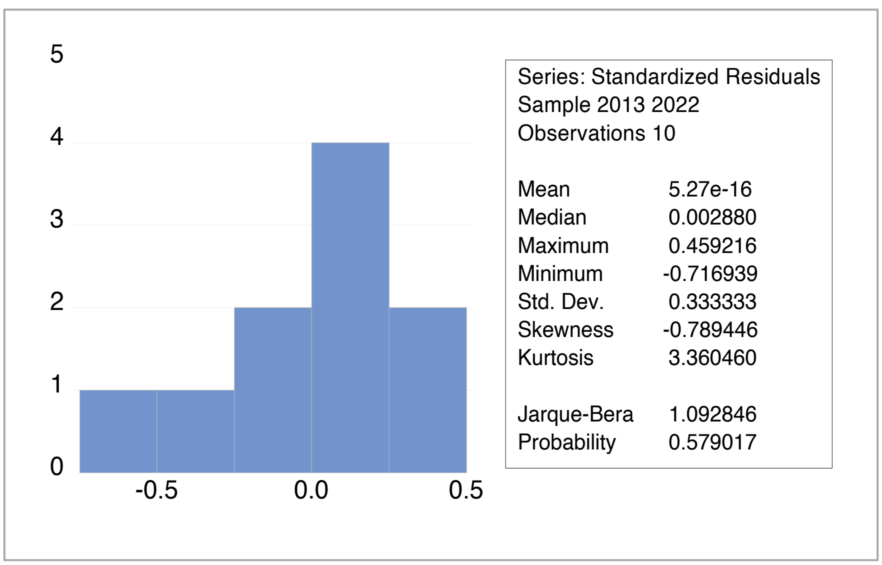
2.4. HC

Dependent Variable: HC
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 15:27
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Identity
Dispersion computed using Pearson Chi-Square
Convergence achieved after 1 iteration
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	0.007906	0.137954	0.057308	0.9543
HEC	-0.463869	1.084562	-0.427701	0.6689
RREP	-0.102370	0.133991	-0.764011	0.4449
ELP	0.142526	0.178452	0.798680	0.4245
TLE	1.127269	0.806148	1.398340	0.1620
EID	0.145340	0.095752	1.517879	0.1290
GC	-1.875920	1.779143	-1.054396	0.2917
ARP	-0.088081	3.134204	-0.028103	0.9776
C	0.687844	0.827697	0.831034	0.4060

Mean dependent var	0.160186	S.D. dependent var	0.010001
Sum squared resid	0.000116	Root MSE	0.003403
Log likelihood	35.62787	Akaike info criterion	-5.325575
Schwarz criterion	-5.053248	Hannan-Quinn criter.	-5.624316
Deviance	0.000116	Deviance statistic	0.000116
Restr. deviance	0.000900	LR statistic	6.771335
Prob(LR statistic)	0.561493	Pearson SSR	0.000116
Pearson statistic	0.000116	Dispersion	0.000116

$p^{*}<0.01; p^{**}<0.05; p^{***}<0.1$

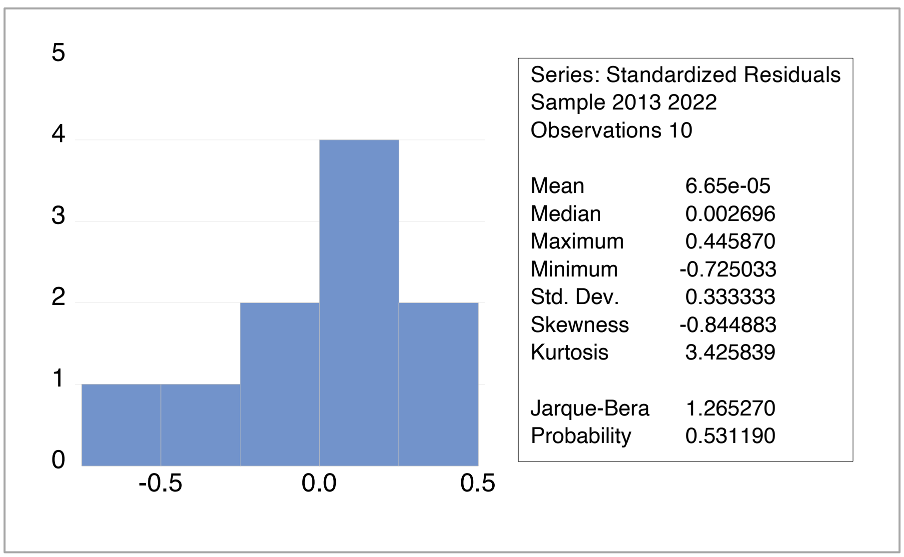


Dependent Variable: HC
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 15:28
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Log
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	0.063521	0.860646	0.073807	0.9412
HEC	-2.901544	7.017141	-0.413494	0.6792
RREP	-0.664662	0.844972	-0.786609	0.4315
ELP	0.863759	1.114504	0.775016	0.4383
TLE	7.272703	5.205586	1.397096	0.1624
EID	0.935644	0.616105	1.518642	0.1289
GC	-12.18799	11.50514	-1.059351	0.2894
ARP	-0.134356	19.69317	-0.006822	0.9946
C	1.516653	5.350375	0.283467	0.7768

Mean dependent var	0.160186	S.D. dependent var	0.010001
Sum squared resid	0.000114	Root MSE	0.003372
Log likelihood	35.71969	Akaike info criterion	-5.343938
Schwarz criterion	-5.071612	Hannan-Quinn criter.	-5.642680
Deviance	0.000114	Deviance statistic	0.000114
Restr. deviance	0.000900	LR statistic	6.915364
Prob(LR statistic)	0.545791	Pearson SSR	0.000114
Pearson statistic	0.000114	Dispersion	0.000114

