

**MASTER IN
ACTUARIAL SCIENCE**

**MASTER'S FINAL WORK
PROJECT**

**THE IMPACT OF CLIMATE CHANGE ON LIFE INSURANCE PREMIUMS:
A PANEL DATA ANALYSIS OF EU COUNTRIES**

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GLOSSARY

EEA - European Environmental Agency

EIOPA - European Insurance and Occupational Pensions Authority

EU - European Union

GDP - Gross Domestic Product

GHG - Greenhouse Gases

IPCC - Intergovernmental Panel on Climate Change

NEU - Northern Europe

WCE - Western and Central Europe

SEU - Southern Europe

TCFD - Task Force on Climate-related Financial Disclosures

UK - United Kingdom

UNFCCC - United Nations Framework Convention for Climate

ABSTRACT

This work examines the relationship between the life insurance market and climate change using four distinct regression models with data from the 27 countries of the European Union (EU), including the United Kingdom (UK), for the period from 2011 until 2019. Two of the models uniquely study the impact of greenhouse gas emissions on life insurance premiums, resorting to distinct panel data models: the pooling model, and the fixed effects model. The other two models feature other climate change-related variables, including the number of fatalities, the deviation of temperature with respect to a baseline climatology, corresponding to the period 1951–1980, and the Gross Domestic Product (GDP), also using the pooling and the fixed effect models. As the name suggests, the pooling model implies the use of a panel data set of all 28 countries together, whereas the fixed effects model requires some type of aggregation. Therefore, for the second panel data set, the countries are grouped into three clusters accounting for historical trends and future climate change projections used in the Assessment Reports of the Intergovernmental Panel on Climate Change (IPCC). The goal is to analyse whether the use of the fixed effects model provides a better tool to understand the variation of life insurance premiums provoked by climate change when compared to the pooling model. The results of the first two models have shown that an increase of one thousand tonnes in greenhouse gas emissions is estimated to increase the total life insurance premiums by, respectively, 0.2099 and 0.2243 million US dollars. However, when the other variables are included in the first two models, these values change to -0.2681 and -0.2660 million US dollars, respectively. Meanwhile, the explicative power of the life insurance premiums variance increases significantly from the first two to the other two models, which may be a positive indicator.

KEYWORDS: Climate Change; Life Insurance Premiums; Greenhouse Gas Emissions; Panel Data; Pooling Model; Fixed Effects Model.

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1 INTRODUCTION

The importance of climate change has risen over the past decades, as a consequence of the rapid increase in the global mean temperature near the surface of our planet, caused by the continued emissions of greenhouse gases (Earth Science Communications Team of NASA 2023*d*). Arrhenius (1896) first predicted that changes in atmospheric carbon dioxide levels could substantially alter the surface temperature through the greenhouse effect, but it was only years after that Callendar (1938) established a connection between the rising levels of carbon dioxide in Earth's atmosphere and the phenomenon of global warming.

Since the 18th century, which aligns with the beginning of industrial times, there has been an increase of about 50% of atmospheric CO_2 , mainly from human activities (Earth Science Communications Team of NASA 2023*a*). CO_2 is a significant heat-trapping gas, commonly referred to as a greenhouse gas, that originates from fossil fuel extraction and combustion, wildfires, as well as natural events like volcanic eruptions.

This rise in greenhouse gas emissions has led to an abnormal increase in the global mean temperature near the surface. Nowadays, Europe is one of the most impacted continents when it comes to the planet's warming, as it has experienced an increase of its average temperature of 2.2°C above the pre-industrial level, whereas the increase of global average temperature stands for 1.2°C for the same period, as stated by Copernicus Climate Change Service (2023*a*). Yet, the warming of the planet in recent years has proven to be more severe than ever. In 2022, Europe experienced its hottest summer and the second warmest year on record (Copernicus Climate Change Service 2023*b*), which the European Parliament (2023) believes to be a consequence of the rise of greenhouse gas emissions produced by human activity.

However, between 1990 and 2019, according to the European Parliament (2023), the EU managed to reduce its total greenhouse gas emissions from 15.2% to 7.3% of the global total, positioning it as the fourth-largest emitter globally, trailing behind China, the US, and India. Nevertheless, the EU plans to go even further. In 2015, under the Paris Agreement, the EU committed to cutting its emissions by at least 40% below 1990 levels by 2030, and later, in 2021, the target was updated in an attempt to address the rapid evolution of climate change that has been witnessed in the last years, planning to reduce at least 55% below to those of 1990 by 2030 and achieving climate neutrality by 2050.

Moreover, the National Geographic Society (2023) clarifies that, even though there is no clear evidence of a direct causality of individual extreme environmental events due to climate change, there is scientific evidence that climate change makes these events

more destructive, and more frequent than they usually would be. The impacts of climate change have been felt through severe weather events, such as forest fires, hurricanes, droughts, heat waves, floods, and storms, even though they sometimes seem unnoticeable. According to the National Geographic Society (2023), this fact has been analysed by computer modeling using actual data, demonstrating a notorious relationship between climate change and the frequency and intensity of such events.

As a consequence of the increased frequency and intensity of these environmental events, it is undeniable that human lives and their well-being will be affected, increasing mortality and morbidity. In a case study presented by Baskerville-Muscutt & Marshall (2021) that resorts to findings of United Nations Office for Disaster Risk Reduction (2017), it is believed that extreme temperatures were responsible for 27% of all deaths caused by weather-related disasters between 1995 and 2015. The majority of these deaths (148,000 out of 164,000, 90%) were due to excessive heat rather than to extreme cold. High-income countries accounted for 92% of heatwave-related deaths, with Europe reporting the highest number at 90%. This correlation can be attributed to the association between heatwave mortality and advanced age.

Besides the effects of climate change on the environment and on human lives, future adverse repercussions are also expected on the global economy in a scenario of no action. Guo et al. (2021) alert to the possibility of a 10% loss on the global economy if the world fails to accomplish net-zero emissions by 2050 and the Paris Agreement targets are not met. Moreover, the current likely temperature-rise trajectories, which predict that by mid-century global average temperature could be from 2.0°C to 2.6°C higher than pre-industrial level, can generate a loss from 11% to 14%, compared to a scenario of no climate change.

Given the possible climate change impacts on the various levels, including the social and economic sectors, it is evident that the insurance industry is extremely sensitive and vulnerable to climate change and its consequences. However, given the obvious distinction between life and non-life¹ insurance lines of businesses, it is expected that climate change will also have distinct impacts. According to Storey et al. (2019), the key implications of climate change for the life insurance industry include the changing of mortality and morbidity risks, diminishing markets, greater capital requirements, changing population dynamics, and the need to address model risk.

The motivation behind this research stems from the growing recognition of the pro-

¹Non-life insurance contracts cover goods (such as houses, cars, and properties) or individuals (including drivers and people). Most of them have short-term duration, usually 12 months, allowing for annual re-pricing of premiums in adjustment to change on the underlying risks (EIOPA 2021).

found impact of climate change on the planet. Climate change is not just an environmental concern; it extends its reach into various aspects of our lives, including the field of insurance. This issue has far-reaching effects on actuarial work, impacting areas like human health, mortality rates, the economy's stability, risks associated with natural disasters, and the value of assets held by insurers. Therefore, this study seeks to delve into the interdependence between climate change and the life insurance market, by analysing the impact that certain climate change figures have on the total life insurance premiums.

However, it matters to highlight that, despite the urgency and the significance of understating the impact of climate change on life insurance, the existing body of literature addressing this topic remains surprisingly scarce. As far as Melnychenko et al. (2021) refer, their study is the first to quantify the impact of climate on life insurance in the EU. The hypothesis that is being tested in their work is whether there is a "positive relationship between the growing effects of climate change and the amounts of life insurance production in the EU" (Melnychenko et al. 2021, p. 5). To answer this question, the authors relied on an unbalanced data set from 28 EU countries for the period from 2011 until 2019, which includes data on life insurance premiums, used as the dependent variable, and data on indicators that are directly related to the effects of climate change, that are used as independent variables. This set of climate-related variables includes greenhouse gas emissions, the deviations of temperature with respect to a baseline climatology, the total number of fatalities, and the environmental conservation costs.

Regarding the methodology used in the authors' work, a panel model was chosen, where the amount of premiums under life insurance contracts is defined as a function of the fundamental factor of climate change, which is the emission of greenhouse gases. Moreover, the number of deaths is also studied as a function of greenhouse gas emissions. This has led them to conclude that increasing the emission of greenhouse gases, increases the amount of life insurance premiums, as well as the number of deaths. While life insurance premiums should increase by EUR0.1786 million per thousand tons of greenhouse gas emitted, there should also be 1.0442 more deaths per thousand tons of greenhouse gas emitted.

In alternative to the methodology adopted by the authors, the fixed effects model was used in this work. It offers a valuable analytical approach with distinct characteristics. This type of panel model is characterized by allowing coefficients to vary among individuals or over time while remaining constant and non-random for each individual or time (Marques 2000). Typically, this modeling technique is well-suited for aggregated samples, such as groups of countries, as it systematically addresses and allows for testing individual differences, a vital aspect of our analysis. In essence, the use of fixed effect

models in this study is methodologically justified, aligning with the research objectives, as it enables the capture and analysis of variations within the groups of EU countries being studied over time, aiding our understanding of evolving trends and patterns.

Additionally to the work done by Melnychenko et al. (2021), we also aim to find a model that better describes the variation of life insurance premiums provoked by climate change-related variables to better comprehend how climate change might be impacting the life insurance market. Therefore, the variables chosen to be included in this study are the number of fatalities, the deviation of temperature with respect to a baseline climatology, corresponding to the period 1951–1980, and the GDP.

This work is organized in the following chapters:

- Chapter 2 covers the subject of climate change, and explores the impacts of this issue on human lives, and on the life insurance industry.
- Chapter 3 briefly describes life insurance products, as well as premium calculation, and pricing methods.
- Chapter 4 addresses the methodology and data used.
- Chapter 5 presents the empirical results and respective discussion.
- Chapter 6 reviews the conclusions.

2 CLIMATE CHANGE AND ITS IMPACTS ON LIFE INSURANCE

2.1 Climate Change

Studies from the Earth Science Communications Team of NASA (2023c) show that, throughout Earth's history, the climate has undergone natural variations, including ice ages and warmer periods, caused by small fluctuations in Earth's orbit, which affect the amount of solar energy reaching our planet. However, the current warming trend is distinct as it has been primarily driven by human activities since the mid-1800s, provoking an increase in the global average temperature of 1.2°C, according to Romanello et al. (2021). The rapid rate of this warming is unprecedented in recent history, as can be observed in Figure 1.

