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Heat, Mortality, and Life-Cycle Welfare ^{*}

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September 23, 2026

Abstract

Climate change increases the frequency and severity of extreme heat. We develop a stochastic life-cycle model at annual frequency in which daily heat shocks raise mortality risk, agents adapt to protect themselves, and health investment slows biological aging. We calibrate the model to U.S. data and study a key damage channel—heat-induced mortality—showing how exogenous differences in wage income translate common heat shocks into a markedly unequal burden. Comparing life-cycle outcomes under daily heat-shock distributions associated with SSP5-8.5 to an SSP1-2.6 benchmark, the average agent loses 0.07 years of life expectancy, with a regressive incidence: 0.26 years (3.1 months) for the bottom decile versus 0.04 years (0.5 months) for the top, a ratio of six to one. Welfare losses are substantial and likewise regressive: 0.80% in CEV on average, ranging from 1.32% to 0.52%, and from 6.65% to 1.11% conditional on survival to age 50. Climate denial raises welfare losses most among the rich.

Keywords: *Daily Heat Shocks, Mortality, Adaptation, Biological Aging, Life-Cycle Model, Welfare, Incidence, Climate Denial*

JEL Classification: *I14; Q54; D63; D15; J17*

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1 Introduction

Motivation. In the summer of 2026, Europe and North America again endured severe heat. In Europe, 252 stations set all-time records, with peaks of 45.1 °C in Spain and 44.3 °C in France; Western Europe recorded its hottest June on record. In the United States, Washington, D.C. reached 103 °F and Philadelphia saw three days above 101 °F for the first time on record.¹ Such extremes have become more frequent and more intense as the climate warms and are projected to intensify further (IPCC, 2023; World Meteorological Organization, 2025).

We develop a theoretical model to analyze the most direct threat that climate-driven warming poses to individual welfare: heat-induced mortality risk. Two aspects appear critical and will be captured in our model. First, exposure to heat operates along both the extensive margin—the frequency of hot days—and the intensive margin—the severity of those days. The latter is especially important when the effect of daily heat on mortality is nonlinear, as documented in climate epidemiology (Ballester et al., 2023; Gasparrini et al., 2015). Two weeks can average 30°C / 86°F: one steady at 30°C, another with two days at 40°C / 104°F and the rest at 26°C / 79°F. With convex heat damages, the second week is likely to generate substantially higher mortality risk despite the same average temperature. Second, adaptation to heat can substantially mitigate the mortality risk of heat waves. Private adaptation spans measures such as air conditioning, exterior shading, added green or blue space, fans, and relocation to a cooler house or city (Beckmann, Hiete, Schneider, & Beck, 2021). Because these measures are costly, income is a central determinant of the level of protection against heat-induced mortality risk (Carleton, Duflo, Jack, & Zappalà, 2024).

Research questions. Our questions are straightforward: (i) How large are the losses in life expectancy and in lifetime welfare from increased heat-induced mortality risk? (ii) How do these losses vary along the income distribution? (iii) What mechanisms shape this incidence, and how much of it comes from differences in adaptation between poor and rich?

The distributional question is subtle; a stylized model shows why. Consider an agent who lives at most one period, consumes her income $c = w > 1$ under log utility, and faces heat-induced mortality risk m ; the utility of death is normalized to zero. Expected utility falls from $\ln w$ to $(1 - m) \ln w$, a loss of $\Lambda(w) \equiv m \ln w$. The consumption equivalent λ , defined by $\ln((1 - \lambda)w) = (1 - m) \ln w$, is the income share needed to

¹European figures from the June 2026 Climate Bulletin of the Copernicus Climate Change Service (Copernicus Climate Change Service (C3S), 2026) and the World Meteorological Organization (World Meteorological Organization, 2026); U.S. figures from National Weather Service records (National Weather Service, 2026).

compensate for the risk: $\lambda = 1 - e^{-\Lambda(w)}$. With m exogenous, $\partial\lambda/\partial w > 0$. The burden is progressive, since a given proportional risk destroys a share of a utility level that rises with income. This is imposed by the setup, and we use it as a reference point.²

Now let the mortality risk depend on income, $m = m(w)$ with $m'(w) < 0$, as under costly private adaptation. Then

$$\Lambda'(w) = \underbrace{m(w)/w}_{\text{utility scale (+)}} + \underbrace{m'(w) \ln w}_{\text{protection (-)}}$$

and the two forces oppose each other. Under mild conditions on $m(\cdot)$, protection dominates above a threshold w^* : the burden remains progressive below it and turns regressive above (Appendix A.1). Endogenous mortality introduces a regressive force. Section 4 allows this dependence to arise endogenously, through adaptation and health investment.