p<0.01;p**<0.05;p***<0.1*

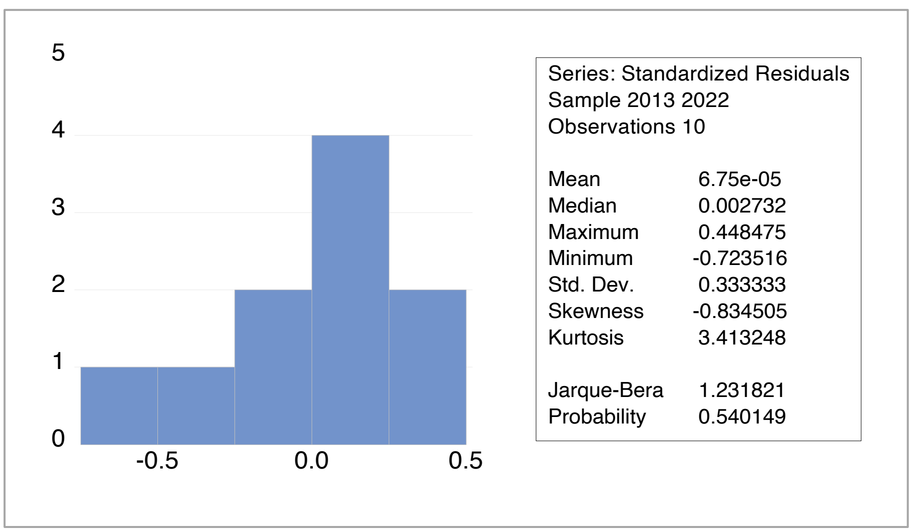


Dependent Variable: HC
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 15:30
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Logit
Dispersion computed using Pearson Chi-Square
Convergence achieved after 2 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	0.072345	1.024877	0.070589	0.9437
HEC	-3.453437	8.300109	-0.416071	0.6774
RREP	-0.785589	1.004181	-0.782318	0.4340
ELP	1.034609	1.326887	0.779727	0.4356
TLE	8.606346	6.158948	1.397373	0.1623
EID	1.107679	0.729453	1.518506	0.1289
GC	-14.40411	13.60818	-1.058489	0.2898
ARP	-0.253472	23.42064	-0.010823	0.9914
C	2.317311	6.329347	0.366122	0.7143

Mean dependent var	0.160186	S.D. dependent var	0.010001
Sum squared resid	0.000114	Root MSE	0.003378
Log likelihood	35.70199	Akaike info criterion	-5.340398
Schwarz criterion	-5.068072	Hannan-Quinn criter.	-5.639140
Deviance	0.000114	Deviance statistic	0.000114
Restr. deviance	0.000900	LR statistic	6.887393
Prob(LR statistic)	0.548829	Pearson SSR	0.000114
Pearson statistic	0.000114	Dispersion	0.000114

p<0.01;p**<0.05;p***<0.1*

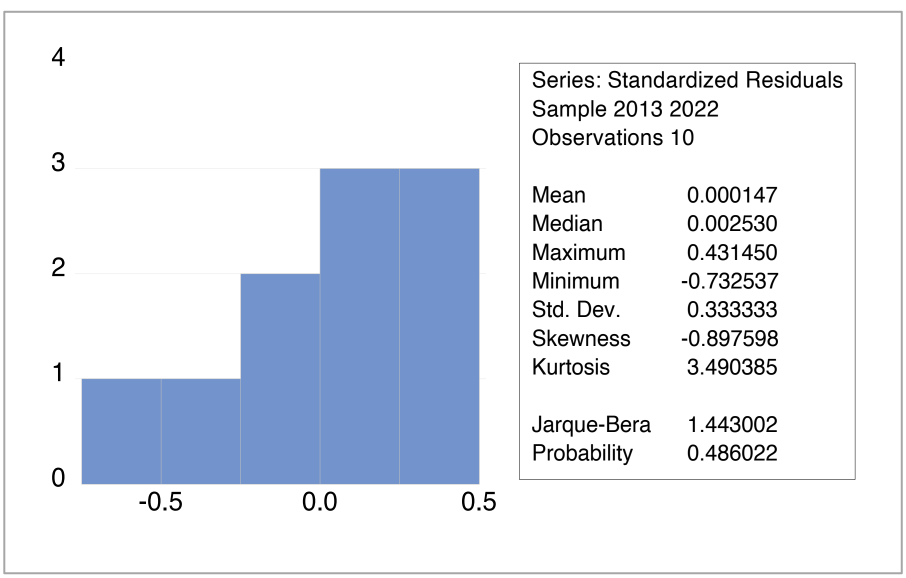


Dependent Variable: HC
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 15:31
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Inverse
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-0.492801	5.376192	-0.091664	0.9270
HEC	18.26575	45.51662	0.401298	0.6882
RREP	4.322997	5.340342	0.809498	0.4182
ELP	-5.246212	6.987800	-0.750767	0.4528
TLE	-47.05449	33.76213	-1.393706	0.1634
EID	-6.037587	3.977607	-1.517894	0.1290
GC	79.43013	74.86683	1.060952	0.2887
ARP	-1.698743	123.8801	-0.013713	0.9891
C	-15.11231	34.73326	-0.435096	0.6635

Mean dependent var	0.160186	S.D. dependent var	0.010001
Sum squared resid	0.000111	Root MSE	0.003338
Log likelihood	35.82227	Akaike info criterion	-5.364454
Schwarz criterion	-5.092128	Hannan-Quinn criter.	-5.663196
Deviance	0.000111	Deviance statistic	0.000111
Restr. deviance	0.000900	LR statistic	7.079434
Prob(LR statistic)	0.528087	Pearson SSR	0.000111
Pearson statistic	0.000111	Dispersion	0.000111

p<0.01;p**<0.05;p***<0.1*



3. GREECE

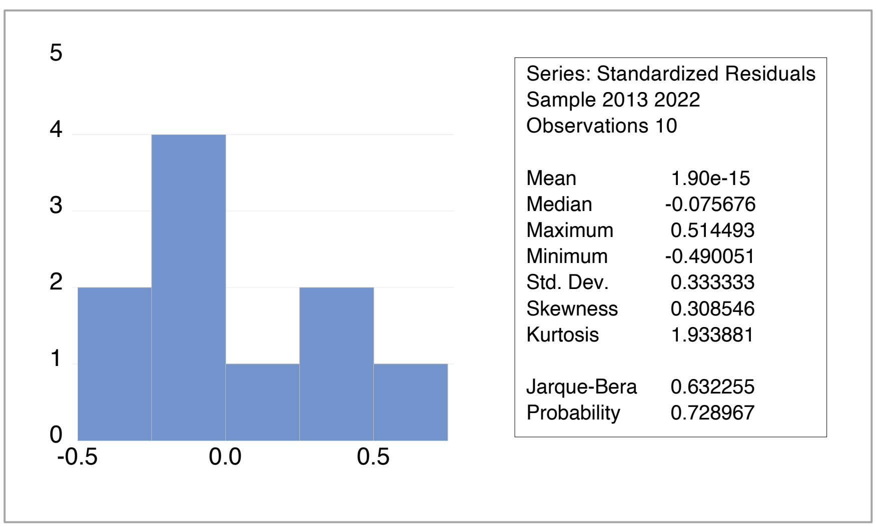
3.1. EPCI

Dependent Variable: EPCI
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/13/24 Time: 20:55
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Identity
Dispersion computed using Pearson Chi-Square
Convergence achieved after 0 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-0.498242	0.616215	-0.808552	0.4188
HEC	-0.764430	0.903375	-0.846194	0.3974
RREP	-0.233952	0.307571	-0.760643	0.4469
ELP	-0.334373	1.809477	-0.184790	0.8534
TLE	-0.702862	2.158835	-0.325575	0.7447
EID	0.500065	0.301644	1.657799***	0.0974
GC	1.277977	4.588792	0.278500	0.7806
ARP	0.489073	2.136442	0.228919	0.8189
C	-0.104602	0.860248	-0.121595	0.9032