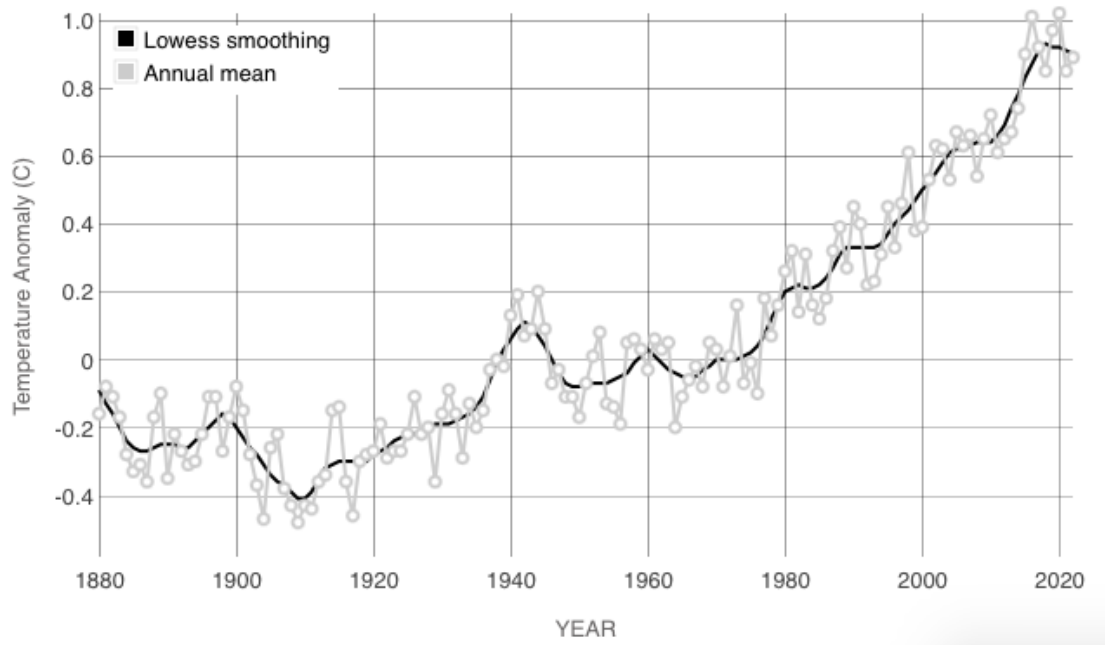


FIGURE 1: Earth's Global Average Surface Temperature since 1880.

Source: Earth Science Communications Team of NASA (2023b)

Human activities causing the emission of greenhouse gases have contributed to the increased retention of solar energy in the Earth system, which has significantly and rapidly impacted the atmosphere, oceans, land, and various ecosystems, provoking adverse social and economic consequences. The Earth Science Communications Team of NASA (2023a) raises awareness for the fact that carbon dioxide CO_2 , which is emitted through activities such as extracting and burning fossil fuels (coal, oil, and natural gas), natural events like wildfires, and natural processes like volcanic eruptions, is a significant contributor for trapping heat. As can be observed in Figure 2, the concentration of the

atmosphere's carbon dioxide has been rapidly and alarmingly rising since 1960.

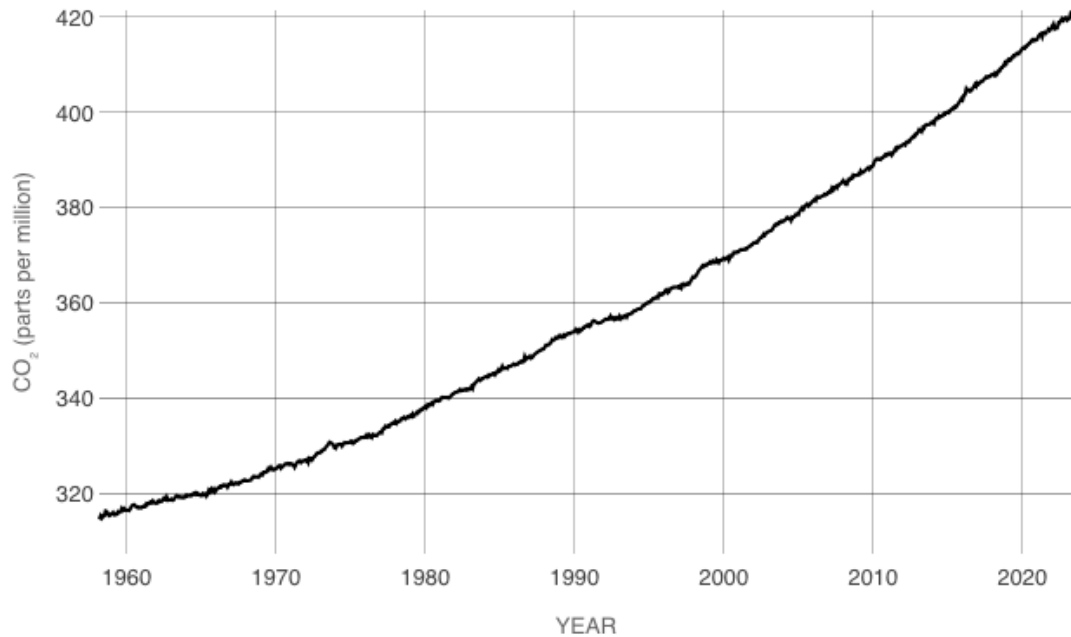


FIGURE 2: Atmospheric CO_2 levels since 1958.

Source: Earth Science Communications Team of NASA (2023a)

In an attempt to minimize the impacts of climate change, the Paris Climate Agreement was created on the 12th of December 2015 by 196 Parties at the United Nations Climate Change Conference (COP21) in Paris, France. The Agreement entered into force on the 4th of November 2016 and one of its key points seeks to enhance global collective action in addressing the challenges posed by climate change, within the framework of sustainable development and poverty eradication, as it is transcribed next:

Article 2: 1. (a) Holding the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels, recognizing that this would significantly reduce the risks and impacts of climate change;

In: *Paris Agreement* (2015), p. 3.

Article 4: In order to achieve the long-term temperature goal set out in Article 2, Parties aim to reach global peaking of greenhouse gas emissions as soon as possible, recognizing that peaking will take longer for developing country Parties, and to undertake rapid reductions thereafter in accordance with best available science, so as to achieve a balance between anthropogenic emissions by sources and removals by sinks of greenhouse gases in the second

half of this century, on the basis of equity, and in the context of sustainable development and efforts to eradicate poverty.

In: *Paris Agreement* (2015), p. 4.

However, in recent years, the overarching goal was limited to 1.5°C by the end of this century, meaning that greenhouse gas emissions must significantly decrease before 2025 at the latest and decline 43% by 2030, as mentioned by the United Nations Framework Convention on Climate Change (UNFCCC) secretariat. To stem the detrimental impacts within the desired time frame, greenhouse gas emissions must be reduced, and there must be a transition to a lower-carbon economy, which means avoiding fossil fuel energy and related physical assets. In fact, the Task Force on Climate-related Financial Disclosures (TCFD) estimates that this transition is expected to “require around \$1 trillion of investments a year for the foreseeable future, generating new investment opportunities.” (TCFD 2017, p. ii).

2.2 *Climate Change Risks*

The TCFD was established by the Financial Stability Board and is currently constituted by 32 global members from various organizations, which all together develop consistent and voluntary climate-related financial disclosures. The task force’s main purpose is to provide investors, lenders, and insurance underwriters with the necessary information to assess and price climate-related risks and opportunities. Thereby, categories for climate-related risks and opportunities were developed, for the sake of encouraging organizations to evaluate and disclose them in their annual financial reports.

Regarding the climate-related risks, TCFD (2017) has divided them into two main categories: transition risks, which are related to the transition to a lower-carbon economy; and physical risks, which are direct consequences of climate change.

Firstly, the transition to a lower-carbon economy may bring forward some risks of financial and reputational nature, depending on their timing and appropriateness. Therefore, the transition risk can be divided into the following sub-categories:

- **Policy and Legal Risks.** Overall, policy measures around climate change aim to "constrain actions that contribute to adverse effects of climate" and "promote adaptation to climate change" (TCFD 2017, p. 5). On the other hand, there is also the risk of noncompliance with current climate legislation, which can bring companies before the court.

- **Technological Risks.** Technological improvements that support the transition to a lower-carbon and energy-efficient economy can affect organizations' competitiveness, production, and demand for their products or services.
- **Market Risk.** Shifts in supply and demand for commodities, products, and services may become more sensitive to climate change. For example, (Nam 2021, p. 1) has found that "climate uncertainty generates a negative supply shock", and also that "market uncertainty generates a negative demand shock on the individual agricultural items".
- **Reputational Risk.** The customer or community's perception of organizations' contribution to (or detraction from) the transition to a lower-carbon economy can benefit or harm their business.

With respect to transitional actions, TCFD (2017) also mentions that, even though changes associated with the transition to a lower-carbon economy may raise numerous and significant risks, opportunities focused on climate change mitigation and adaptation may also arise for organizations.

Physical risks caused by climate change can be classified as acute risks, and are those directly caused by event-driven results from climate change, such as hurricanes or floods, or as chronic risks, which result from long-term shifts in climate patterns that have adverse consequences, such as sea level rise.

The presence of physical risks can cause significant business disruptions, heightened operational risks, damage to physical assets, and potential disruptions in the supply chain, thereby affecting overall business performance, whereas transition risks can result in increased costs driven by policy changes such as carbon taxes, which can fundamentally alter the economic dynamics of the business and lead to necessary changes to its operational model. Moreover, there may be increased liability costs due to legal actions, reduced market demand resulting from changing consumer preferences, and technology-related risks such as the devaluation of assets due to the introduction of new technologies.

Even though organizations face challenges in mitigating and adapting to climate change, there is room for opportunities through "resource efficiency and cost savings, the adaptation of low-emission energy sources, the development of new products and services, access to new markets, and building resilience along the supply chain" (TCFD 2017, p. 6).

2.3 *Impacts of Climate Change on Morbidity, Mortality and Life Insurance*

Studying morbidity and mortality rates is vital for life insurers as they impact insurance premiums, policy terms, and profitability. Analyzing mortality data enables insurers to assess and price risks accurately, establish effective underwriting strategies, and manage overall risk exposure (Gatzert & Wesker 2014). Furthermore, studying mortality also contributes to product development, capital reserves, and long-term financial planning, empowering life insurers to make informed choices for sustainable business operations.

Even though the present work focuses on the direct impacts that climate change has on life insurance premiums, not on the impacts that climate change has on mortality and morbidity, variations in mortality and morbidity, resulting from this issue, can indirectly influence the variations in life insurance premiums. Therefore, this subsection is dedicated to presenting and analysing, firstly, the impacts that the changing of the climate has on human lives, and then comprehending how it can affect life insurers.