To the best of our knowledge, no existing structural framework analyzes how heat-induced mortality risk, resulting from high-frequency daily heat shocks, affects individual welfare conditional on idiosyncratic characteristics such as income, age, health status, and expectations.³ We develop a stochastic life-cycle model and calibrate it to U.S. data to fill this gap.

Method. Our stochastic life-cycle model (Section 4) rests on two building blocks: [Yaari \(1965\)](#), a neoclassical life-cycle framework with uncertain death, and the endogenous health framework of [Dalgaard and Strulik \(2014\)](#), in which biological age evolves through deficit accumulation. We extend them with stochastic daily heat shocks that affect survival, together with costly adaptation that mitigates heat-induced mortality risk. We treat income and climate as exogenous inputs and discipline the model with U.S. data. A subset of model parameters is estimated by the Simulated Method of Moments to match life-cycle mortality, health deficits, health expenditures, income-specific life expectancy, and heat-induced relative mortality risks (Section 5.3). A partial-equilibrium approach appears appropriate, given that adaptation expenditures are far too small to move aggregate prices—roughly 0.14% of expected lifetime consumption in the baseline SSP1-2.6 heat scenario.⁴

Heat shocks are hourly and daily phenomena, whereas life-cycle and macroeco-

²For any increasing u with $u(\text{death}) = 0$, exogenous mortality is progressive iff the income elasticity of the value of a statistical life $\varepsilon_{\text{VSL}} > 1$; log utility delivers $1 + 1/\ln w$, homothetic CRRA exactly one (Appendix A.1).

³The related literature (Section 2) focuses on the value of a statistical life in empirical analyses rather than lifetime utility (LTU) in a structural model, and examines damages across countries rather than the within-country income distribution.

⁴About \$4,000 against \$2.8 million, both computed ex ante as flows weighted by cumulative survival, $\sum_{t=0}^T a_t S_t$ (and $\sum_t c_t S_t$ for consumption).

nomics models typically operate at annual or lower frequencies. We therefore implement a mixed-frequency structure: agents choose annually, while heat shocks occur daily. This allows the model to capture the convex daily temperature–mortality nexus documented in climate epidemiology (Ballester et al., 2023; Gasparrini et al., 2015). The mixed-frequency structure is a key methodological innovation and can be applied to similar problems involving high-frequency nonlinear damages.

We feed CMIP6-based distributions of daily heat shocks—positive deviations of daily mean temperature above the minimum-mortality temperature—into the model and compare the higher-emissions scenarios associated with SSP2-4.5, SSP3-7.0, and SSP5-8.5 with a low-emissions SSP1-2.6 benchmark, as explained in Section 5.2.⁵ The framework yields optimal adaptation expenditures under rational climate expectations and allows us to quantify welfare losses arising from incorrect beliefs about climate change.

We deliberately focus on heat-related mortality and abstract from cold-related mortality. This does not imply that cold mortality is irrelevant. We do not quantify the net welfare effects of changes in the full temperature distribution. Instead, we isolate the mortality channel most directly intensified by global warming: more frequent and severe hot days. Heat and cold mortality are also unlikely to share the same adaptation technology. Heat protection involves cooling, shading, behavioral avoidance, hydration, urban greening, and air conditioning. Cold protection depends more on heating, insulation, housing quality, energy prices, respiratory disease environments, and public-health responses. Combining both in one reduced-form adaptation technology risks conflating distinct mechanisms. Restricting to temperatures above the minimum mortality temperature, our results capture gross heat-induced welfare losses, not net damages from all temperature-mortality channels.

