Aging in the Air: The Impact of Emissions on Health-Related Quality of Life*

Tuan Anh Luong† and Manh-Hung Nguyen ‡

December 2024

Abstract

This paper examines the multifaceted impacts of climate change on quality of life and public health, emphasizing the differential effects across age groups. Building on a theoretical framework, we demonstrate that climate change influences health and quality of life through several channels. Directly, it exacerbates health deficits, leading to a decline in survival probabilities. This, in turn, prompts individuals to reallocate resources from consumption to healthcare, with this effect being particularly pronounced among younger populations. To empirically validate this framework, we utilize data from the Survey of Health, Aging, and Retirement in Europe (SHARE), focusing on the impact of key greenhouse gas emissions, including carbon dioxide, methane, and nitrous oxide. Our findings confirm that climate change adversely affects both quality of life and health, with significant heterogeneity across age groups. Furthermore, our empirical results are robust to a range of alternative specifications, including the use of different datasets, alternative emission measures, controls for endogeneity, and personalized climate change perception data.

Keywords: Climate change; greenhouse gases; carbon dioxide emission; methane emission; nitrous oxide emission; life quality; physical health; frailty.

*We want to thank Holger Strulik, Hai-Anh Dang and participants at the HEDGE 2024 conference for helpful comments and suggestions. Manh-Hung Nguyen acknowledges financial support from ANR under grant ANR-17-EURE-0010 (Investissements d'Avenir program). All the remaining errors are our own.

†Institute of Research in Economics, Environment and Data Science (IREEDS), VietNam and Faculty of Business and Law, Department of Economics and Marketing, De Montfort University. Email: tuan.luong@dmu.ac.uk.

‡Toulouse School of Economics, INRAE, University of Toulouse Capitole, Toulouse, France. Email: manh-hung.nguyen@tse-fr.eu

1 Introduction

Over recent decades, the impacts of climate change have become increasingly evident, manifesting in shrinking glaciers, rising sea levels, and more frequent and intense heat waves. Human activities, particularly the emission of greenhouse gases (GHG), have driven approximately 1.1°C of global warming since the pre-industrial period of 1850–1900 (IPCC, 2021). Moreover, a considerable share of urban populations, especially in low- and middle-income countries in Europe, are exposed to air pollution levels that significantly exceed the World Health Organization's recommended guidelines (Watts et al., 2017). Understanding the relationship between GHG emissions and critical economic and health outcomes is therefore paramount for both researchers and policymakers. Evaluating this "damage function" is crucial for designing policies that can effectively mitigate the adverse effects of climate change and protect public health and well-being in the future.

This paper investigates the "social cost of carbon," which quantifies the marginal damage costs associated with climate change. These costs are fundamental for designing effective Pigouvian taxes and carbon pricing strategies. In the dynamic integrated climate-economy (DICE) model proposed by Nordhaus (1993), the impacts of climate change on human well-being constitute a critical component. While most existing studies focus on national welfare (Tol, 2009), this paper shifts the focus to personal welfare. Specifically, we examine how climate change affects individual quality of life and physical health, offering novel insights into the micro-level implications of environmental changes.

Early efforts to quantify the social costs of climate change often relied on cross-sectional variation, exemplified by the seminal work of Mendelsohn, Nordhaus and Shaw (1994). This approach assumes that landowners optimize land use such that the self-reported value of the land captures its weather-related contributions. A regression framework is then used to estimate the marginal effects of climate variables. However, this method faces significant challenges in establishing a causal relationship between climate change and economic outcomes. While correlations may be strong, the estimates are susceptible to bias due to the presence of confounding factors and the omission of relevant variables.

A more recent approach has been developed to address the issue of omitted variable bias by utilizing panel data. This method exploits year-to-year variations in climate variables within observational units, enabling a more precise identification of their effects. The identification strategy relies on these within-unit temporal variations in both climate factors and the economic outcomes of interest. Building on this approach, our study seeks to achieve three key objectives: (i) develop a theoretical framework to analyze the effects of climate change on individual welfare; (ii) provide empirical evidence to support the proposed framework; and (iii) calibrate the model's parameters and conduct predictive simulations to evaluate future scenarios.

We construct a theoretical model to illustrate how climate change impacts individual welfare. In our framework, an individual's utility depends not only on their consumption level but also on their health deficit. The dynamics of the health deficit are modeled following the approach of Dalgaard and Strulik (2014), where climate change, alongside other factors such as health expenditures, can accelerate or decelerate the aging process. Recognizing heterogeneity within society, we account for variations in this process, assuming that, all else being equal, elderly individuals experience aging at a faster rate than younger individuals.

We solve for the optimal allocation of spending on consumption and healthcare by formulating and solving the Bellman equation. Quality of life is defined as the change in the Bellman value function resulting from an infinitesimal change in the health deficit. Our theoretical model demonstrates how climate change affects overall quality of life, with a particular emphasis on individual health. Specifically, the model identifies three primary channels through which these effects occur. First, greenhouse gas emissions directly exacerbate health deficits. This triggers indirect effects: as health deficits increase, survival probabilities decline, prompting individuals to adjust their consumption behavior by reallocating resources toward healthcare. Additionally, our analysis reveals that the overall impact of climate change on quality of life diminishes as the natural rate of aging increases. Given our assumption that elderly individuals have a higher rate of aging, age serves as a proxy for this rate. In essence, the model suggests that the adverse effects of climate change are more pronounced among younger individuals compared to the elderly.

We test our theoretical framework using a two-pronged approach. First, we calibrate the model and perform simulations. The simulation results align closely with the theoretical predictions, particularly regarding the first- and second-order derivatives of the Bellman value function, which are consistent with our model's expectations. Second, we validate our findings through empirical analysis using data from the Survey of Health, Aging, and Retirement in Europe (SHARE). This cross-national panel dataset encompasses over 140,000 individuals aged 50 and above from 20 European countries and Israel. SHARE provides extensive information on health, socio-economic status, and social and family networks, making it a robust source for examining the impacts of climate change on individual well-being.

For our analysis, we adopt a novel measure of climate change: greenhouse gas (GHG) emissions. While temperature is frequently used as a proxy for climate change, as demonstrated by Dell, Jones and Olken (2012), who found that rising temperatures reduce economic output, growth, and political stability, it also directly impairs human capabilities and productivity. For example, Park et al. (2020) show that elevated temperatures before exams negatively impact the test performance of American high school students. Other indicators, such as sea levels and natural disasters, have also been explored. Shah and Steinberg (2017), for instance, identify rainfall as a critical factor influencing the opportunity costs of education and subsequent human capital investment. However, these measures are often endogenous (Nordhaus, 2017), as they are largely driven by human activities, particularly GHG emissions. Given this, we use GHG emissions as our primary metric for capturing the impacts of climate change.

By selecting GHG emissions as our primary measure, this study can be interpreted as a reduced-form regression analysis for estimating the social cost of carbon. Estimating these costs involves three key steps. The first step is to establish the relationship between GHG emissions and atmospheric concentrations, typically expressed in parts per million (ppm) or parts per billion (ppb)—for context, one ppm is approximately equivalent to one drop of water diluted in 13 gallons of liquid (Pacala and Socolow (2004)). The second step involves modeling how these concentrations translate into changes in temperature, as discussed by Weitzman (2009). The final step is identifying the causal relationship between temperature (or other climate variables) and economic outcomes, as explored in prior studies. This paper contributes specifically to the third step, providing insights into the economic and welfare impacts of climate change.

A distinctive feature of our analysis is its focus on the impact of climate change on human health, in contrast to much of the existing literature, which predominantly examines its effects on agricultural and industrial outputs or economic growth. To address concerns about reverse causation, many previous studies have relied on Integrated Assessment Models (IAMs). Among the most widely recognized are the Dynamic Integrated Climate–Economy (DICE) model (Nordhaus, 2008), the Climate Framework for Uncertainty, Negotiation, and Distribution (FUND) model (Anthoff and Tol, 2009), and the Policy Analysis of the Greenhouse Effect (PAGE) model (Hope, Anderson and Wenman, 1993). These models integrate climate variables and economic outcomes into a unified framework, providing a systematic approach to mitigating reverse causation issues.

In contrast, our study centers on the effects of climate change on human health, a domain where reverse causation is less likely to pose a significant concern. This focus offers a notable advantage, as it enables us to avoid dependence on complex Integrated Assessment Models (IAMs), which require extensive datasets and rely on restrictive assumptions (Nordhaus, 2017). Instead, our approach leverages individual fixed effects (FE) to address a different source of endogeneity—the issue of omitted variables.

Our paper contributes to the growing body of literature examining the effects of climate change on human health. A commonly used metric in this research is the mortality rate. For example, Deschênes and Greenstone (2011) report that each additional day of extreme heat increases the annual age-adjusted mortality rate by 0.11 percent, a finding supported by similar studies (Barreca, 2012; Curriero et al., 2002). Deryugina et al. (2019) demonstrate that a single day of elevated PM 2.5 exposure significantly raises mortality rates, while Heutel, Miller and Molitor (2017) show that cold days are more lethal than hot days. Infant health is another critical measure in this field. For instance, exposure to hot days has been linked to a decline in birth weight of up to 0.009 percent (Deschênes, Greenstone and Guryan, 2009), and natural disasters, such as hurricanes in Texas, are associated with an increased likelihood of newborns experiencing abnormal conditions or complications (Currie and Rossin-Slater, 2013).

Our study contributes to this literature by offering new insights into the effects of climate change on various aspects of human health. Moving beyond a sole focus on mortality rates, we analyze self-reported measures of quality of life and physical health. Many of our findings are consistent with results in the public health literature. For instance, Hanson et al. (2008) show that extreme heat leads to a rise in hospital admissions for mental and behavioral disorders, while Carroll, Fritjers and Shields (2009) demonstrate that drought periods are associated with lower levels of life satisfaction.

To the best of our knowledge, this study is among the first to explore the impact of multiple greenhouse gases—namely carbon dioxide, methane, and nitrous oxide—on various dimensions of quality of life, with a particular focus on physical health. Air pollution in Europe has been estimated to cause nearly half a million premature deaths annually (Organization, 2015). Additionally, natural disasters that result in loss of life, resources, displacement, or the disruption of daily life—such as forced relocation or separation from social support networks—can trigger significant mental health challenges, including post-traumatic stress disorder (PTSD), depression, anxiety, and suicidality (U.S Global Change, 2016). Heat waves have also been linked to mood disorders and anxiety (American Psychological Association, 2017), while rising temperatures have been associated with increasing suicide rates (Burke et al., 2018). **?** found that among flood victims, 20% had been diagnosed with depression, 28.3% with anxiety, and 36% with PTSD. Similarly, extensive research has connected drought conditions to elevated suicide rates (Deshpande, 2002; Hanigan et al., 2012; Sarma, 2004; Guiney, 2012).