2.3.1 *Human Lives*

Given the importance of studying mortality in life insurance, mortality drivers, such as smoking prevalence, lifestyle factors like diet and exercise, advancements in pharmaceuticals, and public policies related to healthcare and social spending have always been studied. In recent times, there has been a notable and increasing concern in comprehending the relationship between climate variables, such as temperature, precipitation, and extreme weather events, and their impact on health outcomes, to help insurers better assess the evolution of mortality, as Baskerville-Muscutt & Marshall (2021) point out.

Human activity has been the primary driver of global warming in recent years, namely, due to the continued emission of greenhouse gases. Not only is the emission of greenhouse gases responsible for causing further warming of the planet but also, consequently, causing disruption of economic and social sectors and making it more difficult to estimate the exact timing and severity of the physical effects of climate change, according to Merk (2022).

This implies that predicting future morbidity and mortality is becoming increasingly difficult, highlighting the need for preparedness and adaptability to unforeseen events and trends. It is crucial for long-term business entities such as life insurance companies to comprehend climate change and its direct and indirect effects on their operations, as variations in mortality may impact business and financial sustainability, as Merk (2022) refers.

Climate exerts its influence on various geophysical, ecological, and socio-economic systems, which in turn impact human health. Some effects are relatively straightforward to measure and quantify, such as the increased mortality caused by heat waves. However, there are also indirect consequences, such as shifts in migration patterns or disruptions in food security, that are more complex and challenging to model accurately. It is important to recognize that climate impacts do not occur in isolation but interact with other significant societal and environmental factors, including changes in land use, biodiversity, urbanization, and economic trends. These factors can directly or indirectly influence patterns of health and disease, both in their own right and by shaping the response to climate change, as Baskerville-Muscutt & Marshall (2021) refer. Next, the various possible impacts of climate change on mortality are explained in more detail.

Extreme Temperature

Numerous studies have been examining the relationship between extreme temperatures and mortality, finding that this relationship is normally a nonlinear U-, V-, or J-shape, as in studies performed by McMichael et al. (2008) and Baccini et al. (2009). Studies have assessed the effects of cold and heat separately, with a threshold temperature delineating the transition from minimal to adverse impacts. The results show that higher heat thresholds in warmer areas suggest acclimatization to heat.

Meanwhile, it is important to understand how extreme temperatures can affect human lives. On one hand, in accordance with Hertel et al. (2009), heat waves are associated with increased mortality from cardiovascular, respiratory, and cerebrovascular diseases, particularly among the elderly, whereas cold temperatures can strain the cardiovascular system and increase the risk of pulmonary infections, meaning that health impacts of extreme cold may take longer to appear, as Huynen et al. (2001) refers. These findings highlight the importance of understanding the links between temperature and mortality for effective public health planning and response.

Air Pollution

Extensive research has established a strong correlation between air pollution and mortality. Air pollution, defined as the alteration of the atmosphere by chemical, physical, or biological agents, has been linked to increased cardiovascular diseases, respiratory conditions, and allergies, according to studies performed by Næss et al. (2006) and Bøve et al. (2019). Particulate matter (PM) and ozone are of particular concern, as exposure to PM, especially smaller and ultra-fine particles, has been directly linked to negative health impacts. Moreover, ozone can constrict airway muscles, exacerbating lung diseases in the short term and potentially leading to long-term lung damage, including abnormal lung development in children. The evidence suggests that both short-term and long-term expo-

sure to air pollutants pose significant health risks.

Windstorms

Research has shown a connection between windstorms and cause-specific mortality, although the evidence is not as robust as the other variables analyzed so far. Goldman et al. (2014) provide a comprehensive overview of this link, highlighting direct and indirect effects. On one hand, direct effects occur during the impact phase of a storm, leading to death and injury from the force of the wind, flying debris, falling trees, and road accidents. Meanwhile, indirect effects include, for instance, falls, lacerations, and puncture wounds during storm preparation or cleanup. Besides that, it matters also to mention that power outages pose significant risks, including electrocution, fires, burns, and carbon monoxide poisoning from generators. Moreover, windstorms can exacerbate chronic illnesses due to limited access to medical care and medication. While further research is needed, these findings shed light on the health impacts associated with windstorms.

Precipitation

Regarding rainy conditions and mortality, it is clear that there is a relationship of causality between precipitation and fatalities, particularly the ones caused by road traffic accidents. In fact, Eisenberg & Warner (2005) found a correlation between precipitation and increased crash rate, and also that the risk associated with precipitation rises with the time since the last rainfall. Apart from road fatalities, there is the risk of death resulting from flooding as well.

On the other extreme, drought also poses risks to morbidity and mortality, as drought conditions can expose individuals to health hazards such as wildfires, dust storms (which contribute to degraded air quality), extreme heat events, flash flooding, and degraded water quality.

Flooding

Extreme precipitation leading to severe flooding poses risks to mortality, as they can provoke drownings, physical injuries, destruction of homes and essential services, and limited access to medical care and medication. Also, contamination of freshwater supplies and the presence of disease-carrying insects are additional health risks. Apart from this, damp indoor environments contribute to respiratory symptoms and infections. However, immediate flood-related deaths are uncommon in high-income countries, except during exceptional events, according to Milojevic et al. (2011).

Vector- and water-borne diseases

Finally, the literature demonstrates a connection between climate, vector-borne diseases,

water-borne diseases, and mortality. While vector-borne diseases are transmitted by arthropods like mosquitoes and ticks, and include, for example, West Nile virus, Dengue fever, or malaria, water-borne diseases are transmitted through water, encompassing various pathogens causing symptoms such as diarrhea, fever, neurological disorders, and liver damage.

According to Levy et al. (2018), the relationship between climate and disease transmission is complex, as climatic factors affect vector survival, reproduction activity patterns, pathogen survival, and water sanitation. The influence of climate on disease outcomes is influenced by social and ecological factors, making it challenging to quantify the direct impact on mortality rates.

Indirect Impacts

In addition to the evident and direct effects of climate change discussed earlier, it is essential to consider the possible indirect consequences, one of them being mental health. According to IPCC (2022), climate change has adversely affected, with very high confidence, not only physical health, but also mental health in regions such as Asia, Europe (excluding the Mediterranean region, which was not assessed), and North America. Results from the assessed regions show that the rising temperatures and the loss of livelihoods and cultural impacts are, with high confidence, strongly linked to certain mental health issues. There is very high confidence also in the connection between trauma resulting from extreme weather events and climate-related incidents.

The neglect of mental health, especially in the context of climate change and mental well-being, raises particular concern. Hayes et al. (2018) show that the psychological impacts of disasters outweigh physical injuries by a significant margin of 40 to 1.

Moreover, Lawrance et al. (2021) provides a comprehensive analysis of the mental repercussions stemming from climate-related events, also examining the significant consequences of past events and their impact, for instance, the floods that occurred between 2011 and 2014 in the UK, and the hurricane Katrina in August 2005 in the United States.

It is highly certain that mental health challenges, such as anxiety and stress, will intensify across all evaluated regions with continued global warming, especially affecting vulnerable groups such as children, adolescents, the elderly, and individuals with pre-existing health conditions, as mentioned by IPCC (2022).

Besides mental health issues, one other significant impact is the displacement and the migration of population, resulting from water scarcity, desertification, the geopolitical conflicts that often arise from resource scarcity, and the rising of sea-level. In fact, there are "150 cities with more than one million inhabitants in coastal areas, and the already

'built-in' sea-level rise of 0.5m by 2100 is threatening the future of these populations" (Merk 2022, p. 5).

2.3.2 *Life Insurance*

In spite of the previous facts, it must be highlighted that the impact of climate change-related risks on insurance liabilities depends on each insurer's unique profile and must be evaluated case-by-case. Therefore, appropriate tools such as sensitivities and customized scenarios, tailored to the duration and composition of the portfolio, are essential for accurate assessment. Merk (2022) lists a series of cases that insurers must take into account when evaluating the potential impacts on their portfolios, which are the following:

1. Type of insurance product. For instance, the spread of vector-borne infectious diseases becoming more frequent and over a wider geographical range does not necessarily affect mortality, such diseases are generally non-fatal, meaning that this driver may only be relevant in disability or medical covers.
2. Region they operate. As an example, the Asian population is more likely to suffer from more severe respiratory illnesses than Europeans, caused by air pollution, meaning that this driver is more relevant for insurers operating in Asia. Moreover, life insurance is not evenly distributed worldwide; it is primarily concentrated in developed countries, which are less vulnerable to many of the risks.
3. Age profile of the population. It is clear that infants and the elderly are particularly vulnerable to the impacts of climate change, which increases the associated risk of mortality and morbidity.
4. Health and socioeconomic status of the population. Generally, the insured population has better socioeconomic status and health than average, which makes them not a good representation of the general population. The Covid-19 pandemic corroborates this effect. As the White House Council of Economic Advisers (2022) refer, in the United States, "over a long period of time, high rates of uninsurance could also be associated with the worse overall health of the underlying population, which could lead to greater vulnerability to severe illness from COVID-19". Nevertheless, wealth can not protect populations from all risks, such as poor air quality.

Finally, besides the physical risks seen so far, transition risks must also be carefully considered, as, according to the Climate Risk Task Force (2021), the risk of transitioning

to a lower carbon economy could have more significant effects on a life insurer's risk profile than immediate physical risks in the short term. Once more, Merk (2022) enumerates potential aspects that can accentuate this significant risk:

1. Shift the public spending from prevention and healthcare towards mitigating and adapting the consequences of climate change.
2. The decrease in the GDP, unemployment in specific sectors due to the transition, and economic downturn have been linked to a rise in suicides and an increase in disability claims.
3. Uneven distribution of the transition costs, with lower-income individuals expected to bear a higher burden, potentially leading to social discontent and unrest.

3 LIFE INSURANCE

Given the main purpose of this work, which is to understand how climate change can influence the life insurance market, particularly in the production of premiums, it is fundamental to have a clear view of how life insurers operate, especially which types of products are available and which techniques are used to price their products. Therefore, in this section, a short description of the main features of life insurance products is given to establish the foundation to better comprehend premium calculations later on.

According to Olivieri & Pitacco (2011), an insurance contract is defined as an agreement involving:

- the insurer, which is the party responsible for undertaking risks arising from diverse causes, which, in the case of life insurance, can be of financial type (such as investment yield and inflation), of demographic nature (including policyholders' lifetimes, lapses, and surrenders), and expenses,
- the insured(s), whose lifetime determines the payment of benefits,
- the policyholder, who makes the contract and pays the premiums, and
- the beneficiary, who receives the benefits.