Major results. Comparing life-cycle outcomes under late-century (2096–2100) daily heat-shock distributions associated with SSP5-8.5 to an SSP1-2.6 benchmark, we find substantial losses in both life expectancy and lifetime welfare. As a direct outcome, the average agent loses about 0.07 years or about 0.8 months of life expectancy, and this loss is regressive: 0.26 years (3.1 months) for the bottom decile versus 0.04 years (0.5 months) for the top decile. That is, the poorest tenth loses over six times as much life expectancy as the richest. Shutting down adaptation raises these losses sharply and renders them almost flat in income, so the income gradient in mortality damages is generated essentially entirely by differential adaptation rather than by differences in health status. In welfare terms, the average agent loses about 0.80% in CEV, measured

⁵Throughout, SSP labels refer only to the CMIP6 climate-model temperature distributions associated with the corresponding forcing pathways; we do not use the socioeconomic assumptions embedded in the SSP narratives.

ex ante over the life-cycle. These losses are likewise regressive: the bottom decile loses 1.32% while the top decile loses only 0.52%. The burden also falls disproportionately on older agents. Conditional on survival to age 50 rather than measured at age 20,⁶ losses are substantially larger and more dispersed, ranging from 6.65% for the bottom decile to 1.11% for the top decile.⁷ Turning to channels, for poorer individuals the dominant channel is reduced survival, whereas for richer individuals forgone consumption from higher adaptation expenditures is relatively more important (Section 6).

For perspective, studies of the direct temperature channel—entering utility through amenities and consumption—find sizable but regionally offsetting effects: [Fried \(2026\)](#) reports RCP 8.5 impacts of roughly -4% to $+2\%$, and [Cruz and Rossi-Hansberg \(2024\)](#) find losses up to 20% in the hottest regions versus gains up to 11% in the coldest (about 6% globally), cumulated by 2200 under sustained RCP 8.5 emissions. We instead isolate the mortality channel, so these magnitudes are not directly comparable; we quantify it for the average agent and trace its incidence and mechanisms along the within-country income distribution.

Structure. Section 2 discusses the related literature. Section 3 examines private adaptation using a reduced-form model with endogenous adaptation to derive key implications analytically. Section 4 develops the stochastic life-cycle model, in which daily heat shocks raise mortality risk. Section 5 describes how we bring the model to the data. Section 6 presents the main results. Section 7 concludes.

2 Literature

This paper relates to four literature strands: (i) climate change impacts, (ii) climate epidemiology, (iii) the economics of adaptation, and (iv) climate change and inequality.

First, there is the literature on the economic and societal impacts of climate change, specifically temperature shocks and extreme events. This large body of literature employs econometric models that focus on GDP and GDP growth ([Bilal & Känzig, 2026](#); [Burke, Hsiang, & Miguel, 2015](#); [Dell, Jones, & Olken, 2012](#); [Kotz, Wenz, Stechemesser, Kalkuhl, & Levermann, 2021](#)); the agricultural sector ([Deschênes & Greenstone, 2007](#); [Gallic & Vermandel, 2020](#)); or labor productivity ([Somanathan, Somanathan, Sudarshan, & Tewari, 2021](#)). While most macroeconomic studies use annual mean temperature as a proxy for temperature extremes, a small but growing literature, for example [Fillon, Linsenmeier, and Wagner \(2025\)](#) and [Rudik, Lyn, Tan, and Ortiz-Bobea \(2021\)](#),

⁶The life-cycle begins at age 20, corresponding to $t = 0$ in model time.

⁷Part of this increase reflects the change in numeraire: conditioning on survival to age 50 removes the discounting and survival-weighting applied to later ages when welfare is evaluated at age 20.

centers its analysis on the intra-annual probability distribution of daily mean temperatures. We follow this probabilistic view of damages from extreme weather. However, we focus specifically on the welfare consequences of heat-induced mortality, accounting for adaptation. Moreover, whereas much of the literature quantifies the net, overall welfare effect of warming, we isolate one channel, namely heat-induced mortality.