Our study offers quantitative evidence consistent with these findings. Specifically, we estimate that a doubling of greenhouse gas (GHG) emissions results in an approximate 4% reduction in quality of life. This result remains robust across a wide range of specifications, including controls for endogeneity, alternative measures of emissions, variations in datasets, and the use of personalized climate change data.

Finally, our paper contributes to the literature by examining age as a vulnerability indicator in the context of climate change impacts. While previous studies have commonly highlighted factors such as income (Dohrenwend et al., 1992), gender (Deryugina et al., 2020), and pre-existing health conditions (A. et al., 2016), our study focuses on age-related vulnerability. The existing evidence on this subject remains mixed. For instance, Deryugina et al. (2019) report that the adverse effects of pollution intensify with age, whereas Salcioglu, Basoglu and Livanou (2007) suggest that younger individuals are more susceptible. In contrast, our findings indicate that the impact of greenhouse gas (GHG) emissions is most pronounced among middle-aged individuals, diminishing with advancing age. Specifically, we find that the effect of GHG emissions decreases by approximately 3% for each additional year of age.

The rest of the paper is organized as follows. In sections 2 and 3 , we will present the theoretical framework and data used in our research. We lay out our identification strategy in Section 4 and report our results in Section 5. We then test the mechanism in Section 6 and provide the robustness checks in Section 7. Section 8 concludes the paper.

2 Theoretical Framework

In this section, we introduce a simple framework to formalize testable hypotheses regarding the potential impacts of greenhouse gas (GHG) emissions on human quality of life. The model integrates key components, including the influence of GHG emissions, health expenditures, and other relevant control factors, to provide a structured basis for analysis.

For each country, an individual i in period t has a health deficit, $d_{i,t}$, which results from

$$d_{i,t+1} = f(d_{i,t}, m_{i,t}, X_t), t = 0, 1..\infty.$$

In this model, health deficit depends on health spending $m_{i,t}$, the country level of GHG emission X_t, and other exogenous parameters discussed below. We utilize the health deficit model proposed by Dalgaard and Strulik (2014), which models health in terms of health deficits to quantify the value of life, following the approach of Hall and Jones (2007). Suppose that the state of health is measured by accumulated health deficits, represented by the equation

$$d_{i,t+1} = d_{i,t} + \mu_i(d_{i,t} - Zm_{i,t} + X_t)$$

in which the parameter μ_i represents the natural aging rate for individual i. The accumulation of health deficits can be mitigated through health expenditures $m_{i,t}$, while X_t captures the environmental factors, modeled as an increasing function of greenhouse gas (GHG) emissions. The parameter Z indicates the effectiveness of the individual health spending $m_{i,t}$, such as the medical technological level of the country. which may depend on factors such as the country's level of medical technology. Since GHG emissions influence human well-being at a macro level, they are treated as exogenous to individuals within the data sample.

We use the natural aging rate, μ_i, to characterize the aging process in our model. Individuals are heterogeneous with respect to μ_i, meaning that each person experiences aging at a different rate. Natural aging rate reflects the biological and physiological differences among individuals that influence how quickly they age. This heterogeneity in aging rates allows us to capture the diverse impacts of GHG emissions on health outcomes across the aging population.

Besides the usual consumption, the utility of an individual $u(c_{i,t}, d_{i,t})$ depends on the health deficit. Let $s_{i,t} = s(d_{i,t}, X_t)$ denote the survival probability that is decreasing in health deficit and decreasing in GHG emissions. Therefore, GHG emissions affect the quality of life in two ways, either by increasing the health deficit or by increasing mortality. The individual's welfare is

$$\sum_{t=0}^{\infty} \beta^t s(d_{i,t}, X_t) u(c_{i,t}, d_{i,t}).$$

Given income $y_{i,t}$, the individual will choose the level of consumption and health spending that maximize the well-being subject to the budget constraint. Let V denote the value function. Given X_t and $y_{i,t}$, the Bellman equation is defined by

$$V(d_{i,t}|X_t, y_{i,t}) = \max_{c_{i,t}, m_{i,t}} \{s(d_{i,t}, X_t)u(c_{i,t}, d_{i,t}) + \beta V(d_{i,t+1}|X_{t+1}, y_{i,t+1})\}$$

s.t

$$\begin{aligned} &y_{i,t} - c_{i,t} - m_{i,t} = 0 \\ &d_{i,t+1} = d_{i,t} + \mu_i(d_{i,t} - Zm_{i,t} + X_t) \\ &d_{i,0} \text{ is given.} \end{aligned}$$

Let λ_t be the Lagrange multipliers on the budget constraint. Define the Lagrangian function

$$\mathcal{L} = s(d_{i,t}, X_t)u(c_{i,t}, d_{i,t}) + \beta V(d_{i,t+1}) + \lambda_t(y_{i,t} - c_{i,t} - m_{i,t}).$$

The first order conditions for $\mathcal{L}$ w.r.t control and state variables read

$$s(d_{i,t}, X_t)u_c(c_{i,t}, m_{i,t}) = \lambda_t, \tag{1}$$

$$\beta \frac{\partial V(d_{i,t+1})}{\partial d_{i,t+1}} \frac{\partial f(d_{i,t}, m_{i,t}, X_t)}{\partial m_{i,t}} = \lambda_t. \tag{2}$$

where $f_m(d_{i,t}, m_{i,t}, X_t) = \frac{\partial f(d_{i,t}, m_{i,t}, X_t)}{\partial m_{i,t}} = -\mu_i Z$.

In order to get a closed-form solution, let's assume that $u(c_{i,t}, d_{i,t}) = \ln(c_{i,t}) - \alpha d_{i,t}$. Since the health deficit is a function of X, we can assume that, ultimately, survival depends solely on emissions. Thus, the survival rate can be expressed as $s = e^{-\gamma X_t}$. We assume the value function in the form:

$$V(d_{i,t}) = A + Bd_{i,t},$$

where A and B are constants to be determined. Given $\frac{\partial V}{\partial d_{i,t}} = B$, Equation 2 becomes

$$\lambda_t = \beta B \mu_i Z.$$

Substitute λ_t back into condition 1 we get

$$c_{i,t} = \frac{e^{-\gamma X_t}}{\beta B \mu_i Z},$$

and

$$m_{i,t} = y_{i,t} - c_{i,t} = y_{i,t} - \frac{e^{-\gamma X_t}}{\beta B \mu_i Z}.$$

Given the optimal values of $c_{i,t}$ and $m_{i,t}$, substitute back into the Bellman equation:

$$\begin{aligned} A + Bd_{i,t} =& e^{-\gamma X_t}\left[-\beta d_{i,t} - \gamma X_t - \ln(\beta B \mu_i Z) - \alpha d_{i,t}\right] \\ &+ \beta\left(A + B\left[d_{i,t} + \mu_i(d_{i,t} - Z(y_{i,t} - \frac{e^{-\gamma X_t}}{\beta B \mu_i Z}) + X_t)\right]\right) \end{aligned}$$

which implies

$$\begin{aligned} A + Bd_{i,t} = \beta A + e^{-\gamma X_t}\left(-\gamma X_t - \ln(\beta B \mu_i Z)\right) + \beta B \mu_i Z y_{i,t} - \beta B \mu_i X_t - \mu_i e^{-\gamma X_t} \\ - \left(e^{-\gamma X_t}(\beta + \alpha) + \beta B + \beta B \mu_i\right) d_{i,t}. \end{aligned}$$

Balancing the coefficients of $d_{i,t}$ we get

$$B = -(\beta + \alpha)e^{-\gamma X_t} - \beta B(1 + \mu_i). \tag{3}$$

Balancing the constant term yields

$$A = e^{-\gamma X_t}(-\gamma X_t - \ln(\beta B \mu_i Z)) + \beta A - \beta B \mu_i X_t + \beta B \mu_i Z y_{i,t}. \tag{4}$$

Solving for B from the identity (3) we get

$$B = -\frac{(\beta + \alpha)e^{-\gamma X_t}}{1 + \beta(1 + \mu_i)}.$$

Substituting into Equation (4) we get

$$A = \frac{e^{-\gamma X_t}\left(-\gamma X_t - \ln\left(\frac{-\beta e^{-\gamma X_t}(\beta+\alpha)\mu_i Z}{1+\beta+\beta\mu_i}\right)\right) - \frac{\beta e^{-\gamma X_t}(\beta+\alpha)\mu_i(Zy_{i,t} - X_t)}{1+\beta+\beta\mu_i} - \mu_i e^{-\gamma X_t}}{1 - \beta}.$$

Given A, B, we obtain the closed-form solution of the value function $V(d_{i,t}) = A + Bd_{i,t}$.

2.1 Impacts on quality of life

Proposition 1. *i) Higher greenhouse gas emissions and increased rates of natural aging generally lead to a lower quality of life. ii) Moreover, the detrimental effects of air pollution are more pronounced among younger age groups.*

Proof i) Let $Q = -\frac{\partial V}{\partial d} \geq 0$ denote the change in well-being associated with the change in health deficit. That is, Q represents the quality of life related to physical health deficits, where an increase in health deficits results in an drop in well-being.

It follows from the first-order conditions that

$$\underbrace{\beta \frac{Q_{i,t+1}}{s(d_{i,t}, X_t) u_c(c_{i,t}, X_t)}}_{\text{quality of life effect}} = \underbrace{\frac{1}{f_m(d_{i,t}, m_{i,t}, X_t)}}_{\text{marginal cost}} \tag{5}$$

The optimal allocation sets health spending and consumption at each age to equate the marginal benefit of life quality to its marginal cost.

Equation(5) can be rewritten as follows:

$$\beta Q_{i,t+1} = \frac{s(d_{i,t}, X_t) u_c(c_{i,t}, X_t)}{\mu_i Z}$$

This equation implies that the discounted value of quality of life is affected by GHG emissions through their impact on survival probability, the marginal utility of consumption, the marginal cost of health expenditures, and the natural health deficit accumulation process.