Mean dependent var	0.239038	S.D. dependent var	0.047217
Sum squared resid	0.000174	Root MSE	0.004173
Log likelihood	33.58924	Akaike info criterion	-4.917847
Schwarz criterion	-4.645520	Hannan-Quinn criter.	-5.216589
Deviance	0.000174	Deviance statistic	0.000174
Restr. deviance	0.020065	LR statistic	114.2311
Prob(LR statistic)	* 0.000000	Pearson SSR	0.000174
Pearson statistic	0.000174	Dispersion	0.000174

p<0.01;p**<0.05;p***<0.1*

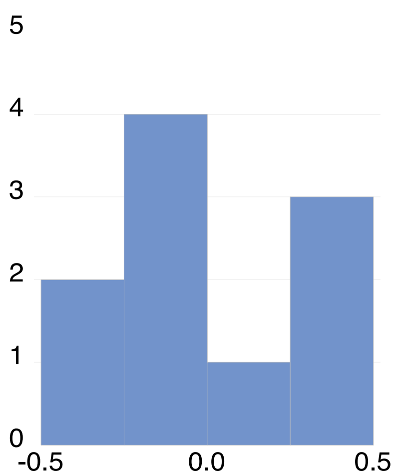


Dependent Variable: EPCI
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/13/24 Time: 20:57
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Log
Dispersion computed using Pearson Chi-Square
Convergence achieved after 4 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-1.729188	2.653203	-0.651736	0.5146
HEC	-3.590548	3.719902	-0.965226	0.3344
RREP	-1.070015	1.106985	-0.966603	0.3337
ELP	-3.514287	8.076300	-0.435136	0.6635
TLE	-5.829136	9.613675	-0.606338	0.5443
EID	2.041046	1.300076	1.569944	0.1164
GC	10.38774	20.15186	0.515473	0.6062
ARP	-0.945798	8.812133	-0.107329	0.9145
C	-3.501348	3.902806	-0.897136	0.3696

Mean dependent var	0.239038	S.D. dependent var	0.047217
Sum squared resid	0.000157	Root MSE	0.003961
Log likelihood	34.11066	Akaike info criterion	-5.022132
Schwarz criterion	-4.749806	Hannan-Quinn criter.	-5.320874
Deviance	0.000157	Deviance statistic	0.000157
Restr. deviance	0.020065	LR statistic	126.8969
Prob(LR statistic)	* 0.000000	Pearson SSR	0.000157
Pearson statistic	0.000157	Dispersion	0.000157

p<0.01;p**<0.05;p***<0.1*



Series: Standardized Residuals
Sample 2013 2022
Observations 10

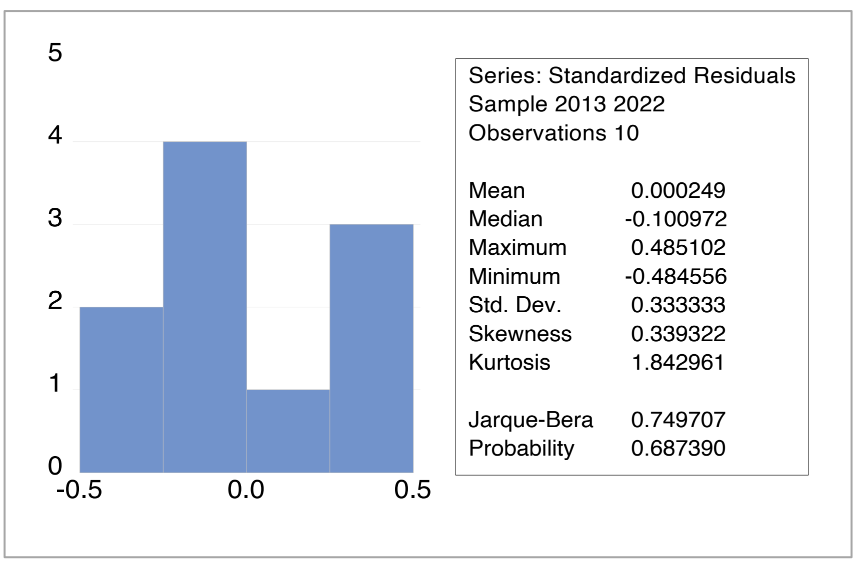
Mean	0.000224
Median	-0.112472
Maximum	0.467552
Minimum	-0.481720
Std. Dev.	0.333333
Skewness	0.366428
Kurtosis	1.836522
Jarque-Bera	0.787816
Probability	0.674416

Dependent Variable: EPCI
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/13/24 Time: 20:58
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Logit
Dispersion computed using Pearson Chi-Square
Convergence achieved after 4 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-2.426949	3.490787	-0.695244	0.4869
HEC	-4.582223	4.941473	-0.927299	0.3538
RREP	-1.373546	1.537005	-0.893651	0.3715
ELP	-3.774005	10.49531	-0.359590	0.7192
TLE	-6.509370	12.50009	-0.520746	0.6025
EID	2.718179	1.704303	1.594892	0.1107
GC	11.56371	26.37865	0.438374	0.6611
ARP	0.009865	11.74454	0.000840	0.9993
C	-3.612282	5.066629	-0.712956	0.4759

Mean dependent var	0.239038	S.D. dependent var	0.047217
Sum squared resid	0.000164	Root MSE	0.004049
Log likelihood	33.89136	Akaike info criterion	-4.978272
Schwarz criterion	-4.705946	Hannan-Quinn criter.	-5.277014
Deviance	0.000164	Deviance statistic	0.000164
Restr. deviance	0.020065	LR statistic	121.4086
Prob(LR statistic)	* 0.000000	Pearson SSR	0.000164
Pearson statistic	0.000164	Dispersion	0.000164

