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Tuan Anh Luong and Manh-Hung Nguyen

Toulouse School of Economics

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Tuan Anh Luong* and Manh-Hung Nguyen †

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Abstract

In this paper, we analyse the impacts of climate change, in particular greenhouse gases on people's life quality in general, and physical and mental health in particular. These outcomes are taken from the Survey of Health, Ageing and Retirement in Europe which took place from 2004 to 2019. We provide a wealth of evidence that shows the adverse impacts of greenhouse gases emission. For instance, doubling the amount of carbon dioxide emission would reduce the quality of life of a person aged 50 by 3.8 percent. The effects on mental health are more noticeable than those on physical health. These effects are, however, not constant across ages. Middle-aged people are more vulnerable than older ones.

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

*Faculty of Business and Law, Department of Economics and Marketing, De Montfort University. Email: tuan.luong@dmu.ac.uk.

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

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1 Introduction

Over the past decades, we have observed more and more the footprints of climate change. Glaciers have shrunk, sea level have risen and longer, more intense heat waves have been occurring at alarming rate. Emissions of greenhouse gases (GHG) from human activities are responsible for approximately 1.1°C of warming since 1850-1900 (IPCC, 2021). Moreover, most Europeans living in urban areas in low and middle-income countries are exposed to the levels of air pollution above the WHO guidelines (Watts et al., 2017). It is then vital to our existence to understand the relationship between GHG emissions and the economically relevant outcomes, from economic growth to human health. Assessing this "damage function" is central to academics and policymakers if they are to provide policy implications to mitigate the impacts of climate change in the future.

This paper aims to provide evidence on the "social cost of carbon", which is the marginal damage costs of climate change. These costs would be the key inputs in designing the optimal Pigouvian taxes or carbon pricing. The first attempt to measure these costs was to rely on cross-section variation. A notable example is Mendelsohn, Nordhaus and Shaw (1994). A crucial assumption in this approach is the optimized use of lands by the owners. As a result, the self-reported value of land would reflect the contribution of weather. A regression framework would then reveal the marginal effect of climate variables. The main problem of this approach is *identifying the causal relationship* between climate change and economic outcomes. While there might be a large correlation between them, the estimates will be biased by the many confounding factors that are very likely to be omitted.

Recently, a new approach has emerged to mitigate the omitted variable problem. This approach makes use of the panel data and calls on using the year-to-year climate variables to identify their effects. The identification strategy is to rely on the within-unit year-to-year variations in both the climate change and the economic variable of interest. We will follow this approach to answer the following research questions: *What are the effects of greenhouse gases emission on human quality of life? Do they have adverse effects on our health, both physically and mentally? Is there a particularly vulnerable group, especially among the aging population?*

In answering these questions, we contribute to the literature on a number of fronts. The first dimension is the measure of climate change. Temperature is often used as such measure. Dell, Jones and Olken (2012) show that rising temperature would reduce output and economic growth, putting political stability at risk. It also affects negatively our capabilities and productivity. Using the test scores of American high school students between 2001 and 2014, Park et al. (2020) find that hot temperatures leading to the exams would reduce students' scores. Other measures such as sea-level or natural disasters are also considered. For instance, Shah and Steinberg (2017) show that rainfall is an important determinant of the opportunity costs of schooling, which then determines investment in human capital. However, these measures are often not exogenous (Nordhaus, 2017). Indeed, they are likely to be the product of human activities, in particular, GHG emissions. For this reason, we take this variable as our measure of climate change.

By choosing GHG emission as the measure of climate change, our paper can be regarded as a reduced-form regression of measuring the social costs of carbon. The complete recipe for measuring such costs would consist of three steps. First, we need to establish the link between GHG emissions and concentrations, or the amount of a particular gas in the air. They are measured in part per million, or sometimes per billion. One part per million is equivalent to one drop of water diluted into about 13 gallons of liquid. An example of this type of study is Pacala and Socolow (2004). Second, a model has to be formulated to convert these concentrations into changes in temperature (see, for example, Weitzman, 2009). The final step is to identify the causal relationship between temperature (or other climate variables) and the economic outcomes, as we have seen above.

In addition to the measure of climate change, we also contribute to the literature with measures of economic outcomes. Most of the literature focuses on how climate change would affect agricultural and industrial outputs, and economic growth. To rule out the reverse causation, these papers mostly rely on the Integrated Assessment Models (IAM). Some of the most well-known models used by the United States Environmental Protection Agency are the Dynamic Integrated Climate–Economy (DICE) model (Nordhaus, 2008); the Climate Framework for Uncertainty, Negotiation and Distribution (FUND) model (see, for example, Anthoff and Tol, 2009); and the Policy Analysis of the Greenhouse Effect (PAGE) model (Hope, Anderson and Wenman, 1993). In these models, all the climate variables and the outcomes of interest are included in an integrated setup to mitigate the reserve causation concern.

Different from these papers, we focus on the impacts of climate change on human health. With this outcome, reverse causation is unlikely to be a major concern. This creates a huge advantage in our analysis. Indeed, we do not have to rely on complicated IAM models, which often require extensive datasets and restrictive assumptions (Nordhaus, 2017). By contrast, we can make use of the individual fixed effects (FE) to mitigate the other source of endogeneity which is the problem of omitted variables.

Our paper is related to a growing literature that makes use of human health. To measure human health, one can use the mortality rate. Deschênes and Greenstone (2011) find that each additional day of extreme heat increased the annual age-adjusted mortality rate by 0.11 percent. Similar statistics are also found in Barreca (2012) and Curriero et al. (2002). Deryugina et al. (2019) show that increase in the PM 2.5 exposure for one day resulted in more deaths. Heutel, Miller and Molitor (2017) find that cold days are more deadly than hot days. Goenka, Liu and Nguyen (2021) highlight economic and health losses due to disease and pollution externalities in a neoclassical growth framework and show that socially efficient outcomes have higher pollution than competitive ones, questioning hopes of a green recovery. Another measure is infant health. Hot days led to a decline in birth weight by up to 0.009 percent (Deschênes, Greenstone and Guryan, 2009). Exposure to natural disasters such as hurricanes in Texas increased the probability of newborns being born with abnormal conditions or complications (Currie and Rossin-Slater, 2013).

Our contribution is to bring a wealth of evidence on the effects of climate change on different dimensions of human health. Instead of the mortality rate, our outcomes are the self-reported quality of life, as well as the self-reported human health, both physically and mentally. Most of the results are found in the public health literature. For example, Hanson et al. (2008) find that extreme heat led to an increase in hospital admissions for mental and behavioral disorders. Periods of drought are associated with a reduction in life satisfaction (Carroll, Fritjers and Shields, 2009).

To the best of our knowledge, we are one of the first to link the emissions of multiple types of greenhouse gas emissions, including carbon dioxide, methane and nitrous oxide emissions, to the various dimensions of life quality, including physical and mental health. It is reported that air pollution in Europe caused nearly half a million premature deaths per year (World Health Organization, 2015). When natural disasters lead to the loss of life and resources, or the disruption of their normal life (e.g. relocation), or the disconnection of social support and networks, people could have the mental problems including post-traumatic stress disorder (PTSD), depression, anxiety and suicidality (U.S Global Change, 2016). Heat waves would cause mood disorders and anxiety (American Psychological Association, 2017). As a result, there is some link between rising temperatures and suicidal rates (Burke et al., 2018). B. et al. (2013) recorded that among the flood victims, 20% had been diagnosed with depression, 28.3% with anxiety and 36% with PTSD. There are amble evidence that drought is connected to suicide (Deshpande, 2002; Hanigan et al., 2012; Sarma, 2004; Guiney, 2012). Our paper provides the quantitative evidence that is consistent with previous findings. More precisely, we find that doubling the amount of carbon dioxide emission would reduce the quality of life of a person aged 20 by 12 percent. This result is robust to various specifications, including the alternative report of emissions and the diverse types of emissions.

There are plenty of evidence pointing to the adverse effects of air pollution on people physical health. For instance, air pollution can affect lung development (Wang et al., 2019), impair the blood vessel function (Riggs et al., 2020), and lead to cancer (Niehoff et al., 2019). Again, our paper contributes to this literature by adding more evidence quantitatively. We show that air pollution affects negatively physical health. A 100 per cent rise in the amount of carbon dioxide emissions, for example, would lower the physical health score of a 20 year-old by 10 percent.