Given the closed form solution of V, we obtain

$$Q = -\frac{\partial V}{\partial d} = \frac{(\beta + \alpha) e^{-\gamma X_t}}{1 + \beta(1 + \mu_i)}.$$

We get the partial derivative of Q with respect to X_t is:

$$\frac{\partial Q}{\partial X_t} = -\gamma \frac{(\beta + \alpha) e^{-\gamma X_t}}{1 + \beta(1 + \mu_i)} < 0$$

and the partial derivative of Q with respect to μ_i is:

$$\frac{\partial Q}{\partial \mu_i} = -\frac{\beta(\beta + \alpha) e^{-\gamma X_t}}{(1 + \beta(1 + \mu_i))^2} < 0$$

Therefore, the quality of life ($Q_{i,t}$) decreases as GHG emissions (X_t) increase. The denominator $1 + \beta(1 + \mu_i)$ indicates that as μ_i increases, the quality of life (Q) decreases. Therefore, higher GHG emissions(X_t) and higher rates of natural aging (μ_i) generally lead to a lower quality of life. These findings are corroborated by the empirical analysis in the subsequent sections.

We implement simulations to find support for these findings. We choose some reasonable values for the parameters values α, β, γ, Z, $y_{i,t}$, and simulate Q, H over a range of X_t, μ_i values. Section 2.4 provides the analysis how to select and obtain the value of parameters.

The simulation results from Figure 1 and Figure 2 highlight the intricate interactions and impacts of GHG emissions on health-related quality of life ($Q_{i,t}$) across different age groups. In Figure 2, the colors range from dark to light, where darker shades represent more negative values of the partial derivative, and lighter shades represent less negative values. As X_t increases, $Q_{i,t}$ declines exponentially, suggesting that aging populations may experience a more pronounced deterioration in physical health under worsening environmental conditions. Furthermore, the influence of μ_i on $Q_{i,t}$ underscores the compounded vulnerability of older adults, as these factors can either mitigate or exacerbate the adverse effects of environmental stressors.

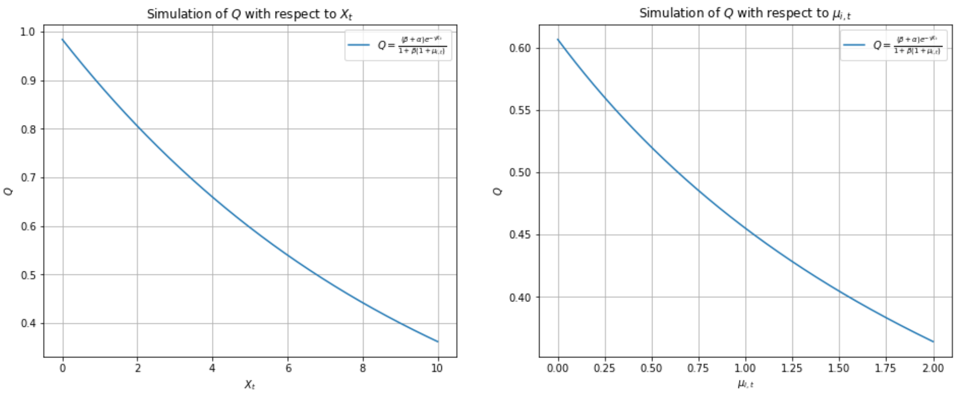

Figure 1: Impacts of Emission and Age on Life quality

ii) We are interested in

$$\frac{\partial^2 Q}{\partial X_t \partial \mu_i}$$

as the marginal effect of age on marginal health related-life quality of emission. Regression use the interaction terms between air pollution and the age groups to characterize this relation.

Note that

$$\frac{\partial Q}{\partial X_t} = -\gamma \frac{(\beta+\alpha)e^{-\gamma X_t}}{1+\beta(1+\mu_i)}$$

Hence

$$\frac{\partial^2 Q}{\partial X_t \partial \mu_i} = \frac{\gamma(\beta+\alpha)\beta e^{-\gamma X_t}}{\frac{1}{(1+\beta(1+\mu_i))^2}} > 0.$$

Therefore the marginal effect of emission on health related life quality $\frac{\partial Q}{\partial X}(\mu)$ is a decreasing convex function of μ as shown in the Figure 3.

Figure 3 illustrates the second partial derivative of Q with respect to X_t and μ_i. This represents how the marginal effects of age (μ_i) influence the marginal life quality impact of emissions (X_t). The analysis reveals that the sensitivity of life quality to changes in emissions is significantly higher for younger individuals with lower μ_i. As age increases, the impact of emissions on life quality diminishes, as indicated by the positive and decreasing trend of $\frac{\partial^2 Q}{\partial X_t \partial \mu_i}$. This aligns with empirical findings in the next sections that show younger populations are more adversely affected by air pollution. The positive coefficients of interaction terms between air pollution and age groups highlight that the

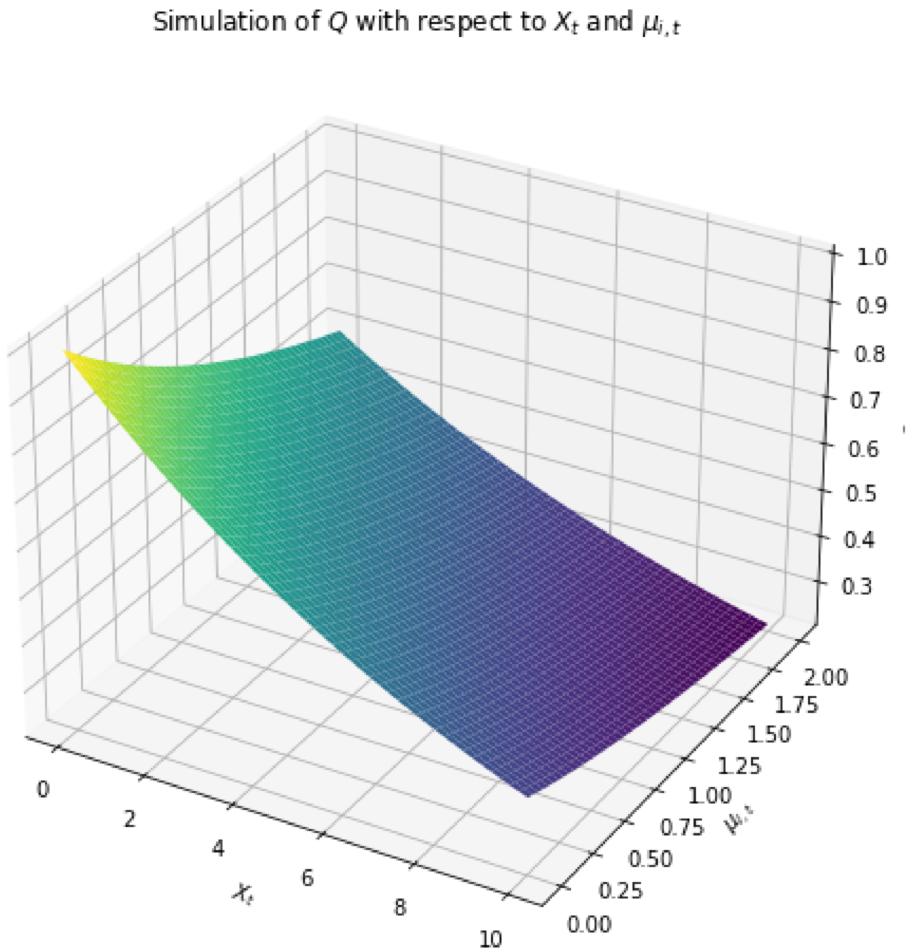

Figure 2: Effects of Q on X and μ

detrimental effects of pollution are more pronounced among younger age groups. The visualization underscores the necessity of targeted interventions to mitigate air pollution, particularly to safeguard the life quality of younger individuals who are more vulnerable to its effects. This analysis, supported by the simulation, emphasizes the importance of reducing emissions to improve overall life quality, with a particular focus on protecting younger demographics.

2.2 Impacts on Physical Health

The concept of physical health deficits is essential for understanding the overall health status of individuals and populations. These deficits encompass impairments or reductions in physical functioning and capacity, often measured by indicators such as mobility limitations, chronic pain, and the presence of chronic conditions like diabetes, cardiovascular diseases, or arthritis. Studies have shown that physical health deficits are shaped by various factors, including age, lifestyle, environmental exposures, and access to healthcare services. For example, aging populations tend to experience greater health deficits due to the natural decline in physiological functions and the cumulative impact of chronic illnesses over time Fried et al. (2001*b*).

Rooted in physiology, health status has frequently been modeled mathematically

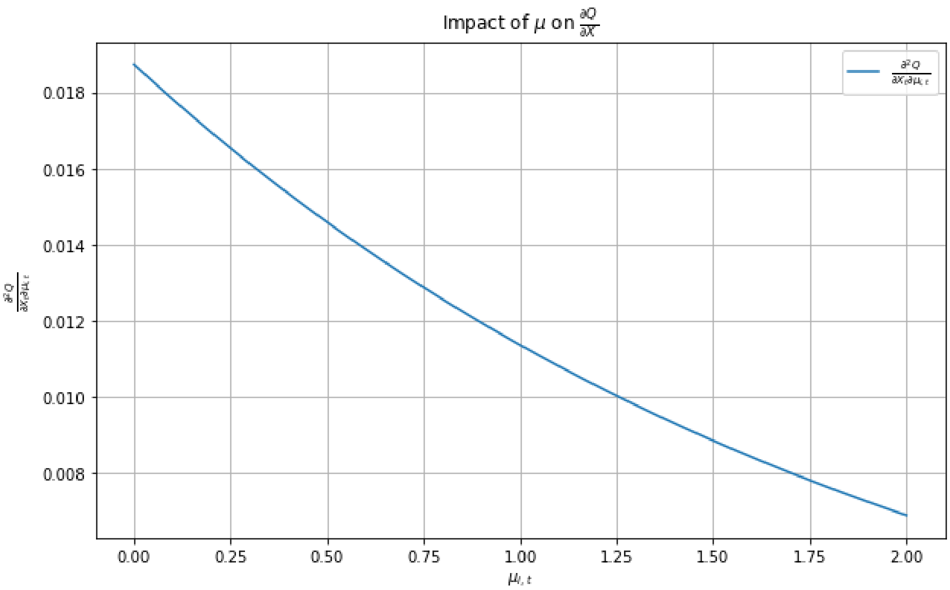

Figure 3: Marginal effects of age on marginal life quality of emission

through biophysical processes, such as health deficits (e.g., Dalgaard and Strulik, 2014; Strulik, 2018; Mitnitski et al., 2002). However, modeling the dynamics of physical health deficits poses significant challenges, especially when quantifying the effects of climate change and greenhouse gas (GHG) emissions on these deficits.