Depending on the nature of benefits offered by the insurance contract, two or even three of the mentioned parties (except the insurer) may coincide.

This chapter will only focus on insurance products involving one insured party. Further information on the remaining products, that involve more than two insured parties, can be found in Dickson et al. (2019).

3.1 *Life Insurance Products*

The primary purpose of a life insurance contract is to provide benefits based on events related to the lifespan of one or more individuals. In fact, there exist numerous types of benefits available, that are paid in different events of the insured(s), giving rise to different life insurance products.

Olivieri & Pitacco (2011) classify the benefits into two main categories: *fixed benefits* and *varying benefits*. The first type of benefit is defined at policy issue. This includes benefits with a fixed amount for the whole policy's duration and benefits with varying

amounts according to a stated rule (e.g., exponentially increasing or arithmetically decreasing). The second type is the benefits that have the initial amount fixed at policy issue and are linked to a varying mechanism. Examples of this type of benefit are inflation-linked benefits, unit-linked benefits (namely, linked to the value of the unit of an investment fund), and increasing benefits via profit participation.

Since life insurance contracts typically cover events of survival and/or death. Olivieri & Pitacco (2011) divide these products into three main groups:

1. Insurance products providing *benefit in the case of survival*. The purpose of this type of product is to provide the beneficiary with deferred amounts, which can be in the format of a lump sum or an annuity. Typically, pure endowment and life annuities belong to this category.
2. Insurance products providing *benefit in the case of death*. The purpose of this type of product is to cover death and related financial consequences, by paying a lump sum benefit to the beneficiary. Commonly, term insurance and whole life insurance belong to this category.
3. Insurance products combining *death and survival benefits*. The payment of these products' benefits is certain, although paid at a random time, and also in the format of a lump sum. Given its nature, typically two beneficiaries are involved, one for the death benefit, and another for the survival benefit. Typically, endowment insurance belongs to this category.

In addition to survival and death benefits, in many countries, in accordance with the legislation and market practices, some products have included disability benefits and benefits linked to the insured's health conditions. These benefits are called *supplementary* (or *rider*) benefits.

Regarding the periodicity of premium payments, Olivieri & Pitacco (2011) distinguish into *single premium*, which is paid at the policy issue, and *periodic premiums*, in which the first one is paid at the policy issue and the remaining premiums are paid regularly (e.g., monthly or annually), until the termination of the contract.

Moreover, if the calculation of premiums allows for the insurance company's expenses, premiums are referred to as *gross premiums*; otherwise are designated *net premiums*.

3.2 Pricing Methods in Life Insurance

Pricing in insurance is essential to ensure the financial viability and sustainability of insurance products and ultimately of insurers. It encompasses (actuarial) premium calculation and considers factors beyond actuarial principles, like market dynamics and competition, to determine the total cost of an insurance product, by also incorporating profit margins and expenses. This comprehensive approach includes setting the product's final price, taking into account the market conditions and business strategies. Sometimes, adjustments can be made to the calculated premiums for competitive positioning and customer appeal. Figure 3 illustrates the workflow of pricing an insurance product, starting from establishing actuarial principles to arriving at the ultimate insurance product price.

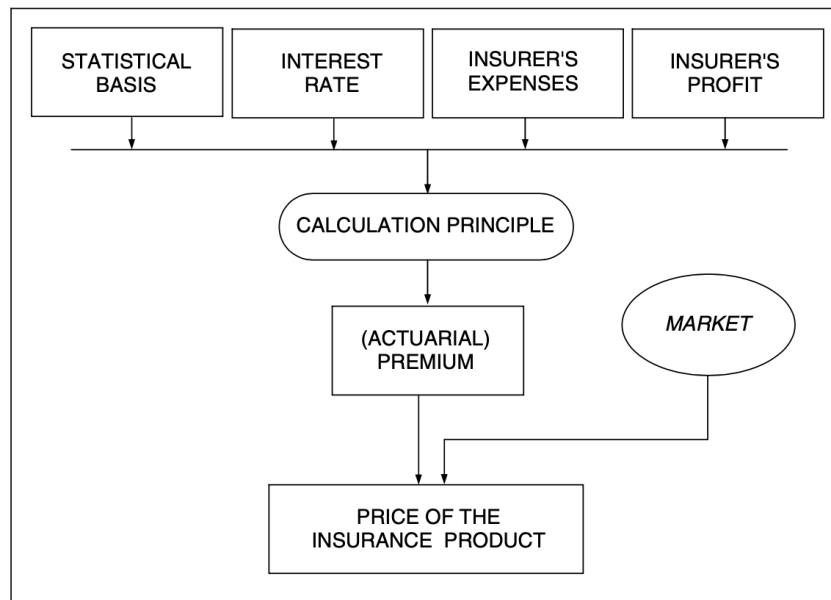


FIGURE 3: Pricing an insurance product.

Source: Olivieri & Pitacco (2011)

3.3 Premium Calculation in Life Insurance

This section focuses on the premium calculation. In life insurance, there are two main principles used by insurers to determine their products' premiums: the equivalence premium principle, and the portfolio percentile premium principle. The first principle is the most common method used by traditional life insurers (Dickson et al. 2019).

According to Dickson et al. (2019), the cash flows for a traditional life insurance contract consist of the insurance or annuity benefit outgo (and associated expenses) and the premium income. The benefit outgo can be a death benefit, a survival benefit, or a

combination of both. These cash flows, including the income and outgo, are typically contingent on the policyholder's future lifetime, except when a contract is acquired at a single premium, as there is no uncertainty regarding the premium income. Hence, the random variable representing the present value of the future loss can be expressed as the present value of future outgo less the present value of future income. When expenses are excluded from this calculation, it is called the *net future loss*, denoted as L_0^n .

$$L_0^n = \text{PV of benefit outgo} - \text{PV of net premium income}$$

If expenses are included, the associated random variable is referred to as the *gross future loss*, denoted as L_0^g .

$$L_0^g = \text{PV of benefit outgo} + \text{PV of expenses} - \text{PV of gross premium income}$$

3.3.1 Equivalence premium principle

According to Dickson et al. (2019), under the equivalence premium principle, the net premium is set such that the expected present value (EPV) of the future loss is zero at the start of the contract, that is

$$\mathbb{E}[L_0^n] = 0. \quad (1)$$

This implies that $\mathbb{E}[\text{PV of benefit outgo} - \text{PV of net premium income}] = 0$, or that the expected present value of the benefit outgo must be equal to the expected present value of net premium income.

$$\text{EPV of benefit outgo} = \text{EPV of net premium income} \quad (2)$$

When the *gross premium* is calculated for an insurance policy or an annuity, the expenses the insurer incurs are considered. These include the three main types of expenses associated with policies - initial, renewal, and termination expenses. The first type of expenses are incurred when a policy is issued and typically include agent commissions and underwriting expenses, and may vary, based on the policy's death benefit. The second type refers to the expenses that are incurred with each premium or annuity payment and cover ongoing operational costs such as staff salaries and office rent. Lastly, the termination expenses are associated with policy expiration, which can be caused by the policyholder's death or term insurance maturity.

Now, the equivalence premium principle applied to gross premiums and benefits states that the EPV of the gross future loss random variable should be equal to zero, this means

$$\mathbb{E}[L_0^g] = 0 \quad (3)$$

or

$$\text{EPV of benefit outgo} + \text{EPV of expenses} = \text{EPV of gross premium income.} \quad (4)$$

3.3.2 Portfolio percentile premium principle

The portfolio percentile premium is an alternative principle to the equivalence premium principle. Assume to have a large portfolio of identical² and independent³ policies, and suppose the sum insured is known for all policies. As the policies are identical, each policy has the same future loss random variable. Let N denote the number of policies in the portfolio and let $L_{0,i}$, with $i = 1, \dots, N$, represent the future loss random variables for the i^{th} policy in the portfolio. Hence, the total future loss in the portfolio is L , given by

$$L = \sum_{i=1}^N L_{0,i}, \quad (5)$$

and the expected value and the variance of the total future loss random variable is given by, respectively,

$$\mathbb{E}[L] = \sum_{i=1}^N \mathbb{E}[L_{0,i}] = N\mathbb{E}[L_{0,1}] \text{ and } \mathbb{V}[L] = \sum_{i=1}^N \mathbb{V}[L_{0,i}] = N\mathbb{V}[L_{0,1}]. \quad (6)$$

This premium calculation principle sets a premium so that there is a specified probability, α , that the total future loss is negative, in other words, $\mathbb{P}[L < 0] = \alpha$. Now, if N is sufficiently large, the central limit theorem tells that L is approximately normally distributed, with mean $\mathbb{E}[L] = N\mathbb{E}[L_{0,1}]$, and variance $\mathbb{V}[L] = N\mathbb{V}[L_{0,1}]$. Therefore,

$$\mathbb{P}[L < 0] = \mathbb{P}\left[\frac{L - \mathbb{E}[L]}{\sqrt{\mathbb{V}[L]}} < \frac{-\mathbb{E}[L]}{\sqrt{\mathbb{V}[L]}}\right] = \Phi\left(\frac{-\mathbb{E}[L]}{\sqrt{\mathbb{V}[L]}}\right) = \alpha, \quad (7)$$

which implies that

$$\frac{-\mathbb{E}[L]}{\sqrt{\mathbb{V}[L]}} = -\Phi^{-1}(\alpha), \quad (8)$$

where Φ is the cumulative distribution function of the standard normal distribution. Even though there is no explicit function defining the premium, it is possible to calculate P , knowing both the mean and the variance of the total future loss random variable, L .

²'Identical' policies mean policies that have the same characteristics, such as premiums, benefits, terms, and same survival model of the policyholders.

³'Independent' policies mean that policyholders are independent of each other with respect to mortality.

4 METHODOLOGY AND DATA

In order to provide a comprehensive overview of the research approach and the sources of information employed, sections 4.1 and 4.2 present a description of the methodology and data used in the study, respectively.

4.1 Methodology

In light of the purpose of our study, this section is destined to present the methodology employed and describe the procedure undertaken. The purpose is to study the impact that climate change, namely certain climate change-related variables, has on total life insurance premiums. This study is based on panel data models, namely the pooling and the fixed effects models applied to two distinct panel data sets. Our contribution aims to provide a model with more explicative power than the one used by Melnychenko et al. (2021), by adding more variables related to climate change. Ultimately, we explore four different models, which will be compared and analysed, to assess whether our alternative model is more appropriate and, also, to assess whether the addition of new variables brings relevant information about the variation of life insurance premiums.