Despite the growing awareness of the impacts of air pollution, there are still limited studies of its effects on mental health. Newbury et al. (2021) established a link between air pollution exposure to the increased use of mental health service in London, United Kingdom. However, as they acknowledge, the use of mental health service is a proxy for the mental health problems. This proxy is influenced by other uncontrolled factors including the health care capacity and risk evaluations. Perhaps the most related to our study is Carroll, Fritjers and Shields (2018) where they exploit a recent Chinese Family Panel Studies and anlyse the impacts of the concentration of very fine particulate matter (PM2.5). What they found is a significant effect of air pollution on people mental illness. We extend their study by looking at a wide range of of mental illness, including the 12 types of illness such as depression, suicidality, sleep problems, irritability and fatigues. Out of these 12 types of mental illness, we find the negative effect of air pollution on 11 of them, except for having guilty feelings where the effect was insignificant.

Another contribution of our paper is to look for the vulnerability indicators as far as the impacts of climate change are concerned. In the literature, these indicators are often income (Dohrenwend et al., 1992), gender (Deryugina et al., 2020) or some health conditions (A. et al., 2016). In this research, we delve into the effects of GHG emissions on mental and physical health, with a specific emphasis on aging. As people age, they encounter more physical and mental health issues, and the risk of adverse outcomes increases as these deficits accumulate.The accumulation of health deficits has been found to be linked to various factors such as unhealthy lifestyles, occupational hazards, and environmental influences (Schünemann, Strulik and Trimborn, 2017, Strulik, 2018, Strulik, 2022). By compiling these accumulated deficits into a single index variable known as the frailty index Mitnitski AB (2002) and Rockwood and Mitnitski (2006) showed that it is possible to measure overall health status in the elderly population.

Studies in the literature provide a mixed picture. While Deryugina et al. (2019) show that the negative effect of pollution increases with age, Salcioglu, Basoglu and Livanou (2007) find that young people are more vulnerable. Our finding is that the effect of greenhouse gases is stronger among middle-aged people than the older ones. For instance, for every additional age, the effect of doubling the level of carbon dioxide emission decreases by 0.5 percentage points.

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. Section 6 concludes the paper.

2 Theoretical Framework

In this section, we present a simple framework to formalize testable hypotheses about the potential effects of GHG emissions on human quality of life. The model incorporates a quality of life component associated with GHG emissions, health spending, and other control factors.

For each country, an individual i in period t has a state of health, $d_{i,t}$, which is produced by

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

In this production function, health status depends on health spending m_t, the global level of GHG emission X_t, and other variables discussed below. We utilize the health deficit model proposed by Dalgaard and Strulik (2014), which models physical health in terms of physiological 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

$$d_{i,t+1} = d_{i,t} + \mu_{i,t}(d_{i,t} - Z_t m_{i,t} + X_t)$$

in which the parameter μ_i represents the intrinsic rate at which health deficits accumulate for an individual i. It reflects the biological and physiological differences among individuals that influence how quickly they age. Factors such as genetics, lifestyle, and pre-existing health conditions can all contribute to variations in μ_i. The accumulation of health deficits can be slowed by health expenditures, while X_t captures environmental influences as an increasing function of GHG emissions. The variable Z_t may influence the health deficit of an individual, such as GDP, population, education, or medical technological level of the country. For the empirical analysis, we will use GDP and life expectancy as proxies for Z_t, as these variables are available in the data. As GHG emissions could affect human life at the aggregate level, it is treated as exogenous to each individual in 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. 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 Z_t, the Bellman equation is defined by

$$V_t(d_{i,t}|X_t, Z_t) = \max_{c_{i,t}, m_{i,t}} \{s(d_{i,t}, X_t)u(c_{i,t}, d_{i,t}) + \beta V_{t+1}(d_{i,t+1}|X_{t+1}, Z_{t+1})\}$$

s.t

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

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

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

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

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

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 guess the value function in the form:

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

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

$$\lambda_t = \beta B \mu_{i,t} Z_t.$$

Substitute λ_t back into the condition 1 we get

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

and

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

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

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

which implies

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

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

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

Balancing the constant term yields

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

Solving for B from the identity (3) we get

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

Substituting into the equation (4) we get

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

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 increase in well-being.

It follows from the first-order conditions that

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

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:

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

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

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

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

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

and the partial derivative of Q with respect to $\mu_{i,t}$ is:

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

Therefore, the quality of life ($Q_{i,t}$) decreases as GHG emissions (X_t) increase. The denominator $1+\beta(1+\mu_{i,t})$ indicates that as $\mu_{i,t}$ increases, the quality of life (Q) decreases. Therefore, higher GHG emissions(X_t) and higher rates of natural aging ($\mu_{i,t}$) generally lead to a lower quality of life. These findings are corroborated by the empirical tests presented in Table 2 in the following section.

We implement some simulations to support for these findings. We assume some reasonable values for the parameters values α, β, γ, Z_t, $y_{i,t}$, and $\mu_{i-1,t-1}$ and simulate Q, H over a range of X, μ values.

Parameter	**Value**	**Description**
α	0.5	Climate sensitivity coefficient
β	0.6	Discounting factor
γ	0.1	Emission induced death rate
Z_t	1.0	GDP
y_t	0.5	Income
μ_{t-1}	0.2	Previous health status and age

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 the 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 $\mu_{i,t}$ 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.

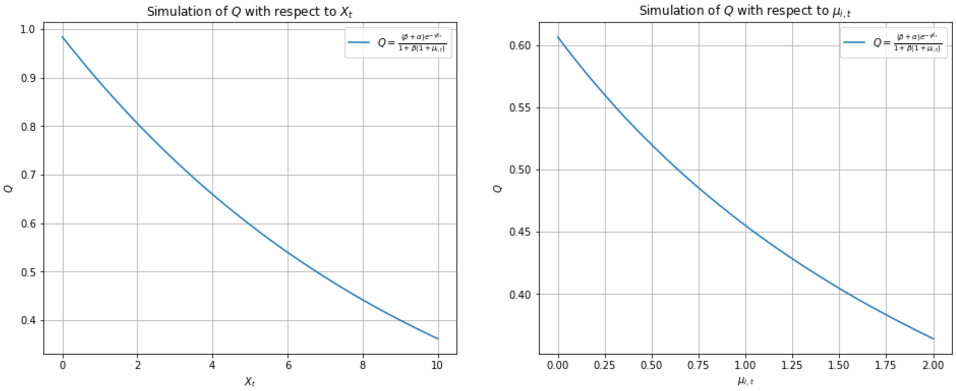

Figure 1: Impacts of Emission and Age on Life quality

ii) We are interested in

$$\frac{\partial^2 Q}{\partial X_t \partial \mu_{i,t}}$$

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

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

Hence

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

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.

The Figure 3 illustrates the second partial derivative of Q with respect to X_t and $\mu_{i,t}$. This represents how the marginal effects of age ($\mu_{i,t}$) 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 $\mu_{i,t}$. As age increases, the impact of emissions on life quality diminishes, as indicated by the positive and decreasing trend of $\frac{\partial^2 Q}{\partial X_t \partial \mu_{i,t}}$. 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 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.