Following Dalgaard and Strulik (2014), we introduce the overall health status H as follows:

$$H_t = H^{\max} - \theta d_t H_t,$$

where $H^{\max}$ is the maximum health. The parameter θ indicates how quickly health deficits impact health status. With this setup, the model enables us to explore the determinants of physical health deficits.

Let θ_p represent the parameter for physical health. We then have:

$$H_p = \frac{H_p^{\max}}{1 + \theta_p d_p}.$$

The analysis of the partial derivatives $\frac{\partial H_p}{\partial X}$ and $\frac{\partial H_p}{\partial \mu}$ provides insightful findings on the impact of GHG emissions and aging on physical health. Let d_p be the frailty index of physical health capital, calculated from the dataset used in this paper. Then, θ_p is identified by estimating H_p with respect to d_p.

Proposition 2. *Higher greenhouse gas emissions and increased rates of natural aging generally lead to lower physical health.*

Proof. Using the optimal health expenditure value from (2), we get:

$$d_{i,t+1} = d_{i,t} + \mu_i [d_{i,t} - Z(y_{i,t} - \frac{e^{-\gamma X_t}}{\beta B \mu_i Z}) + X_t].$$

Substituting B from (3), the final expression for $d_{i,t+1}$ is:

$$d_{i,t+1} = d_{i,t} + \mu_i d_{i,t} - \mu_i Z y_{i,t} - \frac{1+\beta(1+\mu_i)}{\beta(\beta+\alpha)} + \mu_i X_t.$$

Therefore, the health status H is given by:

$$H_{i,t+1} = \frac{H^{\max}}{1+\theta\left(d_{i,t} + \mu_i d_{i,t} - \mu_i Z y_{i,t} - \frac{1+\beta(1+\mu_i)}{\beta(\beta+\alpha)} + \mu_i X_t\right)}.$$

Taking the derivative of H with respect to GHG emissions X, we have:

$$\frac{\partial H_{i,t+1}}{\partial X_t} = -\frac{H^{\max}\theta\mu_i}{\left(1+\theta\left(d_{i,t} + \mu_i d_{i,t} - \mu_i Z y_{i,t} - \frac{1+\beta(1+\mu_i)}{\beta(\beta+\alpha)} + \mu_i X_t\right)\right)^2}.$$

This partial derivative shows that health capital decreases as GHG emissions increase, given that $\theta > 0$ and $\mu_i > 0$. The rate of decrease is influenced by μ_i and other factors such as GDP, mortality, and health expenditure affecting health deficits.

To assess the impact across aging populations, we derive:

$$\frac{\partial H_{i,t+1}}{\partial \mu_i} = -\frac{H^{\max}\theta\left(d_{i,t} - Z y_{i,t} - \frac{1+\beta}{\beta(\beta+\alpha)} + X_t\right)}{\left(1+\theta\left(d_{i,t} + \mu_i d_{i,t} - \mu_i Z y_{i,t} - \frac{1+\beta(1+\mu_i)}{\beta(\beta+\alpha)} + \mu_i X_t\right)\right)^2}.$$

This partial derivative shows that $H_{i,t+1}$ decreases as the natural aging rate μ_i increases when emissions are high enough. The rate of decrease is influenced by the previous health deficit $d_{i,t}$, income $y_{i,t}$, GHG emissions X_t, and other factors such as the medical technological level of the country Z.

Simulation:

The simulation focuses on physical health corresponding to $\theta = \theta_p$. The color gradient, ranging from dark to light, represents the partial derivative values: darker shades correspond to lower (more negative) values, while lighter shades indicate higher (less negative or closer to zero) values. The $\frac{\partial H}{\partial X}$ plot illustrates that as GHG emissions increase, health capital diminishes, underscoring the harmful impact of pollution on health. This relationship is further shaped by factors such as the natural aging rate, mortality risk, and health expenditures. Similarly, the plot of $\frac{\partial H}{\partial \mu}$ shows that as the natural aging rate rises, health capital declines, particularly in the context of high emissions. This decline is influenced by prior health deficits, income levels, and other socio-economic factors.

The plot on the right indicates that, for a given aging rate, health capital decreases as emissions rise. The lowest value of $\frac{\partial H}{\partial \mu}$ ranges from -40 to -36. By comparing data across regions, we observe how differences in emissions and aging rates uniquely affect health outcomes. These regional comparisons highlight specific challenges and can guide targeted interventions to mitigate the adverse health impacts of emissions. The detailed analysis is presented in the following section.

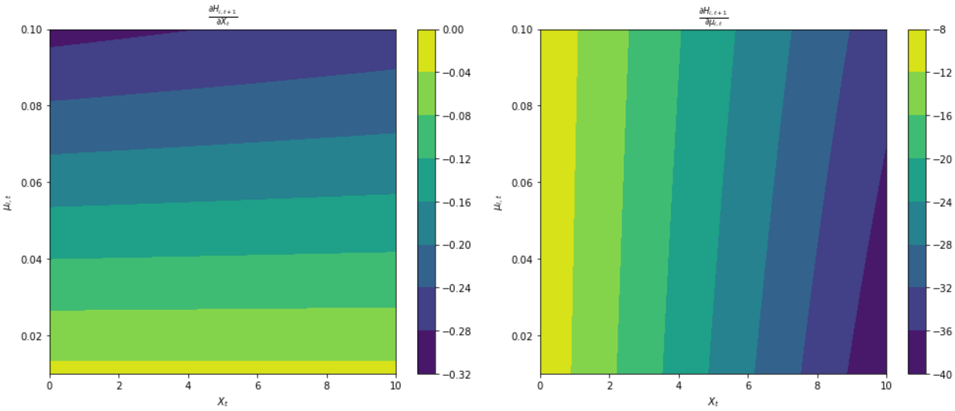

Figure 4: Impact of emission on health across aging populations

2.3 Indirect impact

Denote $P_{i,t} = \frac{\partial Q_{i,t}}{\partial X_t}$ the effect of climate change on the quality of life related to health. In our model, utility u is derived from consumption and health, it essentially reflects the overall quality of life. We define the indirect impact of pollution on the quality of life not related to health, $I_{i,t}$, as the residual impact of pollution on overall quality of life, $W_{i,t} = \frac{\partial V}{\partial X_t}$, after accounting for the direct impact on health, expressed as

$$I_{i,t} = W_{i,t} - P_{i,t} = \frac{\partial V}{\partial X_t} - \frac{\partial Q_{i,t}}{\partial X_t} = \frac{dA}{dX_t} + \frac{d(Bd_{i,t})}{dX_t} - \frac{\partial Q_{i,t}}{\partial X_t}.$$

It follows from the value function $V = A + Bd_{i,t}$, the derivative $\frac{dA}{dX_t}$ is

$$\frac{\left(\beta\mu_i(\alpha+\beta)(\gamma(X_t - Zy_{i,t}) - 1) - \gamma(X_t\gamma + \mu_i + \ln\left(\frac{-Z\beta\mu_i(\alpha+\beta)e^{-X_t\gamma}}{\beta\mu_i+\beta+1}\right))(\beta\mu_i + \beta + 1)\right)e^{-X_t\gamma}}{(\beta-1)(\beta\mu_i+\beta+1)}$$

Thus $W_{i,t} =$

$$\frac{\left(\beta\mu_i(\alpha+\beta)(\gamma(X_t - Zy_{i,t}) - 1) - \gamma(X_t\gamma + \mu_i + \ln\left(\frac{-Z\beta\mu_i(\alpha+\beta)e^{-X_t\gamma}}{\beta\mu_i+\beta+1}\right))(\beta\mu_i + \beta + 1)\right)e^{-X_t\gamma}}{(\beta-1)(\beta\mu_i+\beta+1)}$$
$$+ d_{i,t}\frac{(\beta+\alpha)\gamma e^{-\gamma X_t}}{1+\beta+\beta\mu_i} - \frac{\mu_i}{\mu_i+1}\frac{(\beta+\alpha)e^{-\gamma X_t}}{1+\beta(1+\mu_i)}.$$

Note that

$$\frac{\partial Q}{\partial X_t} = -\gamma\frac{(\beta+\alpha)e^{-\gamma X_t}}{1+\beta(1+\mu_{i,t})}$$

Therefore, indirect impact is measured as $I_{i,t} = W_{i,t} - P_{i,t} =$

$$\frac{\left(\beta\mu_i(\alpha+\beta)(\gamma(X_t - Zy_{i,t}) - 1) - \gamma(X_t\gamma + \mu_i + \ln\left(\frac{-Z\beta\mu_i(\alpha+\beta)e^{-X_t\gamma}}{\beta\mu_i+\beta+1}\right))(\beta\mu_i + \beta + 1)\right)e^{-X_t\gamma}}{(\beta-1)(\beta\mu_i+\beta+1)}$$
$$+ (d_{i,t}+1)\frac{(\beta+\alpha)\gamma e^{-\gamma X_t}}{1+\beta+\beta\mu_i} - \frac{\mu_i}{\mu_i+1}\frac{(\beta+\alpha)e^{-\gamma X_t}}{1+\beta(1+\mu_i)}.$$

To determine the indirect impact of emissions, we calculate the partial derivative of $I_{i,t}$ with respect to X_t:

$$\frac{\partial I_{i,t}}{\partial X_t} = -\gamma \left(\frac{O}{C} + \frac{d_{i,t}+1}{C} - \frac{D}{E} \right) e^{-X_t \gamma}$$

where:

$$O = \frac{\left(\beta\mu_i(\alpha+\beta)(\gamma(X_t - Zy_{i,t}) - 1) - \gamma(X_t\gamma + \mu_i + \ln\left(\frac{-Z\beta\mu_i(\alpha+\beta)e^{-X_t\gamma}}{\beta\mu_i+\beta+1}\right))(\beta\mu_i + \beta + 1)\right)}{(\beta-1)(\beta\mu_i+\beta+1)}$$

$$C = 1 + \beta + \beta\mu_i, \quad D = \frac{\mu_i}{\mu_i+1}(\beta+\alpha), \quad E = 1 + \beta(1+\mu_i).$$

The negative sign of $\frac{\partial I_{i,t}}{\partial X_t}$ indicates that an increase in GHG emissions leads to a decrease for quality of life. The terms O and D are influenced by various factors such as aging rate ($\mu_{i,t}$), previous health status and other socio-economic variables, indicating a complex interplay between emissions and indirect impact.