p<0.01;p**<0.05;p***<0.1*

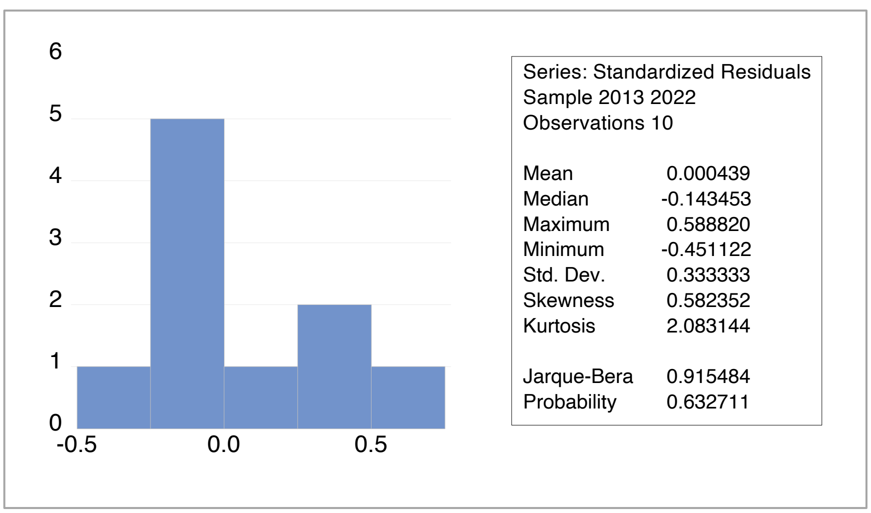


Dependent Variable: EPCI
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/13/24 Time: 21:00
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Inverse
Dispersion computed using Pearson Chi-Square
Convergence achieved after 4 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	5.617794	11.62040	0.483442	0.6288
HEC	17.92871	16.45878	1.089310	0.2760
RREP	4.934425	4.055860	1.216616	0.2238
ELP	25.67064	37.29304	0.688349	0.4912
TLE	39.22939	44.41527	0.883241	0.3771
EID	-8.864848	6.028790	-1.470419	0.1414
GC	-67.96822	88.08920	-0.771584	0.4404
ARP	17.15137	36.07224	0.475473	0.6345
C	16.10875	17.43604	0.923877	0.3556

Mean dependent var	0.239038	S.D. dependent var	0.047217
Sum squared resid	0.000139	Root MSE	0.003726
Log likelihood	34.72172	Akaike info criterion	-5.144344
Schwarz criterion	-4.872018	Hannan-Quinn criter.	-5.443086
Deviance	0.000139	Deviance statistic	0.000139
Restr. deviance	0.020065	LR statistic	143.5227
Prob(LR statistic)	* 0.000000	Pearson SSR	0.000139
Pearson statistic	0.000139	Dispersion	0.000139

p<0.01;p**<0.05;p***<0.1*



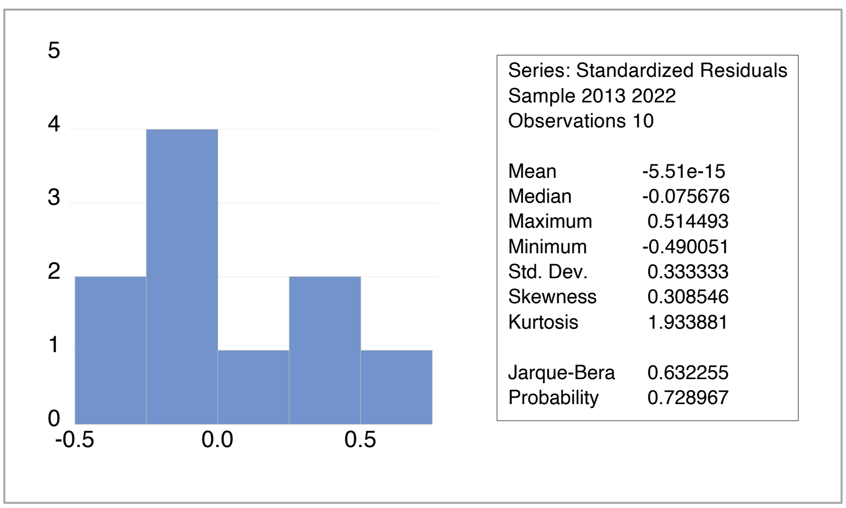
3.2. IKW

Dependent Variable: IKW
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 08:41
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Identity
Dispersion computed using Pearson Chi-Square
Convergence achieved after 0 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	0.267472	0.988419	0.270606	0.7867
HEC	-1.345445	1.449028	-0.928515	0.3531
RREP	-0.387791	0.493349	-0.786038	0.4318
ELP	-0.927730	2.902430	-0.319639	0.7492
TLE	-1.209086	3.462805	-0.349164	0.7270
EID	0.277977	0.483841	0.574520	0.5656
GC	5.080346	7.360494	0.690218	0.4901
ARP	-0.295881	3.426886	-0.086341	0.9312
C	-0.912439	1.379852	-0.661259	0.5084

Mean dependent var	0.240300	S.D. dependent var	0.059837
Sum squared resid	0.000448	Root MSE	0.006693
Log likelihood	28.86413	Akaike info criterion	-3.972826
Schwarz criterion	-3.700500	Hannan-Quinn criter.	-4.271568
Deviance	0.000448	Deviance statistic	0.000448
Restr. deviance	0.032224	LR statistic	70.92780
Prob(LR statistic)	* 0.000000	Pearson SSR	0.000448
Pearson statistic	0.000448	Dispersion	0.000448

p<0.01;p**<0.05;p***<0.1*

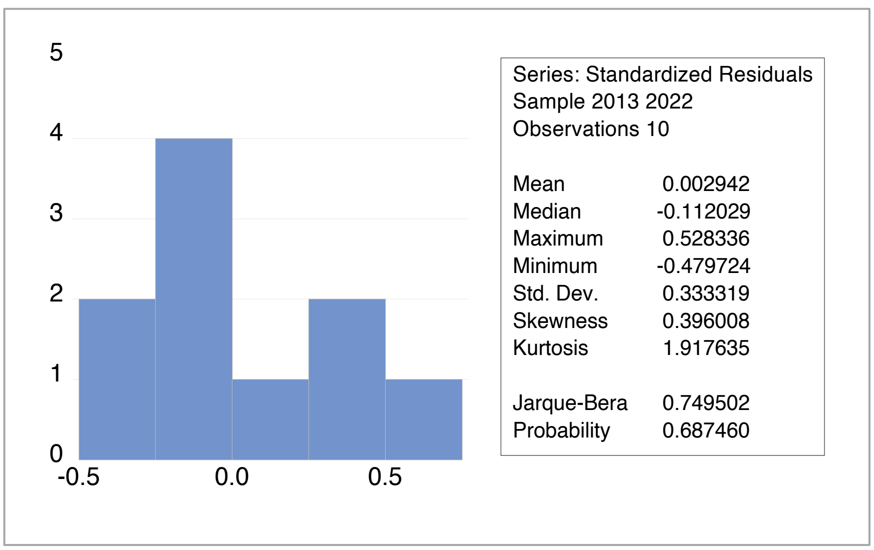


Dependent Variable: IKW
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 08:43
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Log
Dispersion computed using Pearson Chi-Square
Convergence achieved after 4 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	1.085554	3.298170	0.329138	0.7421
HEC	-4.644561	4.472721	-1.038420	0.2991
RREP	-1.340283	1.284149	-1.043712	0.2966
ELP	-4.624290	10.00528	-0.462185	0.6439
TLE	-6.420210	11.87102	-0.540831	0.5886
EID	0.547370	1.569056	0.348853	0.7272
GC	27.61855	25.45522	1.084986	0.2779
ARP	-6.302693	11.02706	-0.571566	0.5676
C	-7.209384	4.988869	-1.445094	0.1484