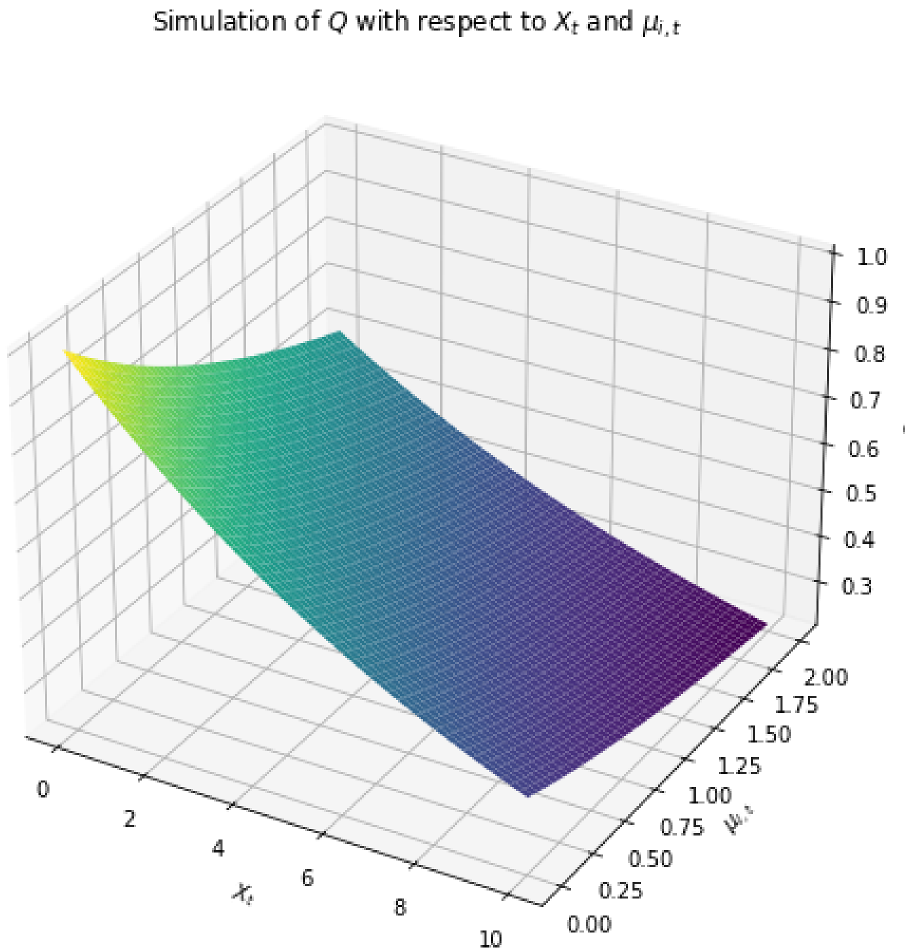

Figure 2: Effects of Q on X and μ

2.2 Impacts on physical health

In this section, we assume the physical health status H of an individual as a decreasing function of health deficit:

$$H = \frac{H_{\max}}{1 + \theta d}$$

where $H_{\max}$ is the maximum possible health status and the positive constant θ representing how quickly health deficits impact health status.

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

Proof. Using optimal health expenditure value from (2) to get

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

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

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

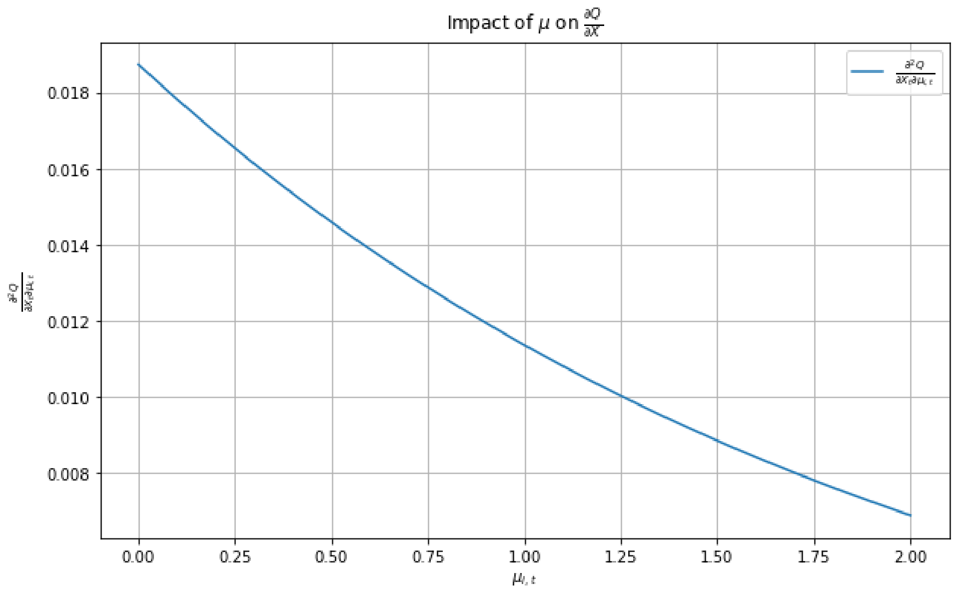

Figure 3: Marginal effects of age on marginal life quality of emission

Therefore, the physical health H is given by

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

Taking derivative of H w.r.t GHG emissions X we have

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

This partial derivative shows that the physical health capital decreases as GHG emissions increase, given that $\theta > 0$ and $\mu_{i,t} > 0$. The rate of decrease is influenced by $(\mu_{i,t})$ and the other factors such as GDP, mortality, health expenditure affecting health deficits.

To qualify the impact across aging population, we derive

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

This partial derivative shows that the physical health $H_{i,t+1}$ decreases as the natural aging rate $\mu_{i,t}$ increases and emission is 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 GDP or medical technological level of the country Z_t.

These findings are confirmed by the empirical tests presented in Table 3 in the next section.

The analysis and visualization of the partial derivatives $\frac{\partial H}{\partial X}$ and $\frac{\partial H}{\partial \mu}$ provide insightful findings on the impact of GHG emissions and aging on physical health capital. The colors range from dark to light, where darker shades represent lower (more negative) values of the partial derivative, and lighter shades represent higher (less negative or closer to zero) values. The plot of $\frac{\partial H}{\partial X}$ demonstrates that as GHG emissions increase, the physical health capital decreases, highlighting the detrimental effects of pollution on health. This relationship is further influenced by factors such as the natural aging rate, GDP, mortality, and health expenditure. Similarly, the plot of $\frac{\partial H}{\partial \mu}$ reveals that as the natural aging rate increases, the physical health capital decreases, particularly when emissions are high. This decrease is affected by previous health deficits, income, and other socioeconomic factors. The plot on the right shows that, given a fixed aging rate, physical health decreases with higher emissions. The lowest value of $\frac{\partial H}{\partial \mu}$ ranges from -40 to -36. By comparing data from different regions, we can observe how variations in emissions and aging rates impact physical health differently across these areas. Such comparisons can help identify region-specific challenges and inform targeted interventions to mitigate the adverse effects of emissions on health. The analysis is implemented in the next section.

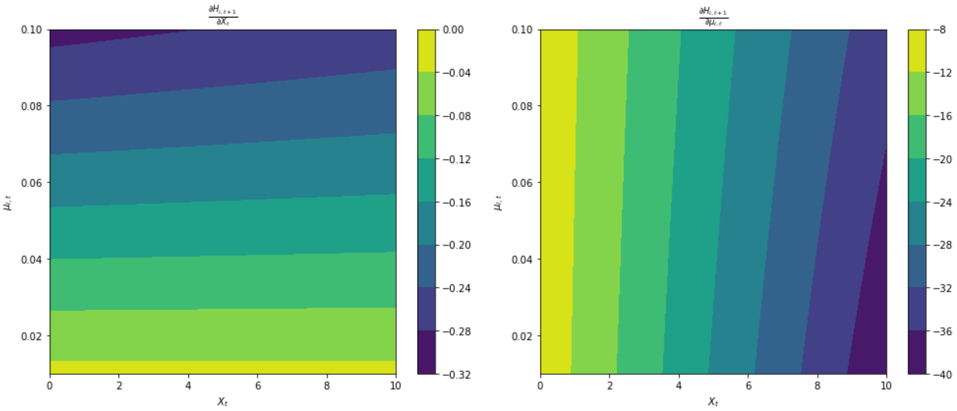

Figure 4: Impact of emission on physical health across aging populations

2.3 Impacts on mental health

In the literature, physical health has often been mathematically modeled in terms of health deficits, as shown in Dalgaard and Strulik (2014), Strulik, 2018, and Mitnitski AB (2002). However, modeling the dynamics of mental health is more challenging, making it difficult to derive an explicit equation to quantify the impact of climate change on mental health. In this paper, we propose a proxy for assessing the impact of climate change on mental health

Denote $P_{i,t} = \frac{\partial Q_{i,t}}{\partial X_t}$ the effect of climate change on the quality of life related to physical health. In our model, utility V is derived from health, it essentially reflects how health impacts the overall quality of life. We define the impact of climate change on the quality of life related to mental health, $M_{i,t}$, as the residual impact of climate change on overall quality of life, $W_{i,t} = \frac{\partial V}{\partial X_t}$, after accounting for the impact on physical health, expressed as