Second, the climate epidemiology literature focuses on the estimation of relative mortality risk associated with temperatures or heat waves. The distinction between temperatures in general, which are temporally unrestricted, and heat waves, which are temporally restricted events, is important. Starting with the latter, there are a number of studies on specific heat wave events, for example [Katsouyanni, Trichopoulos, Zavitsanos, and Touloumi \(1988\)](#) on the 1987 heat wave in Athens, [Whitman et al. \(1997\)](#) on the 1995 heat wave in Chicago, and [Fouillet et al. \(2006\)](#) on the 2003 heat wave in France. These event-specific studies appear to constitute a minor share, while the larger share aims to identify the association between short-term temperature variations and mortality in general, for example in [Gasparrini et al. \(2015\)](#), [Ballester et al. \(2023\)](#), and [Gallo et al. \(2024\)](#). These studies produce temperature-mortality response curves that are typically U-shaped and exhibit a minimum mortality temperature (MMT). Deviations from this “optimal” temperature, in either direction, increase mortality. Such analyses do not rely on specifying an explicit threshold that defines extremes or heat waves and therefore capture more than just the tip of the iceberg. We follow this line of reasoning when formulating our model below.⁸ A more recent development in this literature is moving toward impact-attribution studies, see, for example, [Vicedo-Cabrera et al. \(2021\)](#). Such analyses not only evaluate the historical temperature–mortality relationship but also exploit this relationship to project future damages under climate-change-modified daily mean temperature distributions. [Masselot et al. \(2025\)](#) account for cold-related mortality when examining the net change in mortality under different climate change scenarios, but treat adaptation as exogenous. We proceed in exactly the opposite way by excluding cold-related mortality while introducing endogenous adaptation through structural modeling grounded in economic theory.

Third, there is a growing literature on the economics of adaptation, which has been reviewed by [Carleton et al. \(2024\)](#). [Fouillet et al. \(2008\)](#) provide evidence for adaptation by comparing the 2003 and 2006 heat waves in France and finding that the actual death toll in 2006 was lower than expected according to a model calibrated for 2003. [Barreca, Clay, Deschenes, Greenstone, and Shapiro \(2016\)](#) show that the mortality consequences of heat have decreased substantially in recent decades in the U.S., with the im-

⁸A potential limitation of this approach may arise from the inability to account for the cumulative impact of multiple consecutive days of heat. [Gasparrini and Armstrong \(2011\)](#) address this concern by showing that heat wave effects can be captured by continuous-temperature time-series analyses.

pact declining by 75 percent, possibly due to improved health care and the combined effects of access to electricity and residential air conditioning. Carleton and Hsiang (2016) emphasize that the consequences of climate change, for example mortality, differ for the same absolute exposure to a climate variable, such as high temperatures, across societies, as reflected in heterogeneous dose-response functions. In this work, we build on the evidence provided by Carleton et al. (2022) and account for adaptation that attenuates heat-related mortality. Fried (2026) shows that climate change generates sizable and unequal welfare effects in a heterogeneous-agent housing-and-climate model, where higher temperatures reduce utility through a damage function penalizing deviations of indoor temperature from a bliss point and households adapt via consumption, housing, and heating/cooling choices. Under RCP 8.5 in 2100, welfare effects (CHEV) range from roughly -4% to $+2\%$: in colder regions losses concentrate among low-income households (around -3% to -4%) while middle-income households gain up to $+1\%$, whereas in warmer regions losses peak for middle-income households (about -2%) with smaller effects at the tails.

Finally, there is the literature on inequality and climate change. Numerous studies focus on the distributional consequences of climate mitigation policies, accounting for vertical and horizontal equity, for example in Hänsel, Franks, Kalkuhl, and Edenhofer (2022). Another sub-strand deals with heterogeneous climate damages, mainly comparing exposures across nations, such as in Kotz, Levermann, and Wenz (2024) and Burke et al. (2015). In our model, adaptation is a key mechanism that entails distributional consequences in protection against temperature shocks. Davis, Gertler, Jarvis, and Wolfram (2021) and De Cian, Falchetta, Pavanello, Romitti, and Sue Wing (2025) estimate the adoption of air conditioning as one of the main adaptive measures against heat, showing that it is disproportionately concentrated among high-income groups. We model adaptation as *ex ante*: individuals protect themselves against future heat exposure. As a result, expectations about climate change become a potential source of heterogeneous vulnerability. When agents hold biased beliefs about future climate developments, differences in expectations translate into unequal impacts. Dechezleprêtre et al. (2025) conduct a comprehensive survey of attitudes toward climate change (and related policies) and identify correlations between socioeconomic and lifestyle factors and climate change beliefs, while noting that forecasting beliefs using socioeconomic variables is challenging. Rüttenauer (2024) finds that individuals exposed to heat waves or floods are more likely to update their beliefs about a changing climate. Our analysis shows how climate denial leads to non-optimal and thereby welfare-reducing adaptation.