Mean dependent var	0.240300	S.D. dependent var	0.059837
Sum squared resid	0.000221	Root MSE	0.004706
Log likelihood	32.38759	Akaike info criterion	-4.677518
Schwarz criterion	-4.405191	Hannan-Quinn criter.	-4.976260
Deviance	0.000221	Deviance statistic	0.000221
Restr. deviance	0.032224	LR statistic	144.5260
Prob(LR statistic)	*0.000000	Pearson SSR	0.000221
Pearson statistic	0.000221	Dispersion	0.000221

p<0.01;p**<0.05;p***<0.1*

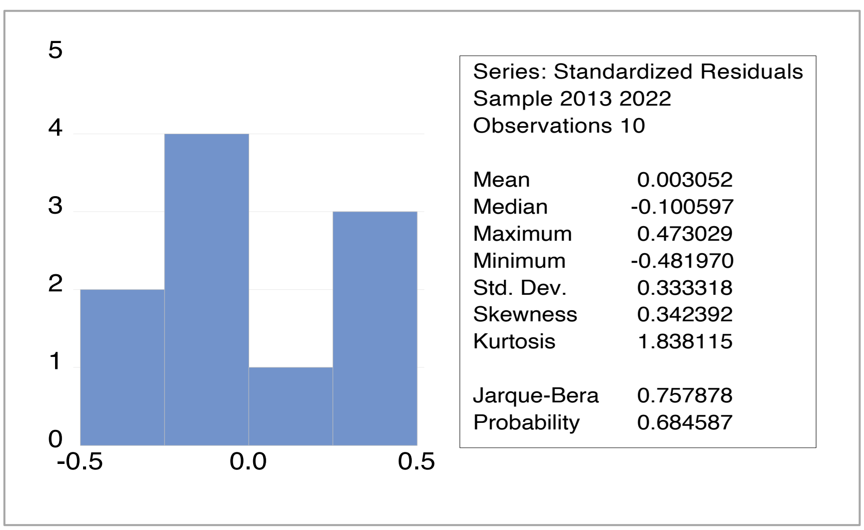


Dependent Variable: IKW
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 08:44
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Logit
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	1.554970	4.858257	0.320068	0.7489
HEC	-6.614319	6.673408	-0.991146	0.3216
RREP	-1.891143	2.022389	-0.935103	0.3497
ELP	-5.974851	14.49894	-0.412089	0.6803
TLE	-8.117127	17.22645	-0.471201	0.6375
EID	0.960818	2.301039	0.417558	0.6763
GC	34.55702	37.16281	0.929882	0.3524
ARP	-6.545941	16.39018	-0.399382	0.6896
C	-8.526997	7.212297	-1.182286	0.2371

Mean dependent var	0.240300	S.D. dependent var	0.059837
Sum squared resid	0.000293	Root MSE	0.005412
Log likelihood	30.98969	Akaike info criterion	-4.397938
Schwarz criterion	-4.125611	Hannan-Quinn criter.	-4.696679
Deviance	0.000293	Deviance statistic	0.000293
Restr. deviance	0.032224	LR statistic	109.0323
Prob(LR statistic)	* 0.000000	Pearson SSR	0.000293
Pearson statistic	0.000293	Dispersion	0.000293

p<0.01;p**<0.05;p***<0.1*

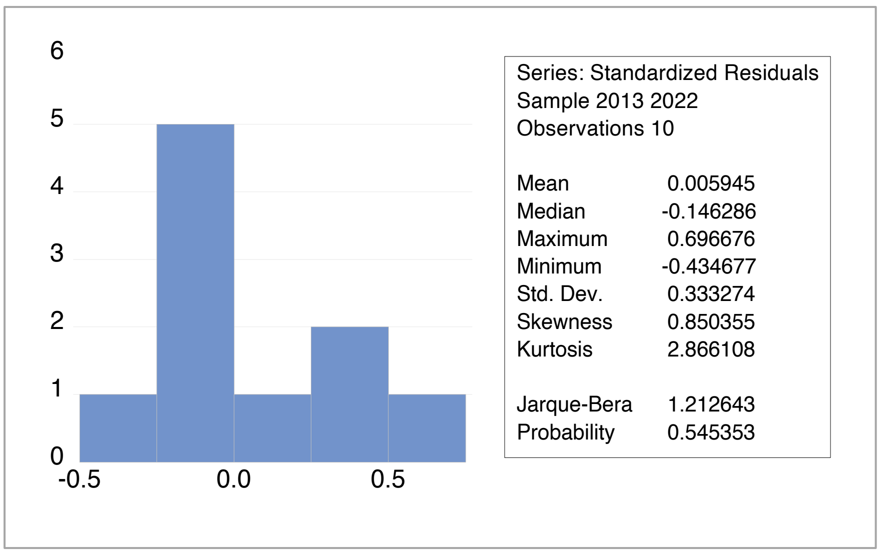


Dependent Variable: IKW
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 08:46
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Inverse
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-1.455223	8.179859	-0.177903	0.8588
HEC	14.06466	11.13423	1.263191	0.2065
RREP	4.439299	2.578668	1.721547	0.0852
ELP	17.23032	26.08372	0.660577	0.5089
TLE	26.58556	30.76797	0.864066	0.3876
EID	-0.061819	4.099707	-0.015079	0.9880
GC	-121.6853	61.88451	-1.966330	0.0493
ARP	38.62372	24.94489	1.548362	0.1215
C	28.11188	12.47073	2.254230	0.0242

Mean dependent var	0.240300	S.D. dependent var	0.059837
Sum squared resid	5.81E-05	Root MSE	0.002409
Log likelihood	39.08108	Akaike info criterion	-6.016216
Schwarz criterion	-5.743889	Hannan-Quinn criter.	-6.314957
Deviance	5.81E-05	Deviance statistic	5.81E-05
Restr. deviance	0.032224	LR statistic	554.0466
Prob(LR statistic)	∗0.000000	Pearson SSR	5.81E-05
Pearson statistic	5.81E-05	Dispersion	5.81E-05