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

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

$$\frac{\left(\beta\mu_{i,t}(\alpha+\beta)(\gamma(X_t-Z_ty_{i,t})-1)-\gamma(X_t\gamma+\mu_{i,t}+\ln\left(\frac{-Z_t\beta\mu_{i,t}(\alpha+\beta)e^{-X_t\gamma}}{\beta\mu_{i,t}+\beta+1}\right))(\beta\mu_{i,t}+\beta+1)\right)e^{-X_t\gamma}}{(\beta-1)(\beta\mu_{i,t}+\beta+1)}$$

Thus $M_{i,t} =$

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

Also, it follows from the value function V we get the physical health related quality of life

$$P_{i,t}=\frac{dQ_{i,t}}{dX_t}=\frac{(\beta+\alpha)\gamma e^{-\gamma X_t}}{1+\beta+\beta\mu_{i,t}}.$$

Therefore, mental health related quality of life is defined as $M_{i,t} = W_{i,t} - P_{i,t} =$

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

To determine the impact of emissions on mental health, we calculate the partial derivative of $M_{i,t}$ with respect to X_t:

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

where:

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

$$C=1+\beta+\beta\mu_{i,t},\quad D=\mu_{i,t-1}(\beta+\alpha),\quad E=1+\beta(1+\mu_{i,t}).$$

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

The theoretical framework derives the equations to illustrate potential mechanisms through which emissions can affect physical health, mental health in relation to quality of life, thus highlighting a possible empirical strategy.

Our main variables of interest for the estimation, Q, H, P, M, will be functions of observable variables such as GHG emissions (X), health spending (m), mortality rate coefficient (γ), and control variables (Z), including GDP and population. The unobserved income and the natural health deficit accumulation process of individuals will be accounted for as individual fixed effects in the empirical model.

The model also highlights that the effect of GHG emissions X_t on health varies across different aging rates characterized by the heterogeneity of $\mu_{i,t}$. These equations include an interaction term involving GHG emission levels and aging rate, $\mu_{i,t}$ and X_t, suggesting that the effect of GHG emissions on quality of life varies across different aging rates. This hypothesis will be examined in the subsequent sections.

3 Data

3.1 Survey of Health, Ageing and Retirement in Europe

The first main dataset used in our research is the Survey of Health, Ageing and Retirement in Europe (SHARE) dataset. More than 140,000 people, aged 50 or over, from 28 countries across Europe and Israel participated in this survey. From 2004 to 2020, 8 waves of questionnaires were conducted. In total, we have nearly 350,000 observations.

In this survey, the respondents were asked to report their life quality. The method to measure life quality is the Control, Autonomy, Self-realization, and Pleasure (CASP) scale (Hyde et al., 2003). This method is based on the four dimensions of need. They are control (i.e. the ability to actively intervene in one's environment), autonomy (i.e. the right of an individual to be free from the unwanted interference of others), self-realization and pleasure (i.e. the active and reflexive processes of being human). In total, there are 19 questions (see Table A). The responses were coded as Often (3), Not often (2), Sometimes (1) and Never (0). Items 1, 2, 4, 6, 8 and 9 were reverse coded. The answers were then combined to obtain one composite score, the CASP-19 index. The range of this index is from 0, which indicates a complete lack of quality of life, to 57, which indicates total satisfaction across four domains: control, autonomy, self-realization, and pleasure. In our analysis, the minimum score is 12 and the maximum score is 48. The mean score is 37 with a standard deviation of 6.3 (see Table 1).

In addition to the life quality, respondents also rated their physical health status. Questions in this domain were based on the 36-item Short Form (SF-36) Survey (see the Appendix). The survey contains information regarding physical and mental health. Answers were coded by a five point Likert scale, from 1 (Excellent) to 5 (Poor). More information about the SF-36 can be found in Ware and Gandek (1998). In the SHARE dataset that we employ here, only the first question was retained. This question asked the general health of the respondents and considered as an indicator of their physical health. The average answer in our dataset is 3.2 with a standard deviation of 1 (see Table 1).

Finally, our data reports the 12 dimensions of mental health used according to the EURO depression scale (EURO-D). The scale was originally developed to derive a common depression symptoms scale from various instruments on late-life depression used in different European countries (Prince et al., 1999). The 12 dimensions are depression, pessimism, suicidality, sleep, interest, appetite, fatigue, irritability, concentration, guilt, enjoyment, and tearfulness. Respondents were asked if they experienced any of these mental health problems (see Table C).

3.2 Frailty index

The richness of the our data allows us to investigate the impact of climate change on frailty. It is a prevalent problem with increasing age. We follow Fried et al. (2001) to calculate the frailty index. It is defined as the presence of more than 2 of the following health problems: Exhaustion, Shrinking, Weakness, Slowness and Low Activity. We adopt their model with our dataset following the literature (Santos-Eggimann et al., 2009, Salaffi et al., 2021). More precisely, Exhaustion was picked up if the respondent answered "Yes" to the following question "In the last month, have you had too little energy to do things you wanted to do?". He(she) would be subject to Shrinking if they responded with a diminution in desire for food to the question "What has your appetite been like?". Weakness was identified as having more than 3 arm function and fine motor limitations. If the respondent had more than 2 mobility limitations the Slowness was flagged. Finally, Low Activity was assigned to respondents who answered "one to three times a month" or "hardly ever or never" to the question "How often do you engage in activities that require a low or moderate level of energy such as gardening, cleaning the car, or going for a walk?"

Based on the answers of the respondents, each of these five dimensions was recorded as a binary state (i.e. Exhaustion or not). We treated the refusal to answer or no answer as missing data. Given that Fried et al. (2001) categorize frailty as having at least 2 of the 5 problems, we classified the respondents as follows. The respondents with zero points (i.e. no problem whatsoever) were coded as non-frail. If they had no more than two points (i.e. no more than two problems), they were pre-frail. Having three or more points were classified as frail. In addition to quality of life, physical health and mental health, we will use the frailty index as another indicator of people's health and investigate how it was related to emissions.

3.3 World Bank - Our World in Data

The second dataset concerns the emission of greenhouse gases. Here we make use of two sources of information. The first source of information is the World Bank Development Indicators. Not only does it report the carbon dioxide (CO2) emissions by metric tons but it also provides the CO2 emission equivalents of other GHG emissions, including methane emission and nitrous oxide emission. These variables are crucial not only for robustness checks but also give us a fuller picture of the effects of climate change.

A problem with the World Bank data is that information from the latest years is missing. In particular, we do not have emissions data in 2019. To complement this dataset, and also to provide further robustness check, we employ a second source of information which is the database provided by Our World in Data (https://ourworldindata.org/). In both our sources of information, data on GHG, methane and nitrous oxide emissions were taken from the CAIT Climate Data Explorer, under the Climate Watch Project (https://www.climatewatchdata.org/). The difference between the two data sources comes from the sourcing of CO2 emissions. While the World Bank still relies on the CAIT database, Our World in Data refers to the Global Carbon Project which releases a new update of CO2 emissions annually. More importantly, they have updates on CO2 emissions up to 2020.