To conclude, the theoretical framework provides equations that illuminate the mechanisms through which emissions directly impact physical health and indirectly influence quality of life via factors such as wealth and adaptive capacities. It also suggests a possible empirical strategy for testing these relationships. Adaptation mechanisms include economic measures such as increasing healthcare funding, subsidizing health-related expenses, and ensuring equitable resource distribution. Economic stability and wealth enhance access to healthcare and promote healthier living conditions, helping to offset the negative effects of physical health deficits.

Our main variables of interest for the estimation, Q, H_p, I, are modelled as functions of observable variables such as GHG emissions (X), health spending (m), mortality rate coefficient (γ), and control variables (y, Z), including GDP and medical technology level. Unobserved factors are captured using individual fixed effects in the empirical model.

The model also highlights the heterogeneous effects of GHG emissions (X) on health, driven by differences in aging rates μ. Interaction terms involving emission levels and aging rates (μ and X), suggest that the impact of GHG emissions on quality of life varies across demographic groups. This hypothesis will be rigorously tested in the following sections.

2.4 Parameter Values for Calibration

Quality-Adjusted Life Years (QALYs) are a standard metric for quantifying health outcomes, where one QALY corresponds to one year of life in perfect health. When an individual's health is less than perfect, their QALYs are proportionally reduced. We reference Brazier, Roberts and Deverill (2002), which derives QALYs from the SF-36 Health Survey and provides critical utility values for QALY calculations in health economics. According to Ware and Gandek (1998), the highest observed QALY value for physical health is 0.92, representing optimal health conditions such as no physical limitations or disabilities, high energy levels, and health self-rated as "excellent" (Table 2, page 909). We adopt this value as the baseline for physical health when health deficits are at their initial stage, i.e., $H_p^{\max} = 92$.

We use the 0–100 General Health Rating Index from AR and JE (1981) as a criterion. We calibrate θ_p as follows:

$$\theta_p = \left(\frac{H^{\max}}{H_p^{\max}} - 1 \right) / d(0) = 3.22.$$

To compute the time discount rate, we will make use of the answers about time preferences in our data. In particular, participants were asked to choose between a certain amount of money in the future versus a lower amount today. Note that the utility of a person is given by:

$$u_t = \ln(c_t) - \alpha d_t.$$

Hence, let us denote:

$$z = \beta \ln(c_2) - \ln(c_1) = \ln \left(\frac{c_2^{\beta}}{c_1} \right),$$

where c_1 and c_2 are the amounts of money offered today and in the future, respectively. We denote the probability of choosing the future money given z as $P(y = 1|z)$. We assume that:

$$P(y = 1|z) = P(z > 0|z) = \frac{1}{1 + e^{-(z - z_0)/s}}. \tag{6}$$

We choose the parameters β, z_0, and s to fit our data.

To compute the survival rate $s = e^{-\gamma X_t}$, we utilize data from Wave 9, which includes information about deceased individuals. This data provides the probability of survival. Additionally, the dataset captures respondents' perceptions of various aspects of climate change. For instance, they were asked whether they observed changes in continuous snow cover, with responses ranging from 2 (significantly increased) to -2 (significantly decreased). We assume that members of the same household share similar perceptions. Consequently, for deceased individuals, their responses are approximated using the average household response. Using this data, we calibrate the impact of climate change (γ) on the survival rate separately for male and female respondents. The calibrated values are 0.147 and 0.111, respectively, providing confidence in these estimates. [1]

Finally, to compute the disutility of health deficits, we use the equation:

$$u = \ln(c_t) - \alpha d_t.$$

To summarize, the following table presents all parameter values chosen for calibration:

3 Data

[1] To account for individual characteristics, we also include respondents' age in the survival equation, modeling the survival rate as $s = e^{-\gamma X - \eta \cdot \text{age}}$. Based on these findings, we use the average value of $\gamma = 0.13$ for all respondents in our analysis.

Table 1: Simulated parameters

Parameter	Meaning	Value	Source
μ	natural rate of aging	0.043	Mitnitski et al. (2002)
Z	medical technology (scale)	0.0014	Dalgaard and Strulik (2014)
α	disutility from health deficits	0.03	
β	time preference rate	0.95	implied
θ_p	physical health deficits	3.22	implied
γ	death rate	0.13	implied
$d(0)$	initial health deficits	0.027	Mitnitski et al. (2002)
$D(T)$	final health deficits	0.10	Mitnitski et al. (2002)
$H^{\max}$	maximum health	100	

3.1 Survey of Health, Ageing and Retirement in Europe

The primary dataset used in our research is the Survey of Health, Ageing and Retirement in Europe (SHARE). This survey includes responses from over 140,000 individuals aged 50 and older across 28 European countries and Israel. Conducted between 2004 and 2020, SHARE comprises eight waves of questionnaires, yielding nearly 350,000 observations in total.

Respondents were asked to report their quality of life using the Control, Autonomy, Self-Realization, and Pleasure (CASP) scale (Hyde et al., 2003). This scale assesses four fundamental dimensions of need: control (the ability to actively influence one's environment), autonomy (freedom from unwanted interference by others), self-realization, and pleasure (the active and reflective processes of being human). The CASP scale consists of 19 items (see Table A), with responses coded as Often (3), Sometimes (2), Not Often (1), and Never (0). Items 1, 2, 4, 6, 8, and 9 were reverse-coded, and responses were aggregated to produce the CASP-19 index. This index ranges from 0 (indicating no quality of life) to 57 (indicating total satisfaction across all four domains). In our analysis, scores ranged from 12 to 48, with a mean of 37 and a standard deviation of 6.3 (see Table 2).

In addition to quality of life, respondents also rated their physical health status. This domain was assessed using a question derived from the 36-item Short Form (SF-36) Health Survey (see the Appendix). While the full SF-36 survey contains extensive information on physical health, the SHARE dataset includes only the first question, which asks respondents to rate their general health. Responses were recorded on a five-point Likert scale, ranging from 1 (Excellent) to 5 (Poor). More details on the SF-36 can be found in Ware and Gandek (1998). This single question serves as an indicator of respondents' physical health in our analysis.

3.2 Frailty index

The richness of our dataset enables us to examine the impact of climate change on frailty, a common issue that becomes more prevalent with age. We calculate the frailty index following Fried et al. (2001*a*), which defines frailty as the presence of more than two of the following health issues: exhaustion, shrinking, weakness, slowness, and low activity.

Our implementation aligns with prior studies (Santos-Eggimann et al., 2009; Salaffi et al., 2021).

Exhaustion: Identified if the respondent answered "Yes" to the question, “In the last month, have you had too little energy to do things you wanted to do?” (relating to the Fatigue symptom, euro9). Shrinking: Flagged if the respondent reported diminished appetite in response to “What has your appetite been like?” (relating to the Appetite aspect, euro8). Weakness: Defined as having more than three limitations in arm function or fine motor skills. Slowness: Identified if the respondent reported more than two mobility limitations. Low Activity: Assigned to respondents who reported engaging in activities requiring low or moderate energy (e.g., gardening, walking) “one to three times a month” or “hardly ever or never.” Each of these five dimensions was recorded as a binary variable (e.g., exhaustion: yes/no). Missing or refused responses were treated as missing data. Following Fried et al. (2001*a*), we categorized respondents as:

Non-frail: No problems (0 points).
Pre-frail: Up to two problems (1–2 points).
Frail: Three or more problems (3+ points).

In addition to indicators such as quality of life, physical health, and mental health, we include the frailty index as another measure of health and investigate its relationship with greenhouse gas emissions.

We also explore an alternative method for calculating the frailty index, as proposed by Dalgaard, Hansen and Strulik (2022), where frailty is measured as the proportion of total potential deficits that a person has. This approach will be applied specifically to physical health deficits.

3.3 World Bank - Our World in Data

The second dataset focuses on greenhouse gas (GHG) emissions, drawing on two key sources of information. The primary source is the World Bank Development Indicators, which provide data on carbon dioxide (CO_2) emissions in metric tons, as well as CO_2 equivalents for other GHGs, including methane and nitrous oxide. These variables are essential for robustness checks and offer a comprehensive view of the effects of climate change. The secondary source is the database from Our World in Data (Ritchie, Rosado and Roser, 2023).

For our baseline analysis, we use the World Bank data because it includes additional variables relevant to overall quality of life and public health. The Our World in Data dataset serves as a robustness check. Both data sources derive GHG, methane, and nitrous oxide emissions from the CAIT Climate Data Explorer, part of the Climate Watch Project (https://www.climatewatchdata.org/). However, the two datasets differ in their CO_2 emission sources: the World Bank relies on the CAIT database, while Our World in Data references the Global Carbon Project, which provides annual updates on CO_2 emissions.

Table 2 summarizes our data. All individuals included in the study were aged 50 or older, with an average age of 66 years. Across the countries analyzed, the average life expectancy is 81 years. On average, a country in our study emitted over 400 million metric

Table 2: Summary Statistics

Variables	(1) Observations	(2) Mean	(3) Standard deviation	(4) Min	(5) Max
Main outcomes					
(log) Life quality	410,267	3.597	0.188	2.485	3.871
(log inverse) Physical health	449,457	-1.103	0.394	-1.609	0
(log inverse) General Health	434,989	-1.105	0.394	-1.609	0
World Bank data					
Unit: Million tones Carbon dioxide equivalent					
Carbon dioxide	353,899	387.5	255.3	1.534	855.2
Methane	353,899	53.54	26.64	0.172	94.32
Nitrous oxide	353,899	53.54	26.64	0.172	94.32
Total Greenhouse gas	353,899	449.6	291.2	2.012	1,012
Our World in Data					
Unit: Million tones Carbon dioxide equivalent					
Carbon dioxide	422,422	377.1	260.0	1.531	885.6
Total Greenhouse gas	356,864	420.9	274.3	2.020	946.1
Covariates from the World Bank					
(log) GDP	422,422	27.94	0.984	23.41	28.99
Life expectancy	353,899	80.91	2.018	74.63	83.90
Age	451,059	66.50	10.68	50	111

Notes: The statistics are computed by the authors. The physical health and General health are rescaled to be consistent with the Life quality (see the text)

tons of greenhouse gases (measured in CO_2 equivalents), with carbon dioxide accounting for nearly 90% of total emissions.

4 Empirical strategy

We implement our identification strategy in the following form:

$$life{-}quality_{ict} = \beta_0+\beta_1*ghg_{ct}*age_{ict}+\beta_2*ghg_{ct}+\beta_3*age_{ict}+\beta_4*X_{ct}+\alpha_1*frail_{ict}+\eta_i+\eta_c+\eta_t+\epsilon_{ict} \quad (7)$$

In this equation, $life-quality_{ict}$ represents the self-reported quality of life (in logarithmic terms) of i living in country c at time t. This quality of life is measured across four dimensions—control, autonomy, self-realization, and pleasure—and is aggregated into an overall score for analysis (see Hyde et al., 2003).