Contribution. Our main contribution is to develop a structural framework that maps climate-induced changes in the distribution of hot days into individual welfare (life-

time utility) through the mortality channel. The closest benchmark is [Carleton et al. \(2022\)](#), who quantify the global mortality consequences of climate change and account for adaptation by exploiting observed heterogeneity in income and historical temperature exposure. We take this empirical evidence as a starting point, but ask a different question. Rather than valuing projected mortality changes through the value of a statistical life, we model the individual decision problem that gives rise to heterogeneous vulnerability and adaptation in the first place. Agents differ exogenously in their life-cycle income profiles and endogenously in their biological age; they choose consumption, savings, health investment, and private adaptation in response to stochastic daily heat risk. This allows us to quantify lifetime-utility losses from heat-induced mortality, conditional on income, age, health, adaptation, and expectations.

Our paper addresses different gaps in the literature. First, relative to climate epidemiology, we endogenize adaptation. Epidemiological studies provide the high-frequency, nonlinear temperature–mortality relationships that motivate our damage specification, but adaptation is typically treated as absent, exogenous, or scenario-based. Our framework instead derives adaptation from an intertemporal cost-benefit trade-off: individuals sacrifice current consumption to reduce future mortality risk. Second, relative to the economics of adaptation, we shift the focus from output losses, property damages, or capital destruction to mortality risk and lifetime utility. Existing dynamic adaptation models, such as [Fried \(2022\)](#) and [Van der Straten \(2023\)](#), study heterogeneous adaptive capacity in settings where climate damages primarily affect assets. We study a different margin: the protection of life itself. Finally, the model’s mixed-frequency structure represents a modeling innovation that is fruitful for the analysis of intensive-margin extreme events in general. Economic choices are made annually, while heat shocks and heat exposure occur daily. This matters because heat damages are nonlinear and concentrated in the upper tail: annual average temperatures would obscure precisely the extreme realizations most relevant for mortality. Our setup preserves the high-frequency nature of heat risk while retaining the tractability of a life-cycle model with forward-looking agents, endogenous health, and uncertain death.

3 Adaptation and the Incidence of Heat

Because private adaptation to heat is central to our analysis, we first discuss it briefly, then use a reduced-form model (Section 3.2) to structure the interpretation of the results from our stochastic life-cycle model (Section 4).

3.1 Private Adaptation to Heat

Individuals can adapt to heat along several dimensions, including physical, informational, and behavioral adaptation. Physical adaptation involves actions such as purchasing air conditioning, installing additional blinds or exterior shading, increasing green or blue areas around the house or on the balcony, buying a fan, or moving to a cooler house or city (Beckmann et al., 2021). Informational adaptation encompasses the use of short-term weather forecasts and an understanding of long-term climate change, while behavioral adaptation pertains to routine activities such as staying indoors during the hottest part of the day or ensuring sufficient water availability. We assume that all these adaptation measures are costly. For example, Deryugina and Hsiang (2014), Carleton et al. (2022), and Carleton et al. (2024) argue that while it is relatively straightforward to quantify the accumulated benefits of adaptation, measuring its costs is difficult due to the wide range of potential actions, each with varying expenses. There are two approaches used to measure adaptation costs. The explicit approach enumerates adaptive measures individually and assesses their costs. The implicit approach, sometimes referred to as the revealed-preference approach (Carleton et al., 2022), assumes that marginal adaptation costs equal marginal adaptation benefits in equilibrium. Both approaches come with advantages and drawbacks.

As we do not aim to evaluate the welfare effects of specific adaptation measures, we model adaptation as a single composite standing in for the full range of protective actions. Rather than pricing individual measures, we specify a protection technology and estimate its effectiveness from observed heat-mortality differences across income and age, so that adaptation costs are inferred from optimizing behavior. This shares the identifying logic of the implicit approach but embeds it in a decision problem, which allows us to study counterfactual adaptation levels below. Moreover, we adopt the concept of ex ante adaptation. That is, individuals choose their level of adaptation before the stochastic heat event is realized. Thus, adaptation choices are made conditional on expectations about the stochastic variable ε , for example by installing air conditioning prior to a heat period. An alternative concept is ex post adaptation, where engagement in adaptation takes place after a heat event occurs, for example through migration flows out of a region following a heat wave. See Carleton et al. (2024) for an overview of the concepts of ex ante and ex post adaptation.