According to Marques (2000), panel data combines cross-sectional and time-specific information, resulting from the observation of multiple individuals or entities over a period of time, allowing for the analysis of both individual and time-specific effects. Panel data models are statistical models that are specifically designed to analyze panel data, by allowing the estimation of parameters that capture both effects, which can be crucial for accurate analysis, as ignoring individual heterogeneity can lead to biased results. However, in the course of this study, as will be explained in detail later (see Section 4.2), only the individual effects are considered given that there are significant differences in the evolution of the variables studied within each group throughout the time period considered.

The basic linear panel models can be described through suitable restrictions of the following general model (Croissant & Millo 2008):

$$y_{it} = \alpha_{it} + \beta_{it}^T \mathbf{x}_{it} + u_{it}, \quad (9)$$

where $i = 1, \dots, n$ is the individual, group, or country index, $t = 1, \dots, T$ is the time index and u_{it} is a random disturbance term of mean zero. Depending on the assumptions made about the parameters, the errors, and exogeneity of the regressors, different models can result from this general model.

The most common one is the model that assumes that there is parameter homogeneity,

which means that $\alpha_{it} = \alpha$ and $\beta_{it} = \beta$, for all i and t . This type of model is given by the following equation:

$$y_{it} = \alpha + \beta^T \mathbf{x}_{it} + u_{it}. \quad (10)$$

The resulting model is a standard linear model pooling all the data across i and t .

On the other hand, to model individual heterogeneity, the error term u_{it} is often assumed to have two separate components, $u_{it} = \mu_i + \epsilon_{it}$, where μ_i is the individual error and ϵ_{it} is the idiosyncratic error. While μ_i is specific to the individual and does not change over time, ϵ_{it} is usually assumed well-behaved and independent of both the regressors, x_{it} , and the individual error component, μ_i . This is called the *unobserved effects model*, and it is present next:

$$y_{it} = \alpha + \beta^T \mathbf{x}_{it} + \mu_i + \epsilon_{it}. \quad (11)$$

Croissant & Millo (2008) mention that the appropriate estimation method for this model depends on the properties of the two error components.

In the *fixed effects model*, which is one of the models adopted in this work, the individual error components, μ_i , are treated as further n parameters to be estimated, assuming $\alpha_{it} = \alpha_i$. This specification results in the following model:

$$y_{it} = \alpha_i + \beta^T \mathbf{x}_{it} + \epsilon_{it}. \quad (12)$$

In order to assess whether the inclusion of the individual fixed effects is relevant in the context of the research question, the statistical *F-test* for fixed effects can be employed. As referred in Park (2011), this statistical test is used in the context of panel data analysis to determine whether individual-specific (or entity-specific) fixed effects significantly contribute to the model. Hence, the null and alternative hypotheses of this test are:

$$H_0 : \forall_i, \alpha_i = 0 \quad \text{vs} \quad H_1 : \exists_i : \alpha_i \neq 0.$$

As the name suggests, this statistical test is based on the F-distribution with $(n - 1, nT - n - k)$ degrees of freedom, where n is the number of individuals or entities considered, k is the number of regressors excluding the intercept term, and T is the number of time periods, under the null hypothesis. Also, this statistical test contrasts the fixed effects model with the pooling model, examining the extent to which the goodness-of-fit measures (Sum of Squared Errors (SSE) or R^2) changed.

Overall, if the null hypothesis is rejected, that is if the *p-value* is less than the significance level, one may conclude that there is a significant fixed effect or significant increase

in goodness-of-fit in the fixed effect model. In such case, the fixed effect model is better than the pooling model.

4.1.1 Model 1

As far as Melnychenko et al. (2021) refer, their work is a pioneer in quantifying the impact of climate on life insurance premiums in the EU. As already explained, the authors use a panel model where the amount of premiums under life insurance contracts is defined as a function of the greenhouse gas emissions using an unbalanced data set from 28 EU countries. This model is based on the pooling model (applied to all countries together).

Therefore, the first step of this work is to apply the same model to all countries together as well, so that, in Chapter 5, we can compare the results obtained with the results presented by Melnychenko et al. (2021). This model, Model 1, is given by the following equation:

$$PREM_{i,t} = \beta_0 + \beta_1 \times GHG_{i,t} + u_{i,t}, \quad (13)$$

where the 28 countries are denoted by the index i , the period of time is denoted by the index $t = 2011, \dots, 2019$, and β_0 and β_1 are the parameters to be estimated by regression analysis. The variables $PREM_{i,t}$ and $GHG_{i,t}$ represent the life insurance premiums and the total greenhouse gas emissions, respectively, in country i and at year t .

It is worth mentioning that the most recent three years of data (from 2020 until 2022) have been excluded from this study. This exclusion is primarily due to the unprecedented and disruptive impact of the COVID-19 pandemic during that period, which has significantly altered various aspects of the data and could introduce distortions into our findings. By focusing on data preceding this exceptional event, we aim to maintain the integrity and reliability of our analysis, allowing us to draw meaningful conclusions within a more stable context.

Model 1 serves as a basis for subsequent comparison with the Model 2, which is described next. This comparison ultimately will show whether the inclusion of individual effects is justified in the context of this study.

4.1.2 Model 2

It may be unrealistic to think that all European territories will suffer from the same impacts of climate change in the upcoming years, as it is assumed in Model 1. IPCC (2021) summarizes the confidence levels associated with projected changes in climatic impact-drivers across Europe for the mid-century. These projections are linked to global warming

levels in the range of 2°C to 2.4°C. For instance, Figure A1 (in Appendix A) shows that the mean precipitation projection indicates contrasting trends for the Mediterranean and Northern regions. In the Mediterranean countries, a decrease in mean precipitation is highly likely, whereas in the Northern region, an increase in this climatic impact-driver is anticipated.

Therefore, to deal with the possible issue of non-homogeneity in the panel data, three different groups of European countries will be considered according to IPCC (2021) division, as shown in Figure 4. This division takes into account historical trends and future climate change projections used in the Assessment Reports of the IPCC WGI, separating geographically the countries into Northern Europe (NEU), Western and Central Europe (WCE), and Southern Europe (SEU). It matters to be mentioned that the Eastern Europe (EEU) group is not considered in this study, given the lack of data for Russia. Table A1 (in Appendix A) shows explicitly the group assignment of each country.

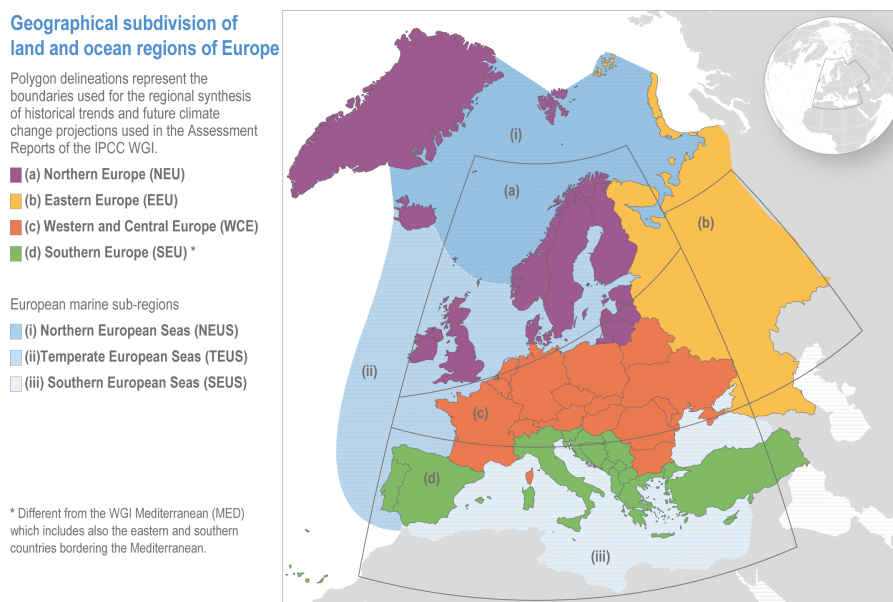


FIGURE 4: Geographical subdivision of land and ocean regions in Europe.

Source: IPCC (2022)

To account for the individual effects, we apply the fixed effects model, which considers individual effects within the three geographical groups of the EU countries. This alternative model offers a valuable analytical approach with distinct characteristics from the pooling model, as this type of panel model is characterized by allowing coefficients to vary among individuals while remaining constant and non-random (Marques 2000). Typically, this modeling technique is well-suited for aggregated samples, such as groups of countries, as it systematically addresses and allows for testing individual differences, a vital aspect of our analysis. Marques (2000) also states that the fixed effects model is the

most appropriate choice for studies using a sample of N countries, as this sample can not be considered a random selection from a population of size tending to infinite.

The following equation describes the fixed effects model, accounting for the individual effects within the NEU, WCE, and SEU, Model 2:

$$PREM_{i,t} = \beta_i + \beta_1 \times GHG_{i,t} + \epsilon_{i,t}, \quad (14)$$

where the groups defined by IPCC (2022) are denoted by the index $i = \text{NEU}, \text{WCE}, \text{SEU}$, the period of time is denoted by the index $t = 2011, \dots, 2019$, β_i and β_1 are the parameters to be estimated by regression analysis. The variables $PREM_{i,t}$ and $GHG_{i,t}$ are as defined above.

To compare Model 1 and Model 2, the statistical measure R^2 and the statistical *F-test* for individual effects are used. The first metric quantifies how well the independent variable (GHG) accounts for the variability observed in the dependent variable ($PREM$), while the second determines whether including individual-specific fixed effects in the model significantly improves its explanatory power compared to the pooling model.

4.1.3 Model 3

According to this work's purpose, we want to find a model that is able to describe the variation of life insurance premiums that results from climate change factors in the time period considered.

Therefore, our third model, Model 3, is based on the pooling model and integrates new variables, that could be related to climate change. These variables are the number of fatalities (FAT), the temperature deviation with respect to a baseline climatology, corresponding to the period 1951–1980 ($TEMP$), and the GDP (GDP).

Climate change also has wide-reaching implications for the work done by actuaries through its potential to impact human health and mortality. (Storey et al. 2019, p. 7-8) mention that "climate change is expected to have a detrimental impact on human health and mortality". On the other hand, actuaries use mortality data to calculate expected claims and set appropriate premium levels. Therefore, including data on the number of deaths seems reasonable.

So far, we have given reasons to believe that the rise of the global temperature near the surface is expected to increase the severity and frequency of extreme weather events, which affect the mortality and morbidity of the global population, including the European. Hence, this factor should also be considered in the study.

While GDP is not inherently a climate-related variable, its inclusion is justified because of its substantial influence on life insurance production. In fact, Lee et al. (2013) have found evidence of "long-run and short-run bidirectional causalities" between life insurance markets and economic growth.