Table 1: Summary Statistics

Variables	(1) Observations	(2) Mean	(3) Standard deviation	(4) Min	(5) Max
Main outcomes					
Life quality	313,219	37.29	6.306	12	48
Physical health	341,633	3.179	1.069	1	5
Mental health					
Depression	282,464	0.396	0.489	0	1
Pessimism	281,857	0.170	0.376	0	1
Suicidality	281,904	0.0688	0.253	0	1
Guilt	281,845	0.0809	0.273	0	1
Sleep	282,680	0.348	0.476	0	1
Interest	282,320	0.0940	0.292	0	1
Irritability	282,395	0.276	0.447	0	1
Appetite	282,929	0.0881	0.283	0	1
Fatigue	282,389	0.355	0.478	0	1
Concentration	281,883	0.180	0.384	0	1
Enjoyment	282,146	0.128	0.334	0	1
Tearfulness	282,390	0.246	0.431	0	1
World Bank data					
Carbon dioxide	295,891	7.736	2.694	3.248	18.68
Methane	295,891	21,299	21,462	220	74,530
Nitrous oxide	295,891	11,505	12,526	40	45,570
Total Greenhouse gases	295,891	209,642	229,256	2,010	952,110
Our World in Data					
Carbon dioxide	342,610	176.3	205.5	1.559	887.1
Methane	229,421	22.14	21.90	0.540	74.53
Nitrous oxide	229,421	11.99	12.85	0.300	45.57
Total Greenhouse gases	229,421	199.1	215.5	10.05	931.3
Covariates					
Population	342,610	2.368e+07	2.534e+07	437,935	8.352e+07
GDP	296,860	8.741e+11	9.941e+11	1.454e+10	3.827e+12
Life expectancy	340,672	80.49	2.071	74.63	83.70
Health spending	295,891	8.968	1.702	5.151	11.90
Age	342,594	67.33	10.22	22	106

4 Methodology

We implement our identification strategy in the following form:

$$life-quality_{ict} = \beta_0+\beta_1*ghg_{ct}*age_{ict}+\beta_2*ghg_{ct}+\beta_3*age_{ict}+\beta_4*X_{ct}+\eta_i+\eta_c+\eta_t+\epsilon_{ict} \quad (6)$$

In this equation, $life-quality_{ict}$ is the self-reported life quality (in log term) of an individual i living in country c at time t. This life quality is scored over 4 dimensions: control, autonomy, self-realization, and pleasure. The overall score is then used in our analysis (see, Hyde et al., 2003).

The variable ghg_{ct} denotes the log of the total GHG emission, as well as the emission of its components, including CO2, methane and nitrous oxide gases. To control for factors that might affect the quality of life of our respondents, we include a vector of the country-time specific variables X_{ct}. This vector contains the factors that might influence the quality of life, including population, GDP, health spending and life expectancy. Crucially, we include the individual fixed effect to control for all personal specific differences. With this inclusion, we compare the life quality within one specific individual over different exposures to GHG emissions. To apply this technique, we had to drop all the individuals who participated only once in the survey.

To address the heteroskedasticity concern, we cluster at the country level which is the level of variation in our treatment variable. Our coefficient of interest is that of the interaction term $ghg_{ct} * age_{ict}$. This coefficient β_1 tells us how GHG emissions affect the respondents in different brackets of ages. Indeed, we expect the coefficient of GHG emissions β_2 to be negative, which indicates a negative impact. As a result, if β_1 is positive, the adverse impact of GHG emissions subsides with age. In other words, the middle-aged respondents would suffer more from polluted air than their older counterparts.

For robustness checks, we employ different treatment variables. More precisely, in addition to the total GHG emissions, we also employ the various components of emissions, including carbon dioxide, methane and nitrous oxide emissions. To be consistent, all of the emissions are scaled in equivalents of carbon dioxide emissions.

To further investigate the impacts on human health, we also employ one specification that replaces life quality with self-reported physical health in Equation 7. This variable takes 5 possible values, from 1 (Excellent) to 5 (Poor). To be consistent with the life quality variable in Equation 6, we rescale this variable so that high value indicates good health.

$$physical-health_{ict} = \beta_0 + \beta_1 * ghg_{ct} * age_{ict} + \beta_2 * age_{ict} + \beta_3 * X_{ct} + \eta_i + \eta_c + \eta_t + \epsilon_{ict} \quad (7)$$

Finally, we look at the various dimensions of mental health problems in Equation 8. These dimensions are depression, pessimism, suicidality, sleep, interest, appetite, fatigue, concentration, enjoyment, and tearfulness. The dependent variable in Equation 8 is a binary variable that indicates whether the respondent experienced one of the mental health problems above.

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

5 Benchmark results

5.1 The effects on the quality of life

Table 2 reports the regression results of Equation 6 using the World Bank data. The main regressor is the level of carbon dioxide emissions. In Columns 1 and 2, the dependent variable is the general quality of life. In Columns 3 and 4, the outcome is the physical health of the respondents. In all columns, we control for several country-year characteristics. They proxy for the size of the country (population), the level of development (GDP), the health care system (health spending), and the general health status (life expectancy). Moreover, the individual fixed effect is included in all columns. Essentially, we exploit the within-student variation in the level of emissions. All the errors are adjusted for clustering at the country level to allow for the possibility that the errors within a group (i.e. a country) are correlated.

Results in Column 1 shows that in general, more carbon dioxide emissions led to a lower quality of life. For a person aged 20, a 100 per cent rise in the level of carbon dioxide emissions resulted in a drop of 12 per cent in the life quality score[1], an equivalent of two-thirds of the standard deviation[2]. Interestingly, it subsides with ages. For every additional age from the perspective of a person aged 20, the effect was lowered by 2.9 per cent[3]. This reduction varies with age. The older the person is, the bigger the reduction is. For a person aged 40, the reduction would be 5.7 per cent.

In Column 2, besides the individual fixed effect, we include the country fixed effect to control for all the time-invariant country related characteristics. For instance, people in one country could have higher life quality in general than in other countries. The estimates are similar to what was found in Column 1. For a typical person aged 20, a 100 per cent rise in the level of carbon dioxide resulted in a drop of 12 per cent in the life quality. Results in this Column also confirm what was found in Column 1, namely the effect decreases with ages. For every additional age from the perspective of a person aged 20, the effect dropped by 2.9 per cent. This reduction is more pronounced with the elderly. For a person aged 40, the reduction would be 5.7 per cent for every additional age.

In Column 3, together with the individual fixed effect, we include the time fixed effect to control for all the time variant factors. For instance, some global events such as the death of Osama Bin Laden in 2011, the founder of al Qaeda, could have had a significant effect on the feelings of global residents. Again, the emissions of carbon dioxide affected negatively the life quality of everyone. For a person aged 20, a 100 per cent rise in the level of emissions of carbon dioxide resulted in a 13 per cent fall in their life quality score. But if that person was 1 year older, the drop was only 12 per cent.

Finally, in Column 4, we have the fully fledged specification where the individual, the country and the time fixed effects are all included. Similar findings to the ones in Columns 1,2 and 3 are shown here. For a person aged 20, doubling the level of carbon dioxide emissions would reduce their life quality score by 13 percent. Getting 1 year older, the effect for this person would be only 12 percent.

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[1] $e^{0.005*20*ln(2)-0.288*ln(2)} = 0.88$

[2] $0.12 * 37.19/6.36 = 0.68$

[3] $0.005 * ln(2)/0.12 = 0.029$

Table 2: Carbon dioxide emissions and the quality of life

	(1)	(2)	(3)	(4)
Dependent variable: Life quality				
ln(CO2 emission)*age	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
ln(CO2 emission)	-0.288***	-0.288***	-0.295***	-0.295***
	(0.073)	(0.073)	(0.075)	(0.075)
age	-0.009***	-0.009***	0.004***	0.004***
	(0.003)	(0.003)	(0.001)	(0.001)
ln(GDP)	0.013	0.013	0.036	0.036
	(0.056)	(0.056)	(0.053)	(0.053)
ln(population)	0.149	0.149	0.113	0.113
	(0.144)	(0.144)	(0.146)	(0.146)
ln(life expectancy)	-1.059*	-1.059*	-1.292*	-1.292*
	(0.612)	(0.612)	(0.720)	(0.720)
ln(health spending)	0.081*	0.081*	0.065	0.065
	(0.045)	(0.045)	(0.055)	(0.055)
Individual Fixed effect	YES	YES	YES	YES
Country Fixed effect	NO	YES	NO	YES
Time Fixed effect	NO	NO	YES	YES
N	254338	254338	254338	254338
R-squared	.731	.731	.731	.731

Note: Robust errors in parentheses. Emission data are provided by the World Bank Development Indicators.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

5.2 Physical health

In this section, we aim to understand how carbon dioxide emissions affect our respondents. More precisely, instead of focusing on the life quality score which is a more general term, we investigate the impact of carbon dioxide emissions on their physical health. In other words, we calculate the estimates from the Equation 7.

Results are reported in Table 3. Note that the physical health was scored from 1 (Excellent) to 5 (Poor). To be consistent with the life quality score when high score means high quality, we calculate the inverse of the physical health in log terms. The estimates in Column 1 show that in general, people's physical health deteriorated with the level of carbon dioxide emissions. For a person aged 20, doubling the amount of carbon dioxide emissions reduced their physical health score by 6.9 per cent. It is lower than the effect of carbon dioxide emissions on the general life quality that we revealed in Table 2.