3.2 Reduced-form Model

The reduced-form, one-period model shows that the welfare burden of heat-induced mortality risk is progressive at low incomes and regressive above an income threshold w^* . It makes explicit the two protective forces behind this pattern: endogenous

adaptation and biological age, which we let fall with income.⁹

Setup. An agent with exogenous income w chooses adaptation $a \in [0, w)$ and consumes $c = w - a$. Utility accrues only upon survival,

$$u(c) = \ln c + \bar{u}, \quad (1)$$

where $\bar{u}$ is usually set to match a target value of life in calibrated models (Hall & Jones, 2007). The utility of death is normalized to zero, and we restrict attention to incomes with $u(w) > 0$, at which life is worth living. Biological age d , an inverse proxy for health status, is described by $d = d(w)$, with $d'(w) < 0$. We write its income elasticity as $\nu \equiv -\frac{d \ln d}{d \ln w} > 0$. A daily heat shock ε is binary, equal to $\bar{\varepsilon} > 0$ with probability ω and to 0 otherwise. The survival probability $s(\cdot)$ combines a baseline hazard rate that depends on d with a heat-related relative risk that depends on ε , according to

$$s(a, d, \varepsilon) = \exp\left(- \underbrace{b_1 d^\psi}_{\text{baseline hazard}} \cdot \underbrace{e^{g(a, d)\varepsilon^\chi}}_{\text{relative risk}}\right), \quad g(a, d) = b_5 d^\eta e^{-\kappa a}, \quad (2)$$

with $\psi, \chi > 1$ and $b_1, b_5, \kappa, \eta > 0$.¹⁰ A heat shock ($\varepsilon > 0$) raises the relative risk; adaptation lowers vulnerability $g(\cdot)$; and biological age d raises both the baseline hazard $b_1 d^\psi$ and the heat loading $b_5 d^\eta$. Optimal adaptation and consumption are

$$a^*(w) = \arg \max_{0 \leq a < w} \mathbb{E}[s(a, d(w), \varepsilon)] u(w - a), \quad c^*(w) = w - a^*(w). \quad (3)$$

Welfare. We now turn to the welfare loss of heat-induced mortality, conditional on income w . Let $\vartheta(a, d) \equiv \mathbb{E}[s(a, d, \varepsilon)]/s_0 \in (0, 1]$ be the heat survival factor, where $s_0(w)$ is the baseline survival $s_0(w) = e^{-b_1 d^\psi}$. The welfare loss, measured by λ from $s_0 u((1 - \lambda)w) = \mathbb{E}[s] u(c^*)$, satisfies

$$\lambda = 1 - e^{-\Lambda(w)}, \quad \Lambda(w) = u(w) - \Phi(w), \quad (4)$$

where $\Phi(w) \equiv \vartheta(a^*, d) u(c^*)$. The burden is progressive when λ rises with income and regressive when it falls. Since λ is increasing in Λ , the two share the same income gradient, and the burden is regressive exactly when $\Phi'(w) > u'(w) = 1/w$.

Benchmark. With $\kappa = 0$, adaptation is ineffective and $a^* = 0$; with $\nu = 0$, d is constant. Then ϑ is constant, $\Phi(w) = \vartheta u(w)$, and $\Phi'(w) = \vartheta/w < 1/w$: the burden is

⁹This is a shortcut: the stochastic life-cycle model in Section 4 derives biological age from income-dependent health investment and generates this relationship endogenously.

¹⁰Parameter labels follow the stochastic life-cycle model (Section 4); b_2 – b_4 govern health-deficit accumulation there and do not appear here.

progressive. This progressivity is conditional on the income elasticity of the value of a statistical life (VSL) exceeding one; under our utility it equals $1 + 1/u(w) > 1$, a property the stochastic life-cycle model inherits from its near-logarithmic CRRA specification, with a value-of-life constant calibrated to an empirical value of life (Hall & Jones, 2007).¹¹