The variable ghg_{ct} denotes the logarithm of total greenhouse gas (GHG) emissions, as well as the emissions of its individual components: carbon dioxide, methane, and nitrous oxide. To account for factors that could influence respondents' quality of life, we include a vector of country-time-specific variables, X_{ct}comprising indicators such as population, GDP, health spending, and life expectancy. To control for individual-specific differences, we include individual fixed effects. This approach enables us to compare changes in quality of life for the same individual across varying levels of GHG exposure. Consequently, we exclude individuals who participated only once in the survey, as fixed effects require at least two observations per individual.

To address potential heteroskedasticity, we cluster standard errors at the country level, which corresponds to the variation level of our treatment variable. Our primary coefficient of interest is that of the interaction term, $ghg_{ct} * age_{ict}$. The interaction term's coefficient β_1 indicates how GHG emissions affect respondents across different age brackets. We hypothesize that the coefficient of β_2 will be negative, reflecting the adverse impact of GHG emissions on quality of life. A positive β_1, however, would suggest that the negative effects of GHG emissions diminish with age, implying that middle-aged respondents are more adversely affected by polluted air than their older counterparts. To mitigate selection bias, we weight the sample using calibrated cross-sectional individual weights (SHARE, 2024).

For robustness checks, we test alternative treatment variables. In addition to total GHG emissions, we examine the impact of specific components - carbon dioxide, methane and nitrous oxide emissions - scaled to CO_2 equivalents for consistency.

To further explore the effects on human health, we also estimate a specification where the dependent variable is replaced by self-reported physical health $health_{ict}$ This variable ranges from 1 (Excellent) to 5 (Poor). For consistency with the life quality variable, we rescale this variable such that higher values indicate better health.

$$physical - health_{ict} = \beta_0 + \beta_1 * ghg_{ct} * age_{ict} + \beta_2 * age_{ict} + \beta_3 * X_{ct} + \eta_i + \eta_c + \eta_t + \epsilon_{ict} \quad (8)$$

To further support our findings, we use an additional measure: general health. Respondents were asked to rate their health in response to the question, "Would you say your health is...?" with options ranging from 1 (Excellent) to 5 (Poor). For consistency with the quality-of-life measure, we rescale these responses in the same way as we did for physical health.

$$general - health_{ict} = \beta_0 + \beta_1 * ghg_{ct} * age_{ict} + \beta_2 * age_{ict} + \beta_3 * X_{ct} + \eta_i + \eta_c + \eta_t + \epsilon_{ict} \quad (9)$$

5 Baseline analysis

Table 3 presents the estimated effects of greenhouse gas (GHG) emissions on quality of life and self-perceived health, accounting for national income and life expectancy—key factors influencing individuals' well-being and physical health. National income is included as a proxy for technological progress (Z) as discussed in the theoretical framework.

In the first two columns, the dependent variable is quality of life, measured as a composite index encompassing four dimensions: control, autonomy, pleasure, and self-realization. This index ranges from 12 to 48, with higher values reflecting greater well-being. Column 1 controls for national income, life expectancy, individual fixed effects, and time fixed effects, capturing person-specific and time-specific factors. The coefficient for the log of GHG emissions is -0.038, indicating that doubling GHG emissions reduces quality of life by approximately 4%. However, this adverse effect diminishes with age, as evidenced by the positive and statistically significant interaction term between GHG emissions and age (0.001), suggesting the impact of emissions decreases by about 2% per year. Column 2 adds country fixed effects to account for time-invariant national characteristics, and the results remain consistent, demonstrating the robustness of these findings.

Columns 3 and 4 shift the focus to general health as the dependent variable, based on respondents' self-assessments. Initial responses ranged from 1 (Excellent) to 5 (Poor) but were rescaled for consistency with the quality-of-life index, where higher values indicate better health. Column 3 includes individual and time fixed effects, while Column 4 adds country fixed effects. Both columns show a negative and significant relationship between GHG emissions and general health, with the adverse impact diminishing with age. The mitigating effect of age in these columns is approximately twice as large as in the quality-of-life analysis.

Finally, Columns 5 and 6 use self-perceived physical health as the dependent variable. The results across these specifications consistently show that GHG emissions negatively affect both quality of life and health outcomes. However, the adverse effects are less pronounced for older individuals. These findings highlight the significant harm of GHG emissions on overall well-being and health, while suggesting that older populations may exhibit a slightly reduced vulnerability to these impacts.

6 Underlying mechanism

Proposition 1 suggests that climate change affect the quality of life and physical health via 3 channels: the direct health deficits and the indirect survival probability and consumption. In this section, we will investigate these channels. More precisely, we run the following specifications:

$$life{-}quality_{ict} = \beta_0+\beta_1*ghg_{ct}*age_{ict}+\beta_2*ghg_{ct}+\beta_3*age_{ict}+\beta_4*X_{ct}+\alpha_1*frailty_{ict}+\eta_i+\eta_c+\eta_t+\epsilon_{ict} \tag{10}$$

$$\begin{aligned} life-quality_{ict} =&\beta_0 + \beta_1 * ghg_{ct} * age_{ict} + \beta_2 * ghg_{ct} + \beta_3 * age_{ict} + \beta_4 * X_{ct} + \alpha_2 * consumption_{ict} \\ &+ \eta_i + \eta_c + \eta_t + \epsilon_{ict} \end{aligned} \tag{11}$$

$$\begin{aligned} y_{ict} =&\beta_0 + \beta_1 * ghg_{ct} * age_{ict} + \beta_2 * ghg_{ct} + \beta_3 * age_{ict} + \beta_4 * X_{ct} + \alpha_1 * frailty_{ict} \\ &+ \alpha_2 * consumption_{ict} + \eta_i + \eta_c + \eta_t + \epsilon_{ict} \end{aligned} \tag{12}$$

The dependent variable, y_{ict}, represents the life quality index, as defined in the benchmark specification (7). The key distinction among the three new specifications lies in the inclusion of additional control variables: the frailty index in specification (10), consumption in specification (11), and both factors in specification (12). Survival probability is

Table 3: Greenhouse gas Emissions on the quality of life and health

	Quality of Life		General Health		Physical Health	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(GHG)	-0.038	-0.038	-0.019	-0.019	-0.023	-0.023
	(0.055)	(0.055)	(0.072)	(0.072)	(0.061)	(0.061)
ln(GHG)*age	0.001*	0.001*	0.001**	0.001**	0.002***	0.002***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
ln(GDP)	0.050	0.050	0.093*	0.093*	0.068	0.068
	(0.056)	(0.056)	(0.046)	(0.046)	(0.043)	(0.043)
Life expectancy	-0.001	-0.001	0.006	0.006	0.007	0.007
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
Time Fixed effect	YES	YES	YES	YES	YES	YES
Individual Fixed effect	YES	YES	YES	YES	YES	YES
Country Fixed effect	NO	YES	NO	YES	NO	YES
N	276800	276800	295634	295634	309677	309677
R-sq	.73	.73	.681	.681	.677	.677
Adj. R-sq	.617	.617	.549	.549	.546	.546

Note: Robust standard errors corrected by clustering variables at the country level are in parentheses.

All the data points are weighted by the calibrated weight. The individual age is controlled by the individual fixed effect.

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

excluded as a control variable because it is directly derived from the frailty index (Strulik and Grossman, 2024).

As outlined in Proposition ??, climate change impacts quality of life through health deficits (measured by the frailty index), survival probability (a function of the frailty index), and consumption. Therefore, we hypothesize that controlling for these mediating factors will eliminate the direct impact of climate change.

Table 4 presents the results. In Columns 1 and 2, we control for the frailty index. Column 1 employs the methodology of Fried et al. (2001*a*), while Column 2 adopts the approach of Dalgaard, Hansen and Strulik (2022). In both cases, once the frailty index is included, the impact of climate change, including its interaction term, becomes statistically insignificant. This indicates that climate change influences quality of life primarily through its effects on frailty.

Columns 3 and 4 incorporate individual consumption as a control variable. Column 3 uses food consumption (outside home) as a proxy, while Column 4 employs telephone consumption. In both cases, the previously significant effects of climate change disappear, suggesting that the observed impact on quality of life operates through reduced consumption levels.

Finally, Columns 5 and 6 include both the frailty index and consumption as control variables. Across these specifications, the results consistently show no significant direct effect of climate change on quality of life. This reinforces the conclusion that the influence of climate change is mediated through its effects on frailty and consumption.

7 Robustness checks

In the previous section, we have provided the evidence that (i) air pollution has a negative impacts on the life quality, physical and mental healths and (ii) young people suffered more from air pollution than the elderly. In this section, we will provide further evidence to check the robustness of these results.

7.1 Endogeneity

This subsection addresses the potential endogeneity of emissions, which may introduce bias into our estimates. In the baseline regressions, we included individual and time fixed effects, operating under the assumption that emissions were exogenous from the perspective of the individuals in the sample. This assumption holds if emissions vary only by time or country. However, we relax this assumption here to assess the robustness of our findings.

To address endogeneity concerns, we employ an instrumental variable (IV) approach, requiring an exogenous variable to instrument for potentially endogenous emissions. We select national fossil fuel subsidies as the instrument, given their strong correlation with emission levels and the low likelihood that they are directly correlated with unobserved factors affecting individual quality of life or physical health. For this analysis, we rely on data from Our World in Data, which consolidates information from sources such as the International Energy Agency, the Organisation for Economic Co-operation and Development, and the International Monetary Fund via the United Nations Global SDG

Table 4: Mechanism

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: Quality of life					
ln(GHG)	-0.024	-0.054	-0.048	-0.229	-0.042	-0.202
	(0.057)	(0.059)	(0.050)	(0.133)	(0.051)	(0.129)
ln(GHG)*age	0.001*	0.001*	0.001	0.004***	0.001	0.003**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(GDP)	0.044	0.053	0.052	0.585***	0.058	0.519**
	(0.062)	(0.058)	(0.093)	(0.185)	(0.097)	(0.220)
Life expectancy	-0.002	-0.007	0.012	-0.034	0.011	-0.040
	(0.008)	(0.008)	(0.008)	(0.028)	(0.008)	(0.031)
Frailty index 1	-0.055***				-0.035***	
	(0.006)				(0.003)	
Frailty index 2		-0.168***				-0.115***
		(0.013)				(0.008)
Food consumptions			0.000		0.000	
			(0.000)		(0.000)	
Telephone consumptions				-0.000		-0.000
				(0.000)		(0.000)
Individual Fixed effect	YES	YES	YES	YES	YES	YES
Time Fixed effect	YES	YES	YES	YES	YES	YES
Country Fixed effect	YES	YES	YES	YES	YES	YES
N	276800	219351	85024	12842	85024	12818
R-sq	.736	.748	.748	.788	.751	.794
Adj. R-sq	.626	.633	.619	.575	.623	.586

Note: Robust standard errors corrected by clustering variables at the industry-year level are in parentheses.
The frailty indices are calculated according to Fried et al. (2001*a*) (Frailty 1)
and Dalgaard, Hansen and Strulik (2022) (Frailty 2). All the data points are weighted by the calibrated weight.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Database. The data includes fossil fuel subsidies as a share of GDP from 2011 to 2019, defined as pre-tax subsidies for the production and consumption of fossil fuels. Our hypothesis is that higher fossil fuel subsidies lead to higher emissions, while these subsidies are unlikely to be linked to unobserved individual factors such as dietary habits.