Model 3, which incorporates the characteristics presented above, is described in the following equation:

$$PREM_{i,t} = \beta_0 + \beta_1 \times GHG_{i,t} + \beta_2 \times FAT_{i,t} + \beta_3 \times TEMP_{i,t} + \beta_4 \times GDP_{i,t} + u_{i,t}, \quad (15)$$

where the 28 countries are denoted by the index i , the period of time is denoted by the index $t = 2011, \dots, 2019$, and β_j , with $j = 0, 1, 2, 3, 4$ are the parameters to be estimated by regression analysis. The variables $PREM_{i,t}$, $GHG_{i,t}$, $FAT_{i,t}$, $TEMP_{i,t}$, and $GDP_{i,t}$ are as defined above.

Again, Model 3 serves as a basis for subsequent comparison with Model 4, which is described in the next section. This comparison ultimately will show whether the integration of individual effects is relevant in the context of this study.

4.1.4 Model 4

Finally, Model 4 combines the alternative panel model, which is the fixed effects model, together with the addition of new variables to the study. Then,

$$PREM_{i,t} = \beta_i + \beta_1 \times GHG_{i,t} + \beta_2 \times FAT_{i,t} + \beta_3 \times TEMP_{i,t} + \beta_4 \times GDP_{i,t} + \epsilon_{i,t}, \quad (16)$$

where the groups defined by IPCC (2022) are denoted by the index $i = \text{NEU, WCE, SEU}$, the period of time is denoted by the index $t = 2011, \dots, 2019$, and β_j , $j = 0, 1, 2, 3, 4$, are the parameters to be estimated by regression analysis. The variables $PREM_{i,t}$, $GHG_{i,t}$, $FAT_{i,t}$, $TEMP_{i,t}$, and $GDP_{i,t}$ are as defined above.

To compare Model 3 and Model 4, the statistical measure $Adj R^2$ and, once again, the statistical F -test for individual effects are used.

4.2 Data

After having outlined the methodology employed in this study, the following steps involve introducing the data sources upon which this research relies and presenting a descriptive analysis of these data sources.

The study performed by Melnychenko et al. (2021) was based on panel models using

unbalanced data. Nevertheless, the use of unbalanced data can be a source of weaknesses when it is not properly addressed. Wooldridge (2009) refers that establishing the consistency of estimators derived from standard methods on an unbalanced panel requires some insight into the mechanism applied for the missing data, which in this case is not possible. Having analysed all data sources used by the Melnychenko et al. (2021), the only variable with missing data was life insurance premiums. So, to achieve balanced panel data, this study uses a different data source for total life insurance production, which will be described later in this section.

Our study uses two balanced panel data (panel data A and B), covering 28 European countries from 2011 until 2019. Panel data A aggregates all 28 countries into one single group, and panel data B separates them geographically into NEU, WCE, and SEU, as described in Figure 4.

The annual data of direct insurance premiums (measured in millions of US dollars) for each studied European country was extracted from *sigma*'s ⁴ database, which was provided by Swiss Re. According to the Swiss Re Institute, direct insurance premiums correspond to the total amount paid by policyholders for insurance coverage, which includes not only the basic insurance premium but also additional commissions, and other related charges. This calculation is done before any portion of the risk is transferred to a reinsurance company. Premium volumes are converted into US dollars, using the average exchange rate for the financial year, to facilitate the comparisons between markets and regions. More importantly, the insurance data originates primarily from national supervisory authorities and, in some cases, from insurance associations, ensuring the reliability and accuracy of the data, and enabling us to draw meaningful conclusions.

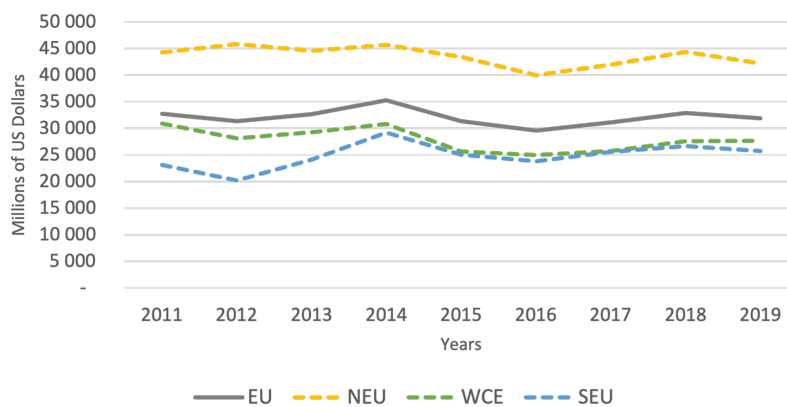


FIGURE 5: Evolution of Direct Life Insurance Premiums (millions of US dollars) for the period 2011-2019.

⁴Source: Swiss Re, *sigma* database. All rights reserved.

In Figure 5, the evolution of the average direct life insurance premiums for all EU countries, as well as the groups defined by IPCC (2022), are shown for the period of time from 2011 until 2019. Overall, there is a small variability of direct life insurance premiums throughout the years for both panel data sets for the period considered. Moreover, the life insurance market in NEU is on average more developed in the sense that the premium amounts are consistently higher when compared to the SEU and WCE.

The annual data on greenhouse gas emissions (measured in thousand of tonnes) was acquired from Eurostat (2023a), which republishes the data sourced from the European Environmental Agency (EEA), granting, once again, reliability and accuracy of the data. This dataset gathers data on carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), perfluorocarbons ($PFCs$), hydrofluorocarbons ($HFCs$), sulphur hexafluoride (SF_6) and nitrogen trifluoride (NF_3) emissions, which are known to be severe air pollutants.

Figure 6 presents the evolution of the average values of greenhouse gas emissions from 2011 until 2019, and it clearly shows a slow decay of air pollutants emissions throughout the years, which aligns with the commitments that have been made in reducing the emission of air pollutants under the *Paris Agreement* (2015).

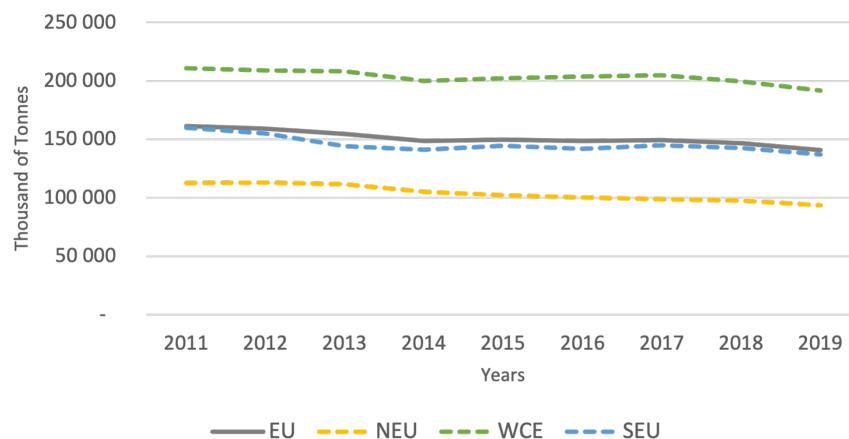


FIGURE 6: Evolution of GHG Emissions (thousands of tonnes) for the period 2011-2019.

The source chosen to extract the annual fatalities was Eurostat (2023b), which presents data on total deaths that occurred in each year and which is provided directly by Member States.

Figure 7 describes the evolution of the average number of fatalities in the time period considered. Although the data on the number of fatalities include all causes of death, the increasing trend observed might be a consequence of the phenomenon of population aging, which has been severely affecting Europe, particularly SEU, as the study of Bengtsson & Scott (2009) shows.

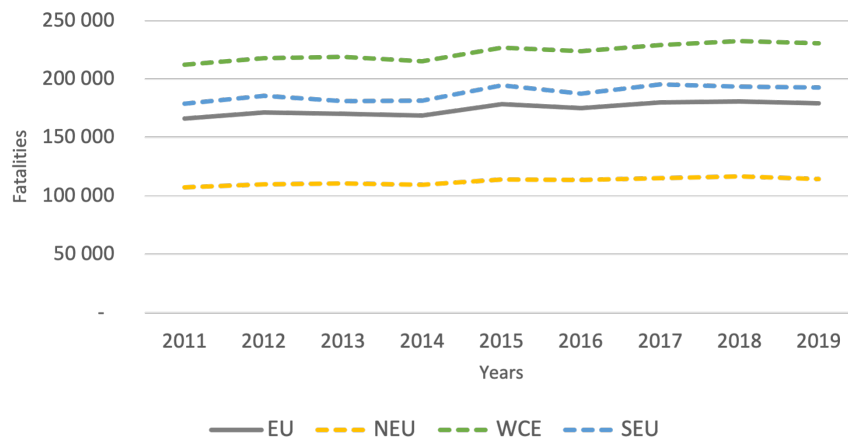


FIGURE 7: Evolution of the Number of Fatalities for the period 2011-2019.

The data on temperature deviation (measured in Celsius degrees, °C) was extracted from FAOSTAT (2023), and it compares each year’s mean surface temperature change with respect to a baseline climatology, corresponding to the period 1951–1980. This dataset is based on the publicly available GISTEMP data, the Global Surface Temperature Change data distributed by the National Aeronautics and Space Administration Goddard Institute for Space Studies (NASA-GISS).

Figure 8 shows the increase of the average temperature deviation with respect to a baseline climatology, corresponding to the period 1951–1980, revealing that, overall, WCE has suffered the highest increase of temperature deviation, compared to the other regions, whereas the SEU has suffered the least.

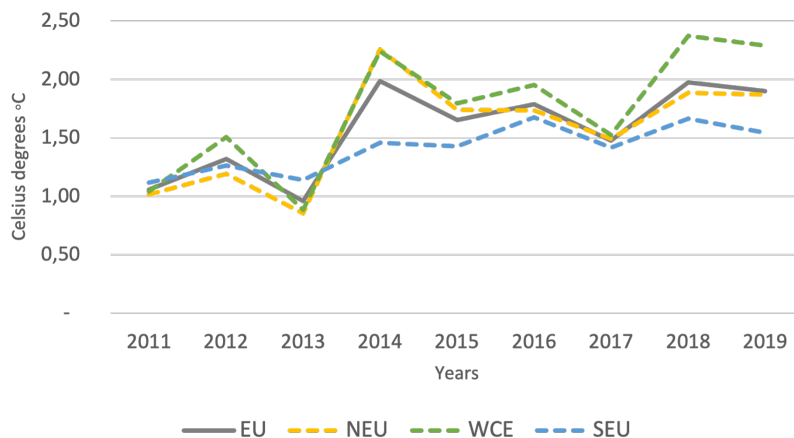


FIGURE 8: Evolution of Temperature Deviation (°C) for the period 2011-2019.