Incidence. Consider now adaptation as an effective means of reducing the mortality threat posed by heat. Let $\rho \equiv g\bar{\varepsilon}^x$ denote the log relative risk and $H_0 \equiv b_1 d^\psi$, $H_1 \equiv H_0 e^\rho$ the hazard without and with heat.¹² The heat survival factor is then $\vartheta = e^{-(H_1 - H_0)}$, so that $1 - \vartheta \approx H_1 - H_0$ is the probability of dying from heat, and it depends on income through both $a^*(w)$ and $d(w)$. By (4), incidence is governed by the sign of $\Lambda'(w) = u'(w) - \Phi'(w)$. Differentiating Φ , applying the envelope theorem and $u'(c) = 1/c$ (Appendix A.2), and multiplying by w :

$$w \Lambda'(w) = \underbrace{(1 - \vartheta)}_{\text{utility scale (+)}} - \underbrace{\vartheta \frac{a^*}{c^*}}_{\text{adaptation (-)}} - \underbrace{\nu \vartheta u(c^*) [\psi(H_1 - H_0) + \eta \rho H_1]}_{\text{biological age (-)}}. \quad (5)$$

This is the decomposition of the stylized model in section 1, $\Lambda'(w) = m/w + m'(w) \ln w$, with m replaced by heat mortality $1 - \vartheta$ and the protection term split into its two sources. We now turn to the three terms on the RHS of (5). (i) Utility scale. Were the extra unit of income entirely consumed, it would raise baseline utility by $u'(w)$ but welfare under heat only by $\vartheta u'(w)$. The wedge $(1 - \vartheta)u'(w)$ is $m u'(w)$ from the stylized model: a given risk destroys more utility when there is more to destroy. (ii) Adaptation. An adapting agent consumes $c^* = w - a^*$, so the marginal utility of consumption is higher and the marginal unit of income is worth $\vartheta u'(c^*)$ rather than $\vartheta u'(w)$. The difference is $\vartheta a^*/(c^* w)$. It vanishes at the corner, where the poor spend nothing on protection, and grows with the resources devoted to it. Setting $\nu = 0$ and using $\vartheta a^*/c^* > 1 - \vartheta \iff a^* > (1 - \vartheta)w$, the burden is regressive if $\frac{a^*}{w} > 1 - \vartheta$. (iii) Biological age. Richer agents are, ceteris paribus, biologically younger, lowering both the hazard scale d^ψ and the loading d^η .

At low income levels, the marginal utility of consumption at $a = 0$ exceeds the marginal survival benefit, so $a^* = 0$ and the adaptation term is identically zero. The burden is then progressive whenever $\nu u(w)(\psi + \eta) < 1$. Adaptation turns on continuously where the first-order condition first binds (Appendix A.2); thereafter the adaptation term rises from zero while residual heat mortality $1 - \vartheta$ falls, and their

¹¹Within-country estimates put this elasticity at 0.5–0.6 (Doucouliagos, Stanley, & Viscusi, 2014; Viscusi & Aldy, 2003), at which even exogenous mortality is regressive; targeting the VSL level instead of its elasticity tilts our calibration against regressivity.

¹²We state the incidence results for a deterministic shock at $\bar{\varepsilon}$; the binary case adds the probability ω without affecting any sign (Appendix A.2).

crossing defines the threshold w^* above which the burden is regressive.¹³

Comparative statics. Three properties (derived in Appendix A.2) carry over to the quantitative model (Section 4). First, the adaptation share a^*/w is hump-shaped in income: zero for the poorest, who do not adapt, and small again for the rich, who are already largely protected. Second, optimal adaptation rises with biological age, $da^*/dd > 0$. Third, and central to our analysis, a mean-preserving spread of the heat distribution—more extreme days at unchanged mean—raises adaptation: since $e^{g\varepsilon^x}$ is convex in ε (reinforced by convex damages, $\chi > 1$), a spread raises expected mortality and hence a^* by Jensen’s inequality. It also raises residual heat mortality $1 - \vartheta$, so both sides of $\frac{a^*}{w} > 1 - \vartheta$ rise and the effect on w^* is ambiguous in general; for our baseline calibration the adaptation response dominates and w^* falls. A hotter, more volatile climate then makes the burden more regressive, consistent with the widening spread of losses across scenarios in Figure 4 below.

The next section embeds these mechanisms in our stochastic life-cycle model with endogenous adaptation, where biological age depends endogenously on health investment, and heat shocks arrive at daily frequency.