p<0.01;p**<0.05;p***<0.1*



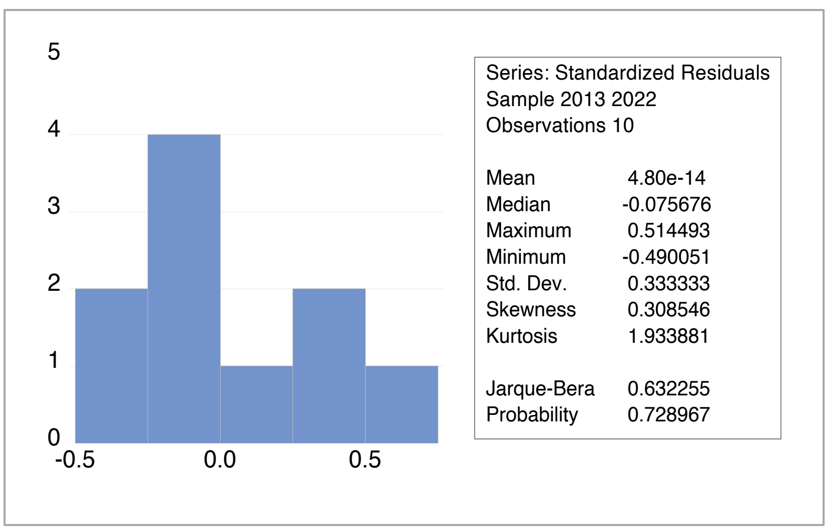
3.3. AUB

Dependent Variable: AUB
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 11:26
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Identity
Dispersion computed using Pearson Chi-Square
Convergence achieved after 1 iteration
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-2.513781	0.232065	-10.83223	* 0.0000
HEC	1.268740	0.340208	3.729301	* 0.0002
RREP	-0.011435	0.115830	-0.098723	0.9214
ELP	3.719388	0.681444	5.458099	* 0.0000
TLE	3.675265	0.813011	4.520561	* 0.0000
EID	0.456790	0.113598	4.021100	* 0.0001
GC	7.680335	1.728125	-4.444316	* 0.0000
ARP	2.364028	0.804578	2.938223	* 0.0033
C	1.761236	0.323967	5.436470	0.0000

Mean dependent var	0.351900	S.D. dependent var	0.052431
Sum squared resid	2.47E-05	Root MSE	0.001571
Log likelihood	43.35503	Akaike info criterion	-6.871006
Schwarz criterion	-6.598680	Hannan-Quinn criter.	-7.169748
Deviance	2.47E-05	Deviance statistic	2.47E-05
Restr. deviance	0.024741	LR statistic	1000.832
Prob(LR statistic)	* 0.000000	Pearson SSR	2.47E-05
Pearson statistic	2.47E-05	Dispersion	2.47E-05

p<0.01;p**<0.05;p***<0.1*

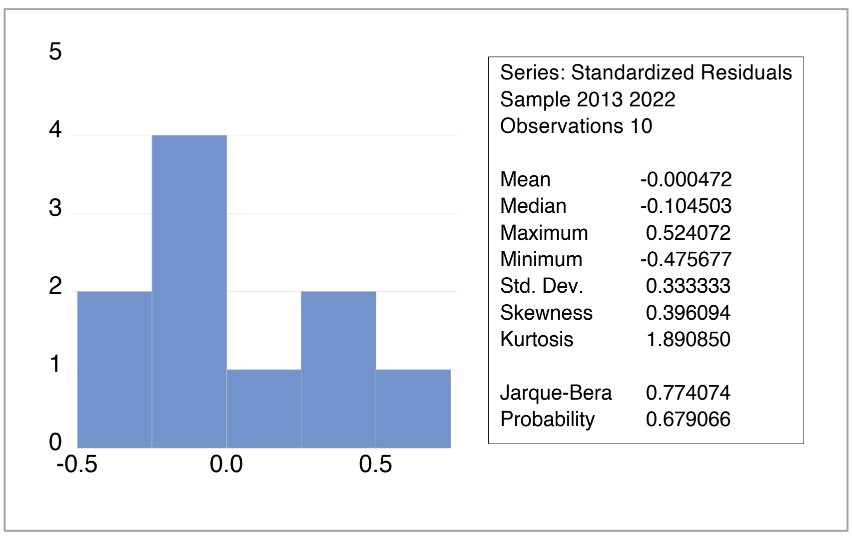


Dependent Variable: AUB
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 11:29
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Log
Dispersion computed using Pearson Chi-Square
Convergence achieved after 4 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-6.995534	0.890786	-7.853215	*0.0000
HEC	3.332922	1.254158	2.657498	*0.0079
RREP	-0.206040	0.387757	-0.531362	0.5952
ELP	9.834566	2.677946	3.672428	*0.0002
TLE	9.352176	3.180820	2.940178	*0.0033
EID	1.193718	0.430724	2.771423	*0.0056
GC	20.74878	6.569957	-3.158130	*0.0016
ARP	5.795300	2.877751	2.013830	*0.0440
C	3.083894	1.266213	2.435525	0.0149

Mean dependent var	0.351900	S.D. dependent var	0.052431
Sum squared resid	3.92E-05	Root MSE	0.001981
Log likelihood	41.03860	Akaike info criterion	-6.407720
Schwarz criterion	-6.135393	Hannan-Quinn criter.	-6.706461
Deviance	3.92E-05	Deviance statistic	3.92E-05
Restr. deviance	0.024741	LR statistic	629.3651
Prob(LR statistic)	* 0.000000	Pearson SSR	3.92E-05
Pearson statistic	3.92E-05	Dispersion	3.92E-05

p<0.01;p**<0.05;p***<0.1*

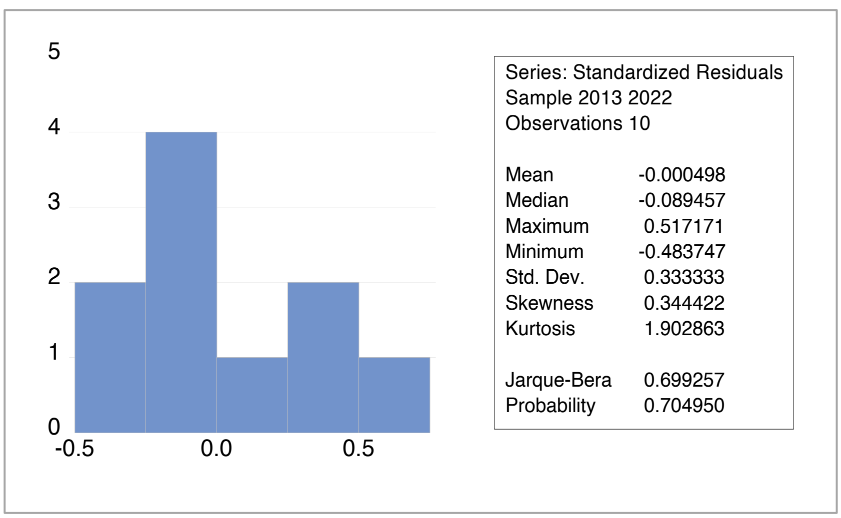


Dependent Variable: AUB
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 11:30
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Logit
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-10.97503	1.192442	-9.203829	* 0.0000
HEC	5.370271	1.715233	3.130927	* 0.0017
RREP	-0.172913	0.558457	-0.309627	0.7568
ELP	15.83664	3.544198	4.468329	* 0.0000
TLE	15.38396	4.219031	3.646325	* 0.0003
EID	1.952975	0.581537	3.358297	* 0.0008
GC	33.15263	8.835437	-3.752235	* 0.0002
ARP	9.820507	3.996536	2.457255	* 0.0140
C	5.704277	1.680312	3.394773	0.0007