Similarly to the general life quality, the effect moderates with ages. For this same person, every additional age would bring down the effect by 5 per cent. This reduction would be even higher for more senior residents. For instance, every additional age would bring down the effect by 10 per cent for a person aged 30.

In Column 2, we include the country fixed effect. All the estimates are similar. A 20 year-old person would have the physical health score reduced by 6.9 per cent if the amount of carbon dioxide emissions doubled. If he was 1 year older, the reduction would be only 6.6 per cent. In other words, the effect was 5 per cent lower.

In Column 3, we include the time fixed effect. The effect of a rise of 100 per cent in the level of carbon dioxide emissions was a 2.3 per cent fall in the physical health score. More importantly, this effect becomes smaller when the person gets older. For a 20 year-old person, every additional age would reduce the effect by 11 per cent.

And finally, in Column 4, we employ a full fledge model where all the fixed effects, including the individual, the country and the time fixed effects are included. We have the same finding as in Table 3. In general, carbon dioxide emissions had an adverse effect on people physical health. However, this effect becomes smaller with more senior residents.

5.3 Mental health

In addition to physical health, our data set also reports the status of people's mental health. It allows us to investigate how carbon dioxide emissions would affect their mental health. There is some evidence that greenhouse gas emissions increased the frequency of droughts from 12% to up to 60% (Stocker et al., 2013; Marvel et al., 2019). And we know that droughts could lead to suicidal thoughts (Deshpande, 2002; Hanigan et al., 2012; Sarma, 2004; Guiney, 2012). Therefore, it is important to find direct evidence that air pollution affects mental illness which is still very limited in the literature.

In this section, we report the estimates from Equation 8. We have a wide range of mental health issues, including depression, suicidality, sleep problems, pessimism, irritability, fatigues, etc. Results are reported in Tables 4a, 4b, and 4c. The dependent variables are the indicators that the respondents did not experience one of the mental health issues. In all specifications, all the fixed effects, including the individual, the country and the time fixed effects are included. All the errors are adjusted by clustering at

Table 3: Carbon dioxide emissions and physical health

	(1)	(2)	(3)	(4)
Dependent variable: Physical health score				
ln(CO2 emission)*age	0.005**	0.005**	0.004**	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
ln(CO2 emission)	-0.200	-0.200	-0.114	-0.114
	(0.139)	(0.139)	(0.138)	(0.138)
age	-0.020***	-0.020***	0.077***	0.077***
	(0.005)	(0.005)	(0.003)	(0.003)
ln(GDP)	-0.002	-0.002	0.029	0.029
	(0.113)	(0.113)	(0.104)	(0.104)
ln(population)	0.020	0.020	0.041	0.041
	(0.201)	(0.201)	(0.157)	(0.157)
ln(life expectancy)	0.216	0.216	1.107	1.107
	(0.806)	(0.806)	(1.133)	(1.133)
ln(health spending)	0.043	0.043	-0.032	-0.032
	(0.049)	(0.049)	(0.055)	(0.055)
Individual Fixed effect	YES	YES	YES	YES
Country Fixed effect	NO	YES	NO	YES
Time Fixed effect	NO	NO	YES	YES
N	284380	284380	284380	284380
R-squared	.7	.7	.701	.701

Note: Robust errors in parentheses. Emission data are provided by the World Bank Development Indicators.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

the country level.

Column 1 in Table 4a shows that in general, people felt more depressed when exposed to air pollution. For instance, for a person aged 40, a 100 per sent increase in the amount of carbon dioxide emissions led to a rise in the probability of having a depression 16 percentage point[4]. Younger people felt more of the effects than their elders. A 20-year old person would feel more depressed by 24 percentage points higher.

Air pollution made people feel pessimistic about the future (Column 2 in Table 4a). A person aged 20 would have his probability of feeling blue about the future increase by 24 percentage points. However, an older person would feel less effect from air pollution. With the same rise in pollution, a person aged 40 would have his probability of feeling pessimistic increase by 15 percentage points.

Our analysis reveals that people started having suicidal thoughts when the environment was more polluted (Column 3 in Table 4a). Take a person aged 50 for example. He would have his probability of having suicidal thoughts increase by 9 percentage points. Younger people thought about suicides more often. With the same rise in the amount of carbon dioxide emissions, a 20-year old person would have a probability of thinking about suicide increase by 13 percentage points.

Air pollution led to people having troubles in their sleeping, although the effect is less significant both statistically and economically (see Column 4 against Columns 1, 2, and 3 in Table 4a). They imply that a person aged 20 would have more sleeping problems by 2 percentage points when the emissions of carbon dioxide doubled.

Table 4b reports more negative effects of air pollution. In Column 1, we find that a person aged 50 would be 9 percentage points less likely to have an interest in things. More importantly, young people would be even more likely to lose interests. The effect on a 20 year-old person was a 22 percentage points.

In Column 2, we see that people were more bothered with air pollution. A person aged 20 would be 2 percentage points more likely to be irritated when the level of carbon dioxide emissions rose by 100 per cent. Air pollution also resulted in the loss of appetite. Column 3 reports that it was 5 percentage points more likely that a person aged 50 would lose his appetite due to a 100 per cent rise in carbon dioxide emissions. It is even more striking with younger people. For a 20 year-old, the likelihood would be 16 percentage points more.

People felt more tired mentally with air pollution. In Column 4, we find that the probability that a 50 year-old felt less energy to do things rise by 13 percentage points with a 100 per cent rise in pollution. Again, younger people felt more strained when the environment deteriorated. For instance, the rise in probability for a 30 year-old was 27 percentage points.

Table 4c brings more evidence of how air pollution affected people mentally. People had difficulty in concentrating with air pollution. The probability that a 20 year-old could not focus on what he/she was doing rose by 24 percentage points when the amount of carbon dioxide doubled. The effect was more moderate for elderly. A person aged 50 only experienced a 6 percentage points rise in probability of concentration loss (Column

[4] Note that we reverse coded all the answers to be consistent with the analysis on life quality and physical health. As a result, 0 means the respondents had the mental issues and 1 if not. Doubling the amount of carbon dioxide would change the answers from 1 to $e^{(40*0.007-0.537)*ln2} = 0.84$, or a 16 percentage point drop.

Table 4a: Carbon dioxide emissions and mental health

	(1) Depression	(2) Pessimism	(3) Suicidality	(4) Sleep
ln(CO2 emission)*age	0.007***	0.008***	0.003***	0.002
	(0.001)	(0.002)	(0.001)	(0.001)
ln(CO2 emission)	-0.537***	-0.558***	-0.265***	-0.074
	(0.118)	(0.131)	(0.069)	(0.117)
ln(GDP)	0.194**	0.273***	0.044	0.050
	(0.073)	(0.064)	(0.044)	(0.081)
ln(population)	-0.098	-0.293*	-0.001	0.078
	(0.218)	(0.155)	(0.111)	(0.179)
ln(life expectancy)	-0.869	-0.215	-0.667	-0.341
	(1.401)	(0.909)	(0.442)	(0.699)
ln(health spending)	-0.006	0.100	-0.057	0.046
	(0.093)	(0.084)	(0.038)	(0.045)
Individual Fixed effect	YES	YES	YES	YES
Country Fixed effect	YES	YES	YES	YES
Time Fixed effect	YES	YES	YES	YES
N	222935	222309	222357	223161
R-squared	.55	.504	.533	.588

Note: Robust errors in parentheses. Emission data are provided by the World Bank Development Indicators.
* p<0.1, ** p<0.05, *** p<0.01

Table 4b: Carbon dioxide emissions and mental health

	(1) Interest	(2) Irritability	(3) Appetite	(4) Fatigue
ln(CO2 emission)*age	0.008***	0.0003	0.006***	0.012***
	(0.001)	(0.002)	(0.001)	(0.002)
ln(CO2 emission)	-0.529***	0.042	-0.378***	-0.809***
	(0.100)	(0.150)	(0.062)	(0.175)
ln(GDP)	0.055	-0.031	0.058	0.018
	(0.033)	(0.094)	(0.036)	(0.126)
ln(population)	0.090	-0.110	0.005	0.253
	(0.070)	(0.271)	(0.086)	(0.273)
ln(life expectancy)	-1.558**	2.101*	0.115	0.218
	(0.631)	(1.133)	(0.573)	(1.529)
ln(health spending)	0.064	0.053	0.026	0.052
	(0.043)	(0.113)	(0.037)	(0.116)
Individual Fixed effect	YES	YES	YES	YES
Country Fixed effect	YES	YES	YES	YES
Time Fixed effect	YES	YES	YES	YES
N	222764	222866	223378	222839
R-squared	.445	.522	.461	.53

Note: Robust errors in parentheses. Emission data are provided by the World Bank Development Indicators.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

1).