To validate the instruments, we conduct a series of tests. The Wu-Hausman endogeneity test yields a Chi-squared P-value of 0.6 (Table 5), indicating that we cannot reject the null hypothesis that emissions and their interaction terms are endogenous. The Hansen J test rejects the hypothesis of model over-identification, and the Cragg-Donald Wald F test rejects the presence of weak instruments.

The first-stage coefficients, shown in the first column of Table 5, confirm that the instruments are strongly correlated with the endogenous variables, particularly the interaction term. Importantly, the estimated coefficients of the independent variables remain consistent with the baseline results, affirming that our findings are robust to potential endogeneity issues.

7.2 Alternative measures of emissions

In our benchmark analysis, total greenhouse gas (GHG) emissions serve as the primary independent variable. Among these emissions, carbon dioxide (CO_2) constitutes the largest share, accounting for approximately two-thirds of total GHG emissions, as highlighted by DEFRA, n.d. and WB, n.d.. To examine the robustness of our findings, we replace total GHG emissions by its components, such as methane (CO_2), methane (CH_4) and nitrous oxide (NO_2)and report the results in Table 6. Notably, the coefficient for the interaction term between different component of emissions and age remains positive, confirming again the robust nature of our results.

7.3 Alternative dataset

Our benchmark analysis utilizes independent variables sourced from Our World in Data. To assess the robustness of our findings to emission data variations, we employ a different dataset, also provided by Our World in Data. As detailed in Section 3.3, both datasets originate from the CAIT Climate Data Explorer, a component of the Climate Watch Project (https://www.climatewatchdata.org/). The key distinction lies in the CO2 emission data, where Our World in Data leverages the Global Carbon Project.

The results obtained using this alternative dataset are presented in Table 7. The estimated coefficients exhibit a high degree of similarity to those observed in the baseline analysis (Table 3). This consistency strengthens the argument for the robustness of our findings.

7.4 Small sample with personalised climate data

Up to this point, our analysis has relied on emissions data aggregated at the country level as independent variables. However, it is plausible that individuals may respond differently to the same level of emissions, depending on personal perceptions and experiences. To address this potential heterogeneity and to strengthen the evidence supporting our findings, we leverage a unique feature of our dataset. Specifically, in waves 8 and 9 of

Table 5: Endogeneity

	(1) GHG	(2) GHG*age	(3) General Health
Fossil fuel subsidies	0.128	26.366**	
	(0.156)	(12.979)	
Subsidies*age	-0.001	-0.314*	
	(0.002)	(0.169)	
ln(GHG)			-0.299
			(0.777)
ln(GHG)*age			0.0004
			(0.009)
ln(GDP)	0.692***	30.353***	0.311
	(0.127)	(9.439)	(0.569)
Life expectancy	-0.073***	-12.031***	-0.046
	(0.028)	(2.485)	(0.110)
N	254382	254382	254382
Wu-Hausman Chi-sq. P-value	.63	.63	
Hansen j stat.	0.9	0.9	
Cragg-Donald Wald F stat.	617	617	
Stock-Wright LM S stat.	.754	.754	
Kleibergen-Paap rk Wald F stat.	.249	.249	
Kleibergen-Paap rk LM stat.	.513	.513	
Chi-sq(1) P-val	0.47	0.47	

Note: Robust standard errors corrected by clustering variables at the industry-year level are in parentheses. The instrument variables are the fossil fuel subsidies to production and consumption. All the data points are weighted by the calibrated weight. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 6: Alternative measures of emissions

	(1)	(2)	(3)
Dependent variable: Quality of life			
ln(CO2)	-0.008		
	(0.060)		
ln(CO2)* age	0.001*		
	(0.001)		
ln(methane)		-0.067*	
		(0.035)	
ln(methane) * age		0.001*	
		(0.001)	
ln(Nitrous oxide)			-0.067*
			(0.035)
ln(Nitrous oxide) * age			0.001*
			(0.001)
ln(GDP)	0.020	0.061	0.061
	(0.064)	(0.045)	(0.045)
Life expectancy	0.003	-0.003	-0.003
	(0.008)	(0.008)	(0.008)
Individual Fixed effect	YES	YES	YES
Time Fixed effect	YES	YES	YES
Country Fixed effect	YES	YES	YES
N	276800	276800	276800
R-sq	.73	.73	.73
Adj. R-sq	.617	.617	.617

Note: Robust standard errors corrected by clustering variables at the industry-year level are in parentheses. All the data points are weighted by the calibrated weight.

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 7: Alternative dataset

	(1) Quality of Life	(2) General Health	(3) Physical Health
ln(GHG)	-0.008	-0.0003	-0.006
	(0.060)	(0.073)	(0.063)
ln(GHG)*age	0.001*	0.001*	0.002**
	(0.001)	(0.001)	(0.001)
ln(GDP)	0.012	0.090**	0.074**
	(0.070)	(0.041)	(0.036)
Individual Fixed effect	YES	YES	YES
Time Fixed effect	YES	YES	YES
Country Fixed effect	YES	YES	YES
N	278642	297488	311531
R-sq	.731	.682	.678
Adj. R-sq	.617	.549	.546

Note: Robust standard errors corrected by clustering variables at the industry-year level are in parentheses. All the data points are weighted by the calibrated weight. The emission data is taken from Our World in Data.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

the SHARE surveys, respondents in Austria were asked about their perceptions and feelings regarding climate change. These questions, used in Table 8, captured self-reported reactions to changes in several climate-related phenomena, including droughts (Column 1), floods (Column 2), average temperatures (Column 3), and extreme weather events (Column 4).

Using these individual-level subjective climate change perceptions, we explore whether individual perceptions align with broader environmental indicators in influencing quality of life and health outcomes. The results, reported in Table 8 are striking. In all columns, the magnitudes of the all the coefficients are significantly higher than what we observe in previous tables. For instance, in Column 1 where we used the individual perception of the Increase in the number and duration of droughts, the coefficient of greenhouse gas emission rose from -0.038 in Table 3 to -0.099. Similarly, the coefficient of the interaction term jumped from 0.001 to 0.016.

8 Conclusion

Climate change has far-reaching consequences on human life, particularly affecting our health and quality of life. This study establishes a theoretical framework to elucidate these impacts. Our model demonstrates that greenhouse gas (GHG) emissions lead to health deficits, which subsequently reduce survival probabilities and compel individuals to allocate more resources to healthcare at the expense of consumption. These factors collectively contribute to a decline in both quality of life and individual health.

Table 8: Personalised climate change

	(1)	(2)	(3)	(4)
Dependent variable: Quality of life				
# and duration of droughts	-0.990			
	(0.840)			
# droughts * age	0.016			
	(0.013)			
# and intensity of floods		-1.133		
		(0.799)		
# floods * age		0.017		
		(0.012)		
temperature			-3.158***	
			(0.952)	
temperature * age			0.043***	
			(0.014)	
# of extreme events				-1.055
				(0.970)
# extreme events * age				0.015
				(0.014)
age	-0.096***	-0.103***	-0.133***	-0.104***
	(0.016)	(0.015)	(0.018)	(0.020)
N	2820	2901	2897	2927
R-sq	.0237	.0284	.0319	.0277
Adj. R-sq	.0227	.0274	.0309	.0267

Note: Robust standard errors corrected by clustering variables at the industry-year level are in parentheses. All the data points are weighted by the calibrated weight. The data is only available in Austria in wave 9 (2019). * $p<0.1$, ** $p<0.05$, *** $p<0.01$

A notable strength of our model is its distinction between physical and mental health, allowing us to leverage data from the Survey of Health, Aging, and Retirement in Europe (SHARE). The empirical evidence from this dataset supports our theoretical framework. Specifically, we find that increased emissions of GHGs, including carbon dioxide, methane, and nitrous oxide, adversely affect people's lives. Interestingly, these effects appear to diminish with age. Understanding these impacts is crucial for accurately assessing the social costs of carbon, which in turn informs the optimal design of Pigouvian taxes or carbon pricing mechanisms. However, it's important to note that our study is limited by the absence of data from individuals under 50 years of age. This limitation presents an opportunity for future research as additional surveys become available.

Our findings underscore the urgent need for effective climate change mitigation strategies and highlight the potential health benefits of reducing GHG emissions. Future studies could expand on this work by incorporating younger demographics and exploring long-term health implications across different age groups. Additionally, research into adaptive measures to mitigate the health impacts of climate change could provide valuable insights for policymakers and healthcare systems.

8.1 Declarations

Conflict of interest The authors declare no competing interest

References

A., Barreca, K. Clay, O. Deschenes, M. Greenstone, and J. Shapiro. 2016. "Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century." *Journal of Political Economy*, 124: 105–59.

American Psychological Association. 2017. "Mental Health and Our Changing Climate: Impacts, Implications, and Guidance."

Anthoff, D., and R. Tol. 2009. "The Impact of Climate Change on the Balanced Growth Equivalent: An Application of FUND." *Environmental and Resource Economics*, 43(3): 351–67.

AR, Davies, and Ware JE. 1981. "Measuring Health Perceptions in the Health Insurance Experiment." *Santa Monica, CA: Rand Corporation*, , (R-2711-HHS).

Barreca, A. 2012. "Climate Change, Humidity, and Mortality in the United States." *Journal of Environmental Economics and Management*, 63(1): 19–34.

Brazier, John, Jennifer Roberts, and Mark Deverill. 2002. "The estimation of a preference-based measure of health from the SF-36." *Journal of Health Economics*, 21(2): 271–292.