Mean dependent var	0.351900	S.D. dependent var	0.052431
Sum squared resid	3.15E-05	Root MSE	0.001775
Log likelihood	42.13716	Akaike info criterion	-6.627432
Schwarz criterion	-6.355105	Hannan-Quinn criter.	-6.926174
Deviance	3.15E-05	Deviance statistic	3.15E-05
Restr. deviance	0.024741	LR statistic	784.2574
Prob(LR statistic)	* 0.000000	Pearson SSR	3.15E-05
Pearson statistic	3.15E-05	Dispersion	3.15E-05

p<0.01;p**<0.05;p***<0.1*

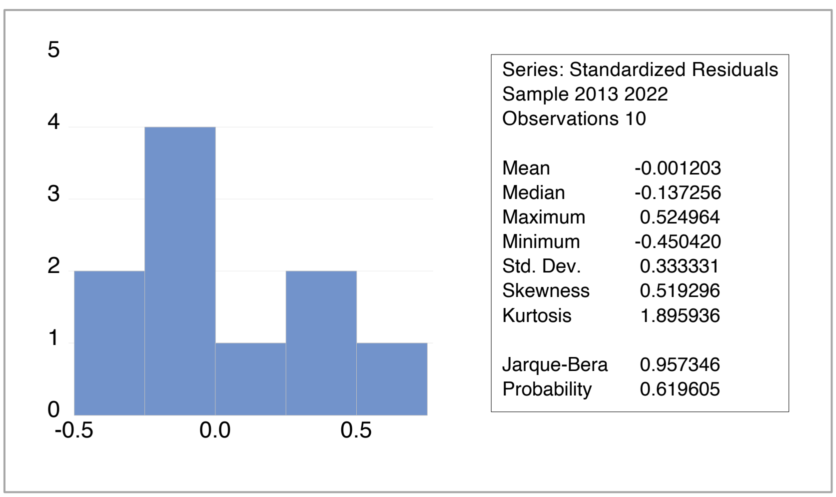


Dependent Variable: AUB
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 11:31
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Inverse
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	19.60263	3.562174	5.502997	*0.0000
HEC	-8.605728	4.945574	-1.740087	**0.0818
RREP	1.039310	1.317696	0.788732	0.4303
ELP	-25.52342	10.93806	-2.333451	**0.0196
TLE	-22.95260	12.94585	-1.772969	***0.0762
EID	-3.207096	1.754105	-1.828337	***0.0675
GC	-55.46076	25.61591	2.165090	**0.0304
ARP	-13.66258	10.48406	-1.303177	0.1925
C	-9.164818	5.056812	-1.812371	0.0699

Mean dependent var	0.351900	S.D. dependent var	0.052431
Sum squared resid	6.36E-05	Root MSE	0.002522
Log likelihood	38.62614	Akaike info criterion	-5.925229
Schwarz criterion	-5.652902	Hannan-Quinn criter.	-6.223971
Deviance	6.36E-05	Deviance statistic	6.36E-05
Restr. deviance	0.024741	LR statistic	388.0891
Prob(LR statistic)	*0.000000	Pearson SSR	6.36E-05
Pearson statistic	6.36E-05	Dispersion	6.36E-05

p<0.01;p**<0.05;p***<0.1*



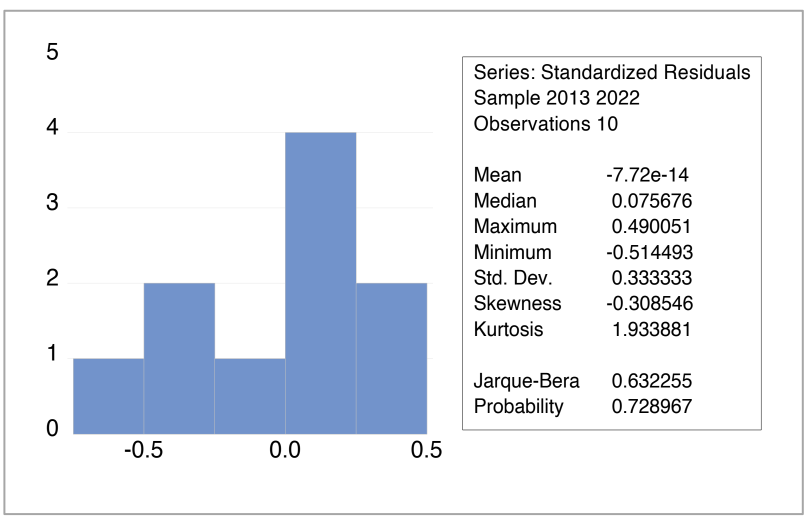
3.4. HC

Dependent Variable: HC
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 15:42
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Identity
Dispersion computed using Pearson Chi-Square
Convergence achieved after 0 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-0.344065	0.037781	-9.106862	* 0.0000
HEC	-0.081391	0.055387	-1.469501	0.1417
RREP	0.099070	0.018857	5.253592	* 0.0000
ELP	0.012600	0.110941	0.113575	0.9096
TLE	-0.051163	0.132360	-0.386543	0.6991
EID	0.243708	0.018494	13.17763	* 0.0000
GC	0.716809	0.281344	-2.547807	** 0.0108
ARP	0.807266	0.130987	6.162926	0.0000
C	0.125390	0.052743	2.377385	0.0174

Mean dependent var	0.133704	S.D. dependent var	0.010204
Sum squared resid	6.55E-07	Root MSE	0.000256
Log likelihood	61.50719	Akaike info criterion	-10.50144
Schwarz criterion	-10.22911	Hannan-Quinn criter.	-10.80018
Deviance	6.55E-07	Deviance statistic	6.55E-07
Restr. deviance	0.000937	LR statistic	1430.638
Prob(LR statistic)	* 0.000000	Pearson SSR	6.55E-07
Pearson statistic	6.55E-07	Dispersion	6.55E-07