Finally, the GDP (measured in US dollars) dataset was obtained from World Bank Group and represents the total gross value added by all resident producers within the

economy, combined with product taxes minus subsidies not accounted for in product value, excluding deductions for asset depreciation and resource degradation. The GDP figures in dollars are converted from local currencies utilizing official exchange rates of a specific year.

Figure 9, which describes the behaviour of the average GDP in the years considered in the study, indicates a steady behaviour throughout the reference period, with WCE as the region with the highest average GDP.

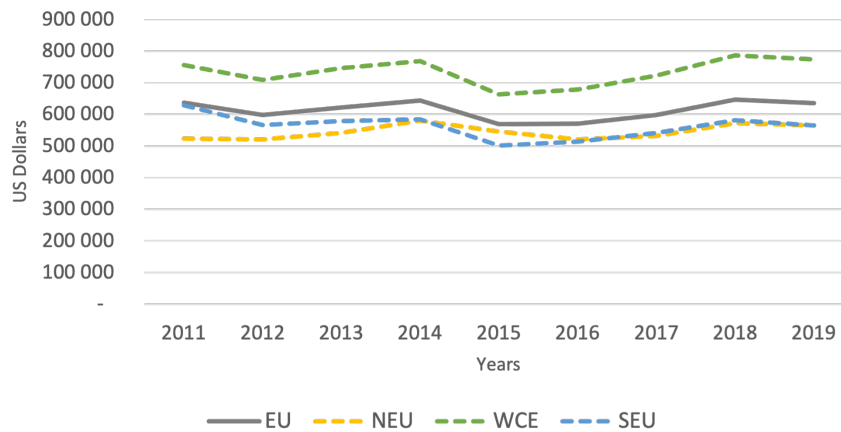


FIGURE 9: Evolution of GDP (US dollars) for the period 2011-2019.

Table I provides a summary of the dependent variables of the two panel data sets with the average values of life premiums, greenhouse gas emissions, the number of fatalities, temperature deviation with respect to a baseline climatology, corresponding to the period 1951–1980, and GDP.

When examining the life insurance production, it becomes evident that NEU leads in terms of the life insurance market, as it registers higher average life insurance premiums. Conversely, NEU registered the lowest average greenhouse gas emissions, while WCE holds the distinction of being the largest polluter within the EU. As for the number of fatalities, in WCE there were more deaths registered. However, according to the data provided by Eurostat (2023c), from 2011 until 2019, WCE also had an average population of 21,386,149, while NEU and SEU had an average population of 12,088,682 and 19,087,341, respectively, which means that each region registered a number of fatalities of around 1% of the total average population for each of the groups. Furthermore, the EU experienced an increase in the average temperature of 1.60°C compared to the 1951-1980 period, with WCE being the most affected region, witnessing a rise in mean temperature of 1.3°C. Lastly, when it comes to GDP, WCE outpaces the other regions with a higher average GDP from 2011 to 2019, while NEU and SEU reported similar average GDP figures.

TABLE I: Mean values of the model's variables across panel data A and B during the period 2011-2019.

Panel Data	Premiums (millions of US dollars)	GHG (thousands of tonnes)	Number of Fatalities	Temperature Deviation (°C)	GDP (US dollars)
<i>Panel A</i>					
EU	31,602	160 552	182,547	1.60	636,940
<i>Panel B</i>					
NEU	43,579	103,907	112,275	1.56	544,450
SEU	24,847	145,734	187,850	1.41	562,431
WCE	27,868	203,390	222,936	1.73	733,978

Table II presents the correlation matrix of the dependent and independent variables being studied. This table shows that life insurance premiums are strongly correlated with greenhouse gas emissions, the number of fatalities, and the GDP, but not so much with the temperature deviation, as the correlation value of -0.158 is relatively low.

TABLE II: Correlation matrix for panel data A.

	PREM	GGE	FAT	TEMP	GDP
PREM	1.000	0.747	0.768	-0.158	0.870
GGE	0.747	1.000	0.975	-0.073	0.946
FAT	0.768	0.975	1.000	-0.050	0.940
TEMP	-0.158	-0.073	-0.050	1.000	-0.080
GDP	0.870	0.946	0.940	-0.080	1.000

Moreover, the correlation value between the emission of greenhouse gases and the deviance of temperature is negative and close to zero for panel data A. Tables III and IV also show a negative correlation between these variables, counteracting an important premise of this work, which posits that the greenhouse effect, driven by the emission of greenhouse gases, is the key driver behind the rise in global mean surface temperatures. This distortion can be caused by different factors. In the first place, there is a possibility of data inconsistency, even though the results shown so far do not indicate any problems with the databases. Secondly, we must take into account that this study only resorts to data from 2011 until 2019, and the effects of such gases are not immediate. This means that the rising of the temperature felt nowadays can be a result of the continued emissions since the mid-20th century, even though, in recent years, there has been an effort to reduce emissions in the EU. This inverse situation may explain these correlation values being low and negative.

Table III displays the correlation matrix of the dependent and independent variables for the NEU countries. In the correlation matrix for NEU countries, we can find similari-

TABLE III: Correlation matrix for NEU.

	PREM	GGE	FAT	TEMP	GDP
PREM	1.000	0.996	0.993	-0.355	0.994
GGE	0.996	1.000	0.985	-0.384	0.986
FAT	0.993	0.985	1.000	-0.331	0.991
TEMP	-0.355	-0.384	-0.331	1.000	-0.361
GDP	0.994	0.986	0.991	-0.361	1.000

ties with the values in Table II, even though the correlation values are overall higher than in the previous table.

TABLE IV: Correlation matrix for WCE.

	PREM	GGE	FAT	TEMP	GDP
PREM	1.000	0.750	0.783	-0.057	0.903
GGE	0.750	1.000	0.974	-0.048	0.933
FAT	0.783	0.974	1.000	-0.031	0.930
TEMP	-0.057	-0.048	-0.031	1.000	-0.026
GDP	0.903	0.933	0.930	-0.026	1.000

Table IV shows the correlation matrix of the dependent and independent variables for the WCE countries. Again, the values presented are very similar to the values in Table II.

TABLE V: Correlation matrix for SEU.

	PREM	GGE	FAT	TEMP	GDP
PREM	1.000	0.888	0.927	0.169	0.927
GGE	0.888	1.000	0.991	0.115	0.990
FAT	0.927	0.991	1.000	0.154	0.989
TEMP	0.169	0.115	0.154	1.000	0.130
GDP	0.927	0.990	0.989	0.130	1.000

Table V presents the correlation matrix of the dependent and independent variables for the SEU countries. For SEU countries, the correlation value between the greenhouse gas emission and temperature deviation variables is now positive, but relatively low, which can still be explained by the argumentation presented before. Regarding the remaining correlation values, they seem consistent.

5 EMPIRICAL RESULTS AND DISCUSSION

This Chapter presents the empirical findings that address and give an answer to the research question: How does climate change affect the life insurance premiums in the EU? The analysis focuses on variables such as the total life insurance premiums, the total greenhouse gas emissions, the total number of fatalities, the temperature deviation with respect to a baseline climatology, corresponding to the period 1951–1980, and the GDP, from 2011 until 2019, in the EU, including the UK.

5.1 Model 1 Results

First of all, similarly to the work done by Melnychenko et al. (2021), Table VI provides a summary of the results obtained using Model 1, where the life insurance premiums are defined as a function of the emission of greenhouse gases. It shows that an increase of one thousand tonnes in greenhouse gas emissions leads to an increase in life insurance premiums of 0.2099 million US dollars, with a zero *p-value* for the significance test.

This result aligns with the findings of Melnychenko et al. (2021), as the authors also concluded that the increasing of the emissions, also increases the life premiums. It is important to highlight that the obtained estimate differs from the results presented in the article. This difference can be attributed to distinct sources for life premiums data and differences in currency. Also, the results in Table VI show that $R^2 = 0.5581$, which means that around 56% of the independent variable's variance is explained by the variance of the dependent variable, *GHG*, while the remaining part of the variance is unexplained and could be due to other factors not included in the model. On the other hand, Melnychenko et al. (2021) obtains a $R^2 = 0.5216$, hence both models seem to be almost equivalent.

TABLE VI: Empirical results of Model 1.

Variable	Estimate	<i>p-value</i>
Intercept	−2,099	0.5056
GGE	0.2099	$< 2E^{-16}$
Statistical Measures		
R squared	0.5581	
Adjusted R squared	0.5564	

5.2 Model 2 Results

Table VII presents a summary of the empirical results of the impact of greenhouse gas emission on the amount of life insurance premiums using Model 2. It shows that an

increase of one thousand tonnes in greenhouse gas emissions leads to an increase in life insurance premiums of 0.2243 million US dollars, with a zero *p-value* for the significance test. Additionally, Table VII displays the unobserved effects for each group of countries (NEU, WCE and SEU) which are constant over time.

Also, the results indicate that $R^2 = 0.6220$, meaning that around 62% of the independent variable's variance is explained by the variance of the dependent variable. Therefore, according to this statistical measure, the fixed effects model applied, which allows for heterogeneity among EU country groups, is more explanatory of the independent variable's variance than the pooling model, where there is no heterogeneity among countries.

TABLE VII: Empirical results of Model 2.

Variable	Estimate	<i>p-value</i>
Intercept		
NEU	20,271	$9.385E^{-6}$
WCE	-17,755	$1.960E^{-5}$
SEU	-7,844	0.1109
GGE	0.2243	$< 2.2E^{-16}$
Statistical Measures		
R squared	0.6220	
Adjusted R squared	0.6174	

Moreover, performing the *F-test* for individual effects helps to assess whether there are significant differences in the outcomes across the different groups of EU countries within the panel, by comparing the fixed effect and pooling models. In this case, the test statistic is $F = 23.37$ and the *p-value* = $5.02E^{-10}$. Therefore, as the *p-value* is almost zero, there is statistical evidence that the null hypothesis can be rejected, indicating that at least one individual-specific effect is statistically significant. This means that the individual-specific effects contribute to the explanation of the variation in the dependent variable, and their inclusion in Model 2 is justified.

5.3 Model 3 Results

After having conducted a comparative analysis with the results presented in Melnychenko et al. (2021), and concluded the suitability of the fixed effects model for this study, it is time to turn attention to the introduction of new variables, including the number of fatalities (*FAT*), the temperature deviation (*TEMP*), and the *GDP*, into both the pooling and fixed effects models and compare the results obtained. By expanding the models with these new variables, we aim to provide a comprehensive understanding of the dynamics at play and enhance the robustness of our findings.