We can see similar findings that air pollution affected people's enjoyment and tearfulness in Columns 2 and 3. For instance, a 50 year-old would be 6 percentage points more likely to cry when air pollution worsened by a 100 per cent. But for a person aged 20, the effect was a rise of 13 percentage points. There is only one dimension (Guilt) that we find no or little effect of air pollution, both in general and across ages (Column 4).

Table 4c: Carbon dioxide emissions and mental health

	(1) Concentration	(2) Enjoyment	(3) Tearfulness	(4) Guilt
ln(CO2 emission)*age	0.008***	0.009***	0.004***	-0.000
	(0.001)	(0.002)	(0.001)	(0.001)
ln(CO2 emission)	-0.554***	-0.547***	-0.290***	0.038
	(0.104)	(0.132)	(0.092)	(0.055)
ln(GDP)	0.019	0.047	0.080*	-0.026
	(0.064)	(0.075)	(0.040)	(0.043)
ln(population)	0.276**	0.164	-0.062	0.091
	(0.125)	(0.151)	(0.144)	(0.103)
ln(life expectancy)	-0.894	-0.446	-1.026	0.281
	(0.949)	(1.025)	(0.904)	(0.695)
ln(health spending)	0.151**	0.054	-0.044	-0.078**
	(0.058)	(0.064)	(0.050)	(0.027)
Individual Fixed effect	YES	YES	YES	YES
Country Fixed effect	YES	YES	YES	YES
Time Fixed effect	YES	YES	YES	YES
N	222417	222585	222823	222311
R-squared	.531	.447	.556	.476

Note: Robust errors in parentheses. Emission data are provided by the World Bank Development Indicators.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

5.4 Frailty

Table 5 shows how greenhouse gas emission, in this case carbon dioxide emission, affects the frailty index. To be consistent with previous tables, we use the non-frail index as the dependent variable. In Column 1, we control for the individual fixed effect. This effect accounts for all the characteristics that are specific to the individuals. Effectively, we analyse how the variation of emissions had an impact on the frailty index within an individual. Consistent with previous findings with the quality of life, physical health and mental health, emissions in general had a negative impact on this health outcome. Indeed, the coefficient of the log of carbon dioxide emission is significantly negative. Again, this effect declines with age.

To account for the fact that the effect of emissions might vary with the location of the respondents, we add the country fixed effect in Column 2. All the effects are unchanged, which show that the results are not driven by the countries where the respondents live in. In Column 3, we replace the country fixed effect with the time fixed effect. Column 4 reports the results with the full set of fixed effects. All the results are similar qualitatively. In summary, Table 5 provides another evidence that emissions have negative impacts on personal health, although the impacts gradually decline with age.

Table 5: Carbon dioxide emissions and frailty

	Dependent variable: Non-frail index			
	(1)	(2)	(3)	(4)
ln(CO2 emission)*age	0.012	0.012	0.005*	0.005*
	(0.007)	(0.007)	(0.003)	(0.003)
ln(CO2 emission)	-1.167*	-1.167*	-0.395	-0.395
	(0.591)	(0.591)	(0.241)	(0.241)
age	-0.079***	-0.079***	0.002	0.002
	(0.014)	(0.014)	(0.006)	(0.006)
ln(GDP)	-0.595	-0.595	0.046	0.046
	(0.508)	(0.508)	(0.218)	(0.218)
ln(population)	0.800	0.800	-0.502	-0.502
	(1.187)	(1.187)	(0.415)	(0.415)
ln(life expectancy)	5.429	5.429	-0.353	-0.353
	(3.747)	(3.747)	(2.169)	(2.169)
ln(health spending)	0.912**	0.912**	0.038	0.038
	(0.354)	(0.354)	(0.122)	(0.122)
Individual Fixed effect	YES	YES	YES	YES
Country Fixed effect	NO	YES	NO	YES
Time Fixed effect	NO	NO	YES	YES
N	285516	285516	285516	285516
R-squared	.52	.52	.562	.562

Robust errors in parentheses

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

6 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. To save spaces, we only report the results regarding life quality. The results related to physical health and mental health are similar and can be provided by requests.

6.1 A different dataset

In our benchmark analysis, we used the emissions data from the World Bank. To check if our findings are robust to the reported emissions, we employ an alternative source of emissions provided by Our World in Data. Results are reported in Table 6. The specifications in this table are similar to the ones applied in our benchmark Table 2. More precisely, we use the carbon dioxide emissions as our main regressor. In all columns the individual fixed effects are included. The country fixed effects are present in Columns 2 and 4, while the time fixed effects are included in Columns 3 and 4.

Compared to Table 2, the estimates in Table 6 point us to similar findings. Take Column 1 for example. Doubling the amount of carbon dioxide emissions would lower the life quality of a 50 year-old by 2 per cent. At the same time, younger people felt more of the effect. A 20 year-old would see their life quality reduced by 4 per cent with the same increase in emissions. These results confirm that our findings are robust to the source of data.

6.2 Different types of emissions

There are essentially three types of greenhouse gases. Besides carbon dioxide (CO_2) that we use in the benchmark case, there are also methane (CH_4) and nitrous oxide (N_2O). In this section, we will test our results with these types of emissions. The procedure is exactly the same as in our benchmark case that was reported in Table 2.

We present the results with methane emissions in Table 7a. With this type of emissions, our results are still consistent. In all columns, the estimates are significant at 99 per cent confidence and the signs are consistent with our benchmark results in Table 2. For instance, in Column 4 when we apply the fully fledged specification, the rise in methane emissions resulted in lower life quality for our respondents. More precisely, doubling the amount of methane emissions reduced the life quality of a 20 year-old by 9 per cent. The effect on older people is more moderate. A 40 year-old only saw their life quality reduced by 7 per cent.

Similar results are also found with nitrous oxide emissions. In Table 7b, we find consistent estimates with what we have found before. Again, we keep the same specifications as in the benchmark Table 2. All the columns show that our results are robust to this type of emissions. For instance, in Column 4, a person aged 20 would have their life quality lowered by 6 per cent if the nitrous oxide emissions rose by 100 per cent. The effect for a person aged 40 is a little lower at 5 per cent.

Finally, we report our results when the total amount of greenhouse gases emissions

Table 6: Carbon dioxide emissions and life quality

	(1)	(2)	(3)	(4)
Dependent variable: Life quality				
ln(CO2 emission)*age	0.001***	0.001***	0.002**	0.002**
	(0.000)	(0.000)	(0.001)	(0.001)
ln(CO2 emission)	-0.079*	-0.079*	-0.099*	-0.099*
	(0.044)	(0.044)	(0.055)	(0.055)
age	-0.009**	-0.009**	0.006***	0.006***
	(0.003)	(0.003)	(0.002)	(0.002)
ln(GDP)	0.064	0.064	0.078	0.078
	(0.050)	(0.050)	(0.051)	(0.051)
ln(population)	0.111	0.111	0.118	0.118
	(0.105)	(0.105)	(0.120)	(0.120)
ln(life expectancy)	-0.327	-0.327	-0.218	-0.218
	(0.698)	(0.698)	(0.862)	(0.862)
ln(health spending)	0.050*	0.050*	0.044	0.044
	(0.028)	(0.028)	(0.037)	(0.037)
Individual Fixed effect	YES	YES	YES	YES
Country Fixed effect	NO	YES	NO	YES
Time Fixed effect	NO	NO	YES	YES
N	254338	254338	254338	254338
R-squared	.731	.731	.731	.731

Note: Robust errors in parentheses. Emission data are provided by Our World in Data.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 7a: Methane emissions and the quality of life