Burke, M., F. Gonzalez, P. Baylis, S. Heft-Neal, C. Baysan, S. Basu, and S. Hsiang. 2018. "Higher temperatures increase suicide rates in the United States and Mexico." *Nature Climate Change*, 8(10): 723–9.

Carroll, N., P. Fritjers, and M. Shields. 2009. "Quantifying the costs of drought: new evidence from life satisfaction data." *Journal of Population Economics*, 22: 445–61.

Currie, J., and M. Rossin-Slater. 2013. "Weathering the Storm: Hurricanes and Birth Outcomes." *Journal of Health Economics*, 32(3): 487–503.

Curriero, F., K. Heiner, J. Samet, S. Zeger, L. Strug, and J. Patz. 2002. "Temperature and Mortality in 11 Cities of the Eastern United States." *American Journal of Epidemiology*, 155(1): 80–87.

Dalgaard, Carl-Johan, and Holger Strulik. 2014. "Optimal Aging and Death: Understanding the Preston Curve." *Journal of the European Economic Association*, 12(3): 672–701.

Dalgaard, C., C. W. Hansen, and H. Strulik. 2022. "Physiological aging around the World." *PLOS ONE*, 17(6).

DEFRA. n.d.. "SMALL BUSINESS USER GUIDE: Guidance on how to measure and report your greenhouse gas emissions." Department for Environment, Food and Rural Affairs.

Dell, M., B. Jones, and B. Olken. 2012. "Temperature Shocks and Economic Growth: Evidence from the Last Half Century." *American Economic Journal: Macroeconomis*, 4(3): 66–95.

Deryugina, T., G. Heutal, N. Miller, D. Molitor, and J. Reif. 2019. "The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction." NBER working paper no. 22796.

Deryugina, T., N. Miller, D. Molitor, and J. Reif. 2020. "Geographic and Socioeconomic Heterogeneity in the Benefits of Reducing Air Pollution in the United States." NBER working paper no. 27357.

Deschênes, O., and M. Greenstone. 2011. "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US." *American Economic Journal: Applied Economics*, 3(4): 152–85.

Deschênes, O., M. Greenstone, and J. Guryan. 2009. "Climate Change and Birth Weight." *American Economic Review*, 99(2): 211–17.

Deshpande, R. 2002. "Suicide by Farmers in Karnataka: Agrarian Distress and Possible Alleviatory Steps." *Economics and Political Weekly*, 37: 2601–10.

Dohrenwend, B., I. Levav, P. Shrout, S. Schwartz, G. Naveh, B. Link, A. Skodol, and A. Stueve. 1992. "Socioeconomic status and psychiatric disorders: The causation-selection issue." *Science*, 255: 946–52.

Fried, L., C. Tangen, J. Walston, A. Newman, C. Hirsch, J. Gottdiener, T. Seeman, R. Tracy, W. Kop, G. Burke, and M. McBurnie. 2001*a*. "Frailty in Older Adults: Evidence for a Phenotype." *Journal of Gerontology: MEDICAL SCIENCES*, 56A(3): 146–56.

Fried, L. P., L. Ferrucci, J. Darer, J. D. Williamson, and G. Anderson. 2001*b*. "Untangling the concepts of disability, frailty, and comorbidity: Implications for improved targeting and care." *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 56(3): M146–M157.

Guiney, R. 2012. "Farming suicides during the Victorian drought: 2001-2007." *Australian Journal of Rural Health*, 20: 11–5.

Hall, R., and C. Jones. 2007. "The Value of Life and the Rise in Health Spending." *Quarterly Journal of Economics*, 122(1): 39–72.

Hanigan, I., C. Butler, P. Kokic, and M. Hutchinson. 2012. "Suicide and drought in New South Wales, Australia 1970–2007." *Proceedings of the National Academy of Sciences*, 109: 13950–5.

Hanson, A., P. Bi, M. Nitschke, P. Ryan, D. Pisaniello, and G. Tucker. 2008. "The effect of heat waves on mental health in a temperate Australian city." *Environmental Health Perspectives*, 116(3): 1369–75.

Heutel, G., N. Miller, and D. Molitor. 2017. "Adaptation and the Mortality Effects of Temperature Across U.S. Climate Regions." NBER working paper no. 23271.

Hope, C., J. Anderson, and P. Wenman. 1993. "Policy analysis of the greenhouse effect: An application of the PAGE model." *Energy Policy*, 21(3): 327–338.

Hyde, M., R. Wiggins, P. Higgs, and D. Blane. 2003. "A measure of quality of life in early old age: The theory, development and properties of a needs satisfaction model CASP-19." *Aging and Mental Health*, 7(3): 186–94.

IPCC. 2021. "Climate Change 2021: the Physical Science Basis." The Intergovernmental Panel on Climate Change.

Mendelsohn, R., W. Nordhaus, and D. Shaw. 1994. "The Impact of Global Warming on Agriculture: A Ricardian Analysis." *American Economic Review*, 84(4): 753–71.

Mitnitski, A.B, AJ Mogilner AJ, C MacKnight C, and K Rockwood. 2002. "The accumulation of deficits with age and possible invariants of aging." *Scientific World*, 28: 1816–1822.

Nordhaus, W. 1993. "Rolling the 'DICE': An optimal transition path for controlling greenhouse gases." *Resource and Energy Economics*, 15(1): 27–50.

Nordhaus, W. 2008. *A Question of Balance—Weighing the Options on Global Warming Policies.* Yale University Press.

Nordhaus, W. 2017. "Revisiting the Social Cost of Carbon." *Proceedings of the National Academy of Sciences of the United States of America*, 114(7): 1518–1523.

Organization, World Health. 2015. "Economic Cost of the Health Impact of Air Pollution in Europe."

Pacala, S., and R. Socolow. 2004. "Stabilization Wedges: Solving the Climate Problem for the Next 50 Years with Current Technologies." *Science*, 305(5686): 968–972.

Park, R., J. Goodman, M. Hurwitz, and J. Smith. 2020. "Heat and Learning." *American Economic Journal: Economic Policy*, 12(2): 306–339.

Ritchie, Hannah, Pablo Rosado, and Max Roser. 2023. "CO2 and Greenhouse Gas Emissions." *Our World in Data*. https://ourworldindata.org/co2-and-greenhouse-gas-emissions.

Salaffi, F., M. Carlo, M. Carotti, S. Farah, and A. Giovagnoni. 2021. "Frailty prevalence according to the Survey of Health, Ageing and Retirement in Europe-Frailty Instrument (SHARE-FI) definition, and its variables associated, in patients with symptomatic knee osteoarthritis: findings from a cross-sectional study." *Aging Clinical and Experimental Research*, 33: 1519–27.

Salcioglu, E., M. Basoglu, and M. Livanou. 2007. "Post-traumatic stress disorder and comorbid depression among survivors of the 1999 earthquake in Turkey." *Disasters*, 31: 115–129.

Santos-Eggimann, B., P. Cuénoud, J. Spagnoli, and J. Junod. 2009. "Prevalence of Frailty in Middle-Aged and Older Community-Dwelling Europeans Living in 10 Countries." *J Gerontol A Biol Sci Med Sci*, 64A(6): 675–681.

Sarma, E. 2004. "Is Rural Economy Breaking Down? Farmers' Suicides in Andhra Pradesh." *Economics and Political Weekly*, 39: 3087–9.

Shah, M., and B. Steinberg. 2017. "Drought of Opportunities: Contemporaneous and Long-Term Impacts of Rainfall Shocks on Human Capital." *Journal of Political Economy*, 125(2): 527–61.

SHARE. 2024. "Release Guide 9.0."

Strulik, H., and V. Grossman. 2024. "The Economics of Aging with Infectious and Chronic Diseases." *Economics and Human Biology*, 52.

Strulik, Holger. 2018. "Smoking kills: An economic theory of addiction, health deficit accumulation, and longevity." *Journal of Health Economics*, 62: 1–12.

Tol, R. 2009. "The Economic Effects of Climate Change." *Journal of Economic Perspectives*, 23(2): 29–51.

U.S Global Change. 2016. "The Impacts of Climate Change on Human Health in the United States: A Scientific Assessment." U.S Global Change Research Program.

Ware, J., and B. Gandek. 1998. "Overview of the SF-36 health survey and the international quality of life assessment (IQOLA) project." *Journal of Clinical Epidemiology*, 51(11): 903–12.

Watts, N., W. Adger, S. Ayeb-Karlsson, Y. Bai P. Byass, D. Campbell-Lendrum, T. Colbourn, P. Cox, M. Davies, M. Depledge, A. Depoux, P. Dominguez-Salas, P. Drummond, P. Ekins, A. Flahault, D. Grace, H. Graham, A. Haines, I. Hamilton, A. Johnson, I. Kelman, S. Kovats, L. Liang, M. Lott, R. Lowe, Y. Luo, G. Mace, M. Maslin, K. Morrissey, K. Murray, T. Neville, M. Nilsson, T. Oreszczyn, C. Parthemore, D. Pencheon, E. Robinson, S. Schütte, J. Shumake-Guillemot P. Vineis, P. Wilkinson, N. Wheeler, B. Xu, J. Yang, Y. Yin, C. Yu, P. Gong, H. Montgomery, and A. Costello. 2017. "The Lancet Countdown: Tracking Progress on Health and Climate Change." *Review*, 389(10074): 1151–1164.

WB. n.d.. "Data Bank - Metadata Glossary." World Bank.

Weitzman, M. 2009. "On Modeling and Interpreting the Economics of Catastrophic Climate Change." *The Review of Economics and Statistics*, 91(1): 1–19.

Appendix

Table A: The 19 questions in CASP-19

Symptom	Questions	Item number
CONTROL	My age prevents me from doing the things I would like to	1
	I feel that what happens to me is out of my control	2
	I feel free to plan for the future	3
	I feel left out of things	4
	I can do the things that I want to do	5
	Family responsibilities prevent me from doing what I want to do	6
AUTONOMY	I feel that I can please myself what I can do	7
	My health stops me from doing the things I want to do	8
	Shortage of money stops me from doing the things that I want to do	9
	I look forward to each day	10
	I feel that my life has meaning	11
PLEASURE	I enjoy the things that I do	12
	I enjoy being in the company of others	13
	On, balance, I look back on my life with a sense of happiness	14
	I feel full of energy these days	15
SELF- REALIZATION	I choose to do things that I have never done before	16
	I feel satisfied with the way my life has turned out	17
	I feel that life is full of opportunities	18
	I feel that the future looks good for me	19