p<0.01;p**<0.05;p***<0.1*

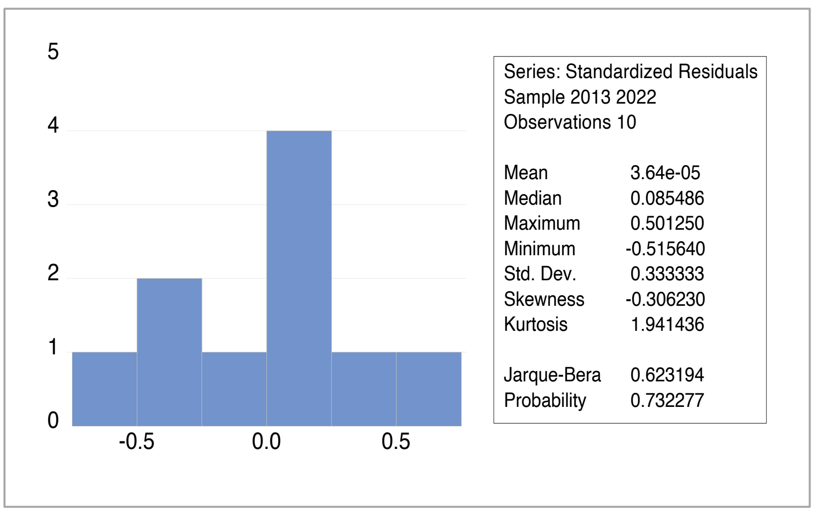


Dependent Variable: HC
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24   Time: 15:44
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Log
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-2.415622	0.269580	-8.960700	*0.0000
HEC	-0.670989	0.387116	-1.733305	***0.0830
RREP	0.655674	0.129778	5.052256	*0.0000
ELP	-0.163618	0.807336	-0.202664	0.8394
TLE	-0.717298	0.962579	-0.745183	0.4562
EID	1.772215	0.130173	13.61427	*0.0000
GC	4.664227	2.048046	-2.277403	**0.0228
ARP	5.610636	0.935126	5.999869	*0.0000
C	-2.138632	0.386638	-5.531361	0.0000

Mean dependent var	0.133704	S.D. dependent var	0.010204
Sum squared resid	5.74E-07	Root MSE	0.000240
Log likelihood	62.16608	Akaike info criterion	-10.63322
Schwarz criterion	-10.36089	Hannan-Quinn criter.	-10.93196
Deviance	5.74E-07	Deviance statistic	5.74E-07
Restr. deviance	0.000937	LR statistic	1632.292
Prob(LR statistic)	*0.000000	Pearson SSR	5.74E-07
Pearson statistic	5.74E-07	Dispersion	5.74E-07

p<0.01;p**<0.05;p***<0.1*

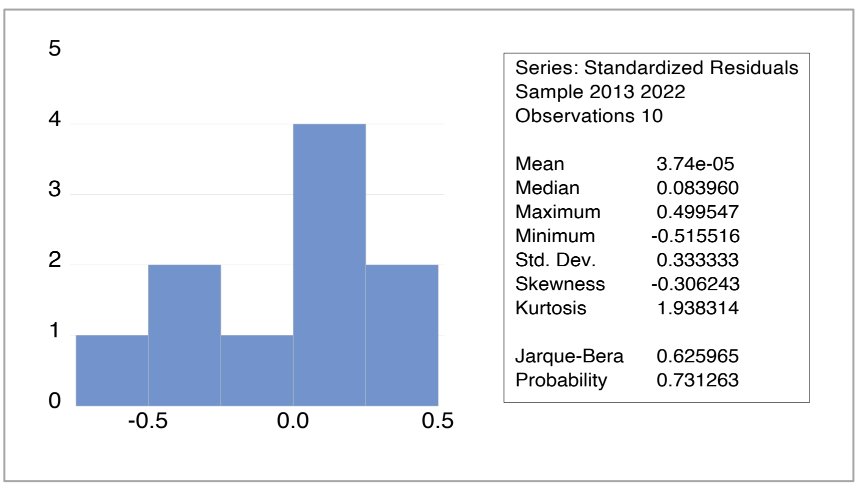


Dependent Variable: HC
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 15:46
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Logit
Dispersion computed using Pearson Chi-Square
Convergence achieved after 2 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	-2.816916	0.313753	-8.978141	*0.0000
HEC	-0.763953	0.451929	-1.690430	***0.0909
RREP	0.772158	0.151889	5.083703	*0.0000
ELP	-0.142881	0.936905	-0.152503	0.8788
TLE	-0.768322	1.117177	-0.687735	0.4916
EID	2.055123	0.151816	13.53692	*0.0000
GC	-5.509787	2.377057	-2.317903	**0.0205
ARP	6.554053	1.088603	6.020610	*0.0000
C	-2.002984	0.448304	-4.467918	0.0000

Mean dependent var	0.133704	S.D. dependent var	0.010204
Sum squared resid	5.87E-07	Root MSE	0.000242
Log likelihood	62.05445	Akaike info criterion	-10.61089
Schwarz criterion	-10.33856	Hannan-Quinn criter.	-10.90963
Deviance	5.87E-07	Deviance statistic	5.87E-07
Restr. deviance	0.000937	LR statistic	1596.232
Prob(LR statistic)	*0.000000	Pearson SSR	5.87E-07
Pearson statistic	5.87E-07	Dispersion	5.87E-07

p<0.01;p**<0.05;p***<0.1*

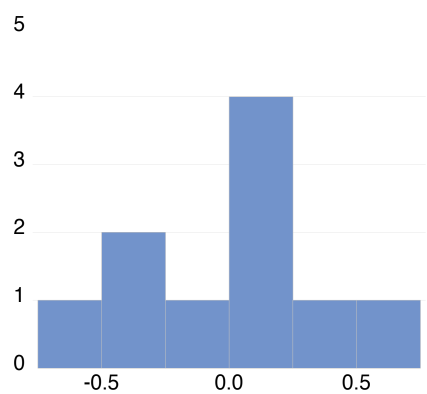


Dependent Variable: HC
Method: Generalized Linear Model (Newton-Raphson / Marquardt steps)
Date: 05/14/24 Time: 15:47
Sample: 2013 2022
Included observations: 10
Family: Normal
Link: Inverse
Dispersion computed using Pearson Chi-Square
Convergence achieved after 3 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RREC	16.96276	1.928552	8.795591	*0.0000
HEC	5.529539	2.723835	2.030057	**0.0424
RREP	-4.290805	0.892994	-4.804967	*0.0000
ELP	3.201905	5.874277	0.545072	0.5857
TLE	7.946709	7.000460	1.135170	0.2563
EID	-12.94326	0.924409	-14.00166	*0.0000
GC	-29.75995	14.85819	2.002933	**0.0452
ARP	-38.88822	6.661463	-5.837790	*0.0000
C	8.911729	2.821608	3.158386	0.0016

Mean dependent var	0.133704	S.D. dependent var	0.010204
Sum squared resid	4.99E-07	Root MSE	0.000223
Log likelihood	62.86280	Akaike info criterion	-10.77256
Schwarz criterion	-10.50023	Hannan-Quinn criter.	-11.07130
Deviance	4.99E-07	Deviance statistic	4.99E-07
Restr. deviance	0.000937	LR statistic	1876.500
Prob(LR statistic)	*0.000000	Pearson SSR	4.99E-07
Pearson statistic	4.99E-07	Dispersion	4.99E-07

p<0.01;p**<0.05;p***<0.1*



Series: Standardized Residuals
Sample 2013 2022
Observations 10

Mean	7.25e-05
Median	0.095994
Maximum	0.509192
Minimum	-0.513607
Std. Dev.	0.333333
Skewness	-0.313229
Kurtosis	1.965795
Jarque-Bera	0.609180
Probability	0.737426