	(1)	(2)	(3)	(4)
Dependent variable: Life quality				
ln(methane)*age	0.001***	0.001***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
ln(methane)	-0.173***	-0.173***	-0.185***	-0.185***
	(0.045)	(0.045)	(0.049)	(0.049)
age	-0.017***	-0.017***	-0.002	-0.002
	(0.005)	(0.005)	(0.004)	(0.004)
ln(GDP)	0.081**	0.081**	0.090**	0.090**
	(0.038)	(0.038)	(0.037)	(0.037)
ln(population)	0.217*	0.217*	0.231*	0.231*
	(0.111)	(0.111)	(0.127)	(0.127)
ln(life expectancy)	-0.256	-0.256	-0.093	-0.093
	(0.744)	(0.744)	(0.895)	(0.895)
ln(health spending)	0.001	0.001	-0.009	-0.009
	(0.026)	(0.026)	(0.034)	(0.034)
Individual Fixed effect	YES	YES	YES	YES
Country Fixed effect	NO	YES	NO	YES
Time Fixed effect	NO	NO	YES	YES
N	254338	254338	254338	254338
R-squared	.731	.731	.731	.731

Note: Robust errors in parentheses. Emission data are provided by the World Bank Development Indicators.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 7b: Nitrous oxide emissions and the quality of life

	(1)	(2)	(3)	(4)
Dependent variable: Life quality				
ln(nitrous oxide)*age	0.001**	0.001**	0.001**	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
ln(nitrous oxide)	-0.085**	-0.085**	-0.108**	-0.108**
	(0.030)	(0.030)	(0.043)	(0.043)
age	-0.013**	-0.013**	0.002	0.002
	(0.006)	(0.006)	(0.004)	(0.004)
ln(GDP)	0.079*	0.079*	0.097**	0.097**
	(0.042)	(0.042)	(0.042)	(0.042)
ln(population)	0.113	0.113	0.124	0.124
	(0.098)	(0.098)	(0.110)	(0.110)
ln(life expectancy)	-0.549	-0.549	-0.453	-0.453
	(0.737)	(0.737)	(0.786)	(0.786)
ln(health spending)	0.035	0.035	0.023	0.023
	(0.024)	(0.024)	(0.031)	(0.031)
Individual Fixed effect	YES	YES	YES	YES
Country Fixed effect	NO	YES	NO	YES
Time Fixed effect	NO	NO	YES	YES
N	254338	254338	254338	254338
R-squared	.731	.731	.731	.731

Note: Robust errors in parentheses. Emission data are provided by the World Bank Development Indicators.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

were used as the main regressor in Table 7c. Given all the types of emissions yielded consistent results, it is no surprise that results in this Table are also in line with those in Table 2. In other words, our findings are robust with all types of emissions.

Table 7c: Greenhouse gas emissions and the quality of life

	(1)	(2)	(3)	(4)
Dependent variable: Life quality				
ln(GHG)*age	0.001***	0.001***	0.002**	0.002**
	(0.000)	(0.000)	(0.001)	(0.001)
ln(GHG)	-0.069	-0.069	-0.100	-0.100
	(0.060)	(0.060)	(0.074)	(0.074)
age	-0.018**	-0.018**	-0.005	-0.005
	(0.007)	(0.007)	(0.006)	(0.006)
ln(GDP)	0.064	0.064	0.082	0.082
	(0.054)	(0.054)	(0.054)	(0.054)
ln(population)	0.086	0.086	0.099	0.099
	(0.107)	(0.107)	(0.119)	(0.119)
ln(life expectancy)	-0.365	-0.365	-0.293	-0.293
	(0.673)	(0.673)	(0.812)	(0.812)
ln(health spending)	0.057*	0.057*	0.047	0.047
	(0.029)	(0.029)	(0.038)	(0.038)
Individual Fixed effect	YES	YES	YES	YES
Country Fixed effect	NO	YES	NO	YES
Time Fixed effect	NO	NO	YES	YES
N	254338	254338	254338	254338
R-squared	.731	.731	.731	.731

Note: Robust errors in parentheses. Emission data are provided by the World Bank Development Indicators.
* p<0.1, ** p<0.05, *** p<0.01

6.3 Age groups

In the benchmark case, we interact emissions with ages to see the impacts of air pollution across different ages. A particular feature in our dataset is that most of the respondents in our survey are over 50s. The average age is 67 (see Table 1). As a result, there are only a few observations of young respondents which might bias our results. To address this issue, we group the respondents into the 20s, 30s, 40s, and so on.

Table 8 reports our results. In this Table, we replace the respondents' age with their age group that indicates whether they were in the 20s, 30s, 40s, etc. by the time they were surveyed. What we find is that the results in this Table are consistent with what we unveiled in the previous Tables. The coefficients of carbon dioxide emissions are all negative across all Columns. They imply that in general, air pollution lowered residents' life quality. The coefficients of the interaction terms between air pollution and the age groups are all positive. They show that the effects of air pollution on life quality are more pronounced among younger groups. Moreover, by grouping the respondents into age groups which essentially increases the number of observations in each age category, we highlight the interactive effect of emissions and age. The coefficients of the interactions are now more significant economically than those shown in the benchmark Table 2.

Table 8: Carbon dioxide emissions and the quality of life

	(1)	(2)	(3)	(4)
Dependent variable: Life quality				
ln(CO2 emission)*age groups	0.031***	0.031***	0.030***	0.030***
	(0.007)	(0.007)	(0.006)	(0.006)
ln(CO2 emission)	-0.152**	-0.152**	-0.158**	-0.158**
	(0.064)	(0.064)	(0.063)	(0.063)
age groups	-0.060***	-0.060***	-0.059***	-0.059***
	(0.016)	(0.016)	(0.012)	(0.012)
ln(GDP)	0.016	0.016	0.038	0.038
	(0.049)	(0.049)	(0.050)	(0.050)
ln(population)	0.143	0.143	0.108	0.108
	(0.133)	(0.133)	(0.137)	(0.137)
ln(life expectancy)	-0.747	-0.747	-0.977	-0.977
	(0.509)	(0.509)	(0.674)	(0.674)
ln(health spending)	0.073	0.073	0.056	0.056
	(0.045)	(0.045)	(0.051)	(0.051)
Individual Fixed effect	YES	YES	YES	YES
Country Fixed effect	NO	YES	NO	YES
Time Fixed effect	NO	NO	YES	YES
N	254338	254338	254338	254338
R-squared	.731	.731	.731	.731

Note: Robust errors in parentheses. Emission data are provided by the World Bank Development Indicators.
* p<0.1, ** p<0.05, *** p<0.01

7 Conclusion

We provide evidence that climate change, via the emission of greenhouse gases, has adverse effects on our quality of life. We show that all types of greenhouse gases, from carbon dioxide to methane and nitrous oxide reduce our life quality. Our work highlights the impacts of these gases on human health, especially mental health. We also show that the impacts vary across ages. Knowing these impacts would help us to understand the social costs of carbon, which lead to the optimal design of the Pigouvian taxes or carbon pricing. Our study is limited, however, by the lack of answers from people younger than 50 years of age. This will leave to future research when additional surveys are available.

7.1 Declarations

Conflict of interest The authors declare no competing interest

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Appendix

Survey

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

Table C: EURO-D mental issue questions

Symptom	Questions
Depression	Have you been sad (depressed, miserable, in low spirits, blue) recently?
Pessimism	How do you see your future? (Pessimistic, empty expectations or bleak future)
Suicidality	Have you ever felt that you would rather be dead? (Has ever felt suicidal or wished to be dead)
Guilt	Do you tend to blame yourself or feel guilty about anything? (Obvious guilt or self blame)
Sleep	Have you had trouble sleeping recently? (Trouble with sleep or recent change in pattern)
Interest	What is your interest in things? (Less interest than is usual)
Irritability	Have you been irritable recently?
Appetite	What has your appetite been like? (Diminution in the desire for food)
Fatigue	Have you had too little energy (to do the things you want to do)? (Listlessness or subjective energy restriction)?
Concentration	How is your concentration? (Difficulty in concentrating on entertainment or reading)
Enjoyment	What have you enjoyed doing recently? (Almost nothing enjoyed)
Tearfulness	Have you cried at all?