Model 3 defines life premiums as a function of all independent variables mentioned before, using the pooling model. Table VIII presents a summary of the empirical results obtained, indicating that the greenhouse gas emissions and the GDP variables are statistically significant at 0% significance level, while the variable related to the temperature deviation is significant at 1% significance level and, for number of fatalities variable, the significance level is 5%. The results also show that an increase of one thousand tonnes in greenhouse gas emissions, maintaining the other independent variables constant, leads to a decrease in life insurance premiums of 0.2681 million US dollars, with a zero *p-value* for the significance test. In the same way, an increase uniquely in the number of deaths increases 0.0767 million US dollars in life insurance premiums. Also, a rise of 0.1°C in the temperature is estimated to reduce 0.9702 million US dollars in life insurance premiums. Lastly, the life insurance premiums are estimated to increase by 0.0925 million US dollars if the GDP per capita increases by 1 US dollar. Additionally, Table VII displays the unobserved effects for each group of countries (NEU, WCE and SEU) which are constant over time.

TABLE VIII: Empirical results of Model 3.

Variable	Estimate	<i>p-value</i>
Intercept	17, 271	0.0007
GGE	-0.2681	$6.136E^{-12}$
FAT	0.0767	0.0203
TEMP	-9, 702	0.0007
GDP	0.0925	$< 2.2E^{-16}$
Statistical Measures		
R squared	0.8212	
Adjusted R squared	0.8183	

The statistical measure *Adjusted R*², which is a more realistic estimator of the model's generalization capability as it considers the number of variables and penalizes the inclusion of unnecessary ones, has a value of *Adj R*² = 0.8183. This means that approximately 82% of the dependent variable's variance is explained by the variance of the independent variable, after adjusting for the number of variables and sample size. The observed increase in this statistical measure is a promising sign of the model's improvement. It suggests that the inclusion of these variables seems to have a positive impact on the model's capacity to explain the variance in the dependent variable, all while considering the number of predictors involved. Overall, these results indicate that Model 3 is a better fit for the data when studying the impact of these climate change-related variables on life insurance premiums.

5.4 Model 4 Results

Table IX provides the empirical results of the same dependent and independent variables as before, but now applying the fixed effects model. The results indicate that the greenhouse gas emissions and the GDP variables are statistically significant at a 0% significance level, while the variables related to the number of fatalities and temperature deviation are significant at a 1% significance level. Regarding the individual intercepts, NEU, WCE, and SEU are statistically significant at 0%, 5% and 10% significance levels, respectively.

The results of this model show that an increase of one thousand tonnes in greenhouse gas emissions, excluding the other independent variables, leads to a decrease in life insurance premiums of 0.2660 million US dollars, with a zero *p-value* for the significance test. In the same way, an increase uniquely in the number of deaths increases 0.1157 million US dollars in life insurance premiums. Also, a rise of 0.1°C is estimated to reduce 0.9895 million US dollars in life insurance premiums. Lastly, the life insurance figures are estimated to increase by 0.0837 million US dollars if the GDP per capita increases by 1 US dollar.

Regarding the statistical measure of *Adjusted R²*, the conclusion is almost identical to the previous model, as approximately 83% of the dependent variable's variance is explained by the variance of the independent variable, after adjusting for the number of variables and sample size. Again, the results suggest that Model 4 is a good fit for the data when studying the impact of these climate change-related variables on life insurance premiums.

TABLE IX: Empirical results of Model 4.

Variable	Estimate	<i>P-value</i>
Intercept		
NEU	28,083	$4.906E^{-7}$
WCE	11,898	0.0409
SEU	8,760	0.0988
GGE	-0.2660	$7.17E^{-12}$
FAT	0.1157	0.0006
TEMPD	-9,895	0.0006
GDP	0.0837	$< 2.2E^{-16}$
Statistical Measures		
R squared	0.8332	
Adjusted R squared	0.8291	

Finally, performing the *F-test* for individual effects for the last two models results in a test statistic of $F = 10.97$ and $p\text{-value} = 2.74E^{-5}$, therefore, as the *p-value* is almost zero, there is statistical evidence that the null hypothesis can be rejected, indicating that at least

one individual-specific effect is statistically significant. This means that the individual-specific effects contribute to the explanation of the variation in the dependent variable, and their inclusion in Model 4 is justified.

5.5 Discussion of the Empirical Results

Overall, the key takings from the results obtained are that the fixed effects model is statistically a better fit for the data when compared to the pooling model, as it allows for heterogeneity among the groups of EU countries as indicated by IPCC (2021). Moreover, the addition of other variables related to the number of fatalities, temperature deviation, and GDP to the study seems to have improved the statistical measures, R^2 and *Adjusted R²*, implying that the models become more informative, which consequently helps understanding how life insurance premiums change in response to variation of such variables.

However, we should also note that the coefficient estimated for the variable of greenhouse gas emission in Models 1 and 2 was positive, but, after adding the new variables to both models, it became negative. In other words, when studying uniquely the impact of greenhouse gas emissions on life insurance premiums, the results indicate that an increase in the emissions is estimated to generate an increase in total life insurance premiums, while the opposite behaviour is obtained when our model includes more variables.

Recalling the correlation matrices presented in Section 4.2 for panel data A and for the three clusters of panel data B, we have seen that the variable of greenhouse gas emissions is negatively and slightly correlated with the temperature deviation variable for most cases. This situation might be interfering with the results in Tables VIII and IX, as the addition of the temperature deviation variable with a misleading correlation to greenhouse gas emission may be causing this extreme change in the estimated coefficient.

It is important to enhance that this study only resorts to data from 2011 until 2019, which is marked mainly by the rising of the global mean temperature near the surface, provoked by the continued and overall increase of greenhouse gas emissions since the beginning of the industrial times. Meanwhile, in recent years, great importance has been given to reducing emissions (*Paris Agreement 2015*). Consequently, since we are only studying the last decade, we are not considering the many relevant years that have led to the increase in temperatures. This means that, in order to have more trustworthy and reliable results on the impact that climate change has on the life insurance market, it is essential to have more records and data on these variables studied.

6 CONCLUSIONS

Undoubtedly, we find ourselves in an era where climate change stands as one of the biggest concerns worldwide. There is a growing recognition of the profound impact of climate change on, not only the environment and human lives, but also on the field of insurance. This issue has far-reaching effects on actuarial work, as it impacts human health, the economy's stability, natural disasters, and the value of assets held by insurers.

Thus, this research aimed to study the interdependence between climate change and the life insurance market, by analysing the impact that certain climate change-related factors have on total life insurance premiums in the EU, including the UK. This study used data from the period from 2011 until 2019 and was based on panel data models. To reach its main goal, two different panel data models were used: the pooling model, using a panel data set of all 28 EU countries; and the fixed effects model, where the 28 countries were grouped according to IPCC (2022) clusters. For each panel model, two different approaches were used, the first being the usage of only the greenhouse gas emissions to describe the total life insurance premiums, whereas the second considers three more variables, which were the number of fatalities, the deviation of temperature with respect to a baseline climatology, corresponding to the period 1951–1980, and the GDP.

Regarding the first approach used, the results revealed that an increase of one thousand tonnes in the emission of greenhouse gases is estimated to increase the total life insurance premiums by 0.2099 million US dollars, pooling all EU countries, and 0.2243 million US dollars, considering the individual effects. These results align with the work done by Melnychenko et al. (2021). Nevertheless, it matters to highlight that the use of the new methodology, which is the fixed effects model, was proven to be statistically more accurate in this study than the pooling model, used by Melnychenko et al. (2021). The reason for this can be attributed to the individual characteristics exhibited by each group of countries, manifesting distinct patterns in total life insurance premiums and varying levels of greenhouse gas emissions over the studied time frame. Consequently, allowing for these individual-specific effects that are constant over time and may impact the dependent variable, helps us obtain more accurate parameter estimates.

Concerning the second approach, the coefficient estimate of the greenhouse gas emissions variable changed to -0.268 , using the pooling model, and -0.2660 , using the fixed effects model. This effect can be caused by different factors. However, a very plausible reason might be the use of a short period of time (2011-2019) in our study. As mentioned before, the correlation between the greenhouse gas emissions and the temperature deviation has been shown not to be in line with the premise of this work, as for our data this

value is negative and low. In fact, in the 10 years considered, greenhouse gas emissions have been slowly decreasing because of the efforts to reduce the impact of climate change in the future. It is also known that the rising temperatures are a consequence of the increase of the greenhouse effect, provoked by the continued and increased greenhouse gas emissions since the beginning of industrial times. This, consequently, might prove that the model of the second approach may not be suitable for the data used.

With this in mind, it becomes relevant to mention that the development of new models and new techniques is fundamental to deeply understand the impact of climate change on life insurance entrance, as this subject is still in its early stages. Also, it is important and essential to have bigger and more meaningful samples as the impact of climate change is known to be prolonged in time.

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A APPENDICE

Region	Climatic Impact-driver																					
	Heat and Cold			Wet and Dry				Wind			Snow and Ice			Coastal and Oceanic			Other					
Mediterranean (MED)	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●
Western and Central Europe (WCE)	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●
Eastern Europe (EEU)	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●
Northern Europe (NEU)	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●

1. Excluding southern UK.
 2. Along sandy coasts and in the absence of additional sediment sinks/sources or any physical barriers to shoreline retreat.
 3. The Baltic Sea shoreline is projected to prograde if present-day ambient shoreline change rates continue.
 4. For the Alps, conditions conducive to landslides are expected to increase.
 5. Low confidence of decrease in the southernmost part of the region.
 6. General decrease except in Aegean Sea.
 7. Medium confidence of decrease in frequency and increase in intensities.
 8. Except in the northern Baltic Sea region.
 ● Already emerged in the historical period (medium to high confidence)
 ● Emerging by 2050 at least in scenarios RCP8.5/SSP5-8.5 (medium to high confidence)
 ● Emerging after 2050 and by 2100 at least in scenarios RCP8.5/SSP5-8.5 (medium to high confidence)

High confidence of decrease Medium confidence of decrease Low confidence in directional change Medium confidence of increase High confidence of increase Not locally relevant

FIGURE A1: Summary of the confidence levels associated with projected changes in climatic impact-drivers across Europe for the mid-century
Source: IPCC (2021)

TABLE A1: Group Assignments of Countries.

Northern Europe (NEU)	Western and Central Europe (WCE)	Southern Europe (SEU)
Denmark	Austria	Croatia
Estonia	Belgium	Cyprus
Finland	Bulgaria	Greece
Ireland	Czechia	Italy
Latvia	France	Malta
Lithuania	Germany	Portugal
Sweden	Hungary	Spain
United Kingdom	Luxembourg	
	Netherlands	
	Poland	
	Romania	
	Slovakia	
	Slovenia	