4 Stochastic Life-Cycle Model: Daily Heat Shocks and Adaptation

We now extend the one-period reduced-form model to a stochastic life-cycle model, with protective adaptation to heat, endogenous health, and daily heat shocks. Time is discrete, with two indices: the outer index $t \in \{0, \dots, T\}$ counts years and the inner index $\tau \in \{1, \dots, 365\}$ counts days within year t . Agents live for at most $T + 1$ years, with an endogenous expected lifespan.

Utility. In each period t , conditional on survival, the agent’s period utility is CRRA with an additive constant,

$$u(c_t) = \frac{c_t^{1-\sigma} - 1}{1-\sigma} + \bar{u}, \quad (6)$$

where $c_t \geq 0$, $\sigma > 0$ and $\bar{u} \in \mathbb{R}$, with $\sigma = 1$ understood as the limiting case $u(c_t) = \ln c_t + \bar{u}$. The value of death is normalized to zero. As in Hall and Jones (2007), the constant $\bar{u}$ pins down the value of life; we choose it so that the implied value of a statistical life is consistent with empirical estimates (Eichenbaum, Rebelo, & Trabandt,

¹³This is the analytic counterpart of Figures 4 and 6 from the stochastic life-cycle model, where the poor bear the burden through reduced survival (low ϑ) and the rich through forgone consumption (high a^*).

2022). This also ensures that life is worth living, $u(c) > 0$, at the lowest consumption level observed in the simulations, and hence throughout.

Biological aging. We assume that an agent's vulnerability to heat depends, besides adaptation to heat, on her health status. Following Mitnitski, Mogilner, and Rockwood (2001), the health status is conceptualized by the number of health deficits d_t that accumulate over the life-cycle. Accumulated health deficits, synonymous with biological age and measured by the frailty index, predicts mortality far more accurately than chronological age (Mitnitski et al., 2001). Two individuals can be 50 years old in terms of chronological age but may differ substantially in their health conditions. To model the evolution of d_t , we build on Dalgaard and Strulik (2014), who integrate biological age into a neoclassical life-cycle model and introduce health expenditures that slow down biological aging. The law of motion of biological age read as follows (Strulik & Grossmann, 2025):

$$d_{t+1} - d_t = \begin{cases} \mu [d_t - b_2(1 + b_3 d_t)^\alpha h_t^\gamma - b_4], & \text{if } d_t > b_2(1 + b_3 d_t)^\alpha h_t^\gamma + b_4 \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

The case distinction on the RHS formalizes that aging cannot be reversed. The case greater than 0 captures the natural process of health deficit accumulation μd_t with its strength being determined by $\mu \geq 0$. The term including h_t^γ captures, given $b_2 > 0$, that health expenditures h_t can slow down the accumulation of deficits. This mitigation effect of health expenditures on deficit accumulation, given $\gamma \in (0, 1)$, exhibits declining returns. Moreover, health expenditures become more effective at higher (biological) ages, when multiple deficits can be treated simultaneously. Initial health deficits are given by $d_0 \geq 0$.

Daily heat shocks and survival probabilities. The probability s_t of surviving period t , conditional on being alive at the end of period $t - 1$, is described in log notation by

$$\begin{aligned} \ln(s_t) &= \ln \left(\prod_{\tau=1}^{365} e^{-\frac{b_1 d_t^\psi}{365} RR_{t,\tau}} \right) = \ln \left(e^{-\frac{b_1 d_t^\psi}{365} \sum_{\tau=1}^{365} RR_{t,\tau}} \right) \\ &= - \underbrace{\frac{b_1 d_t^\psi}{365}}_{\text{annual baseline hazard}} \cdot \underbrace{\sum_{\tau=1}^{365} RR_{t,\tau}}_{\text{average relative risk}}, \end{aligned} \quad (8)$$

where $\psi > 1$ and $b_1 \geq 0$. The inner time index $\tau \in \{1, \dots, 365\}$ indexes days within year t . The life-cycle model is calibrated at an annual frequency, so that $\{s_t\}$ denote annual conditional survival probabilities. Survival is determined by two components.

First, the annual baseline hazard increases with biological age d_t (Dalgaard & Strulik, 2014). Second, the average relative risk depends on daily relative risk $RR_{t,\tau}$ given by

$$RR_{t,\tau} = e^{g_t \varepsilon_{t,\tau}^\chi}, \quad (9)$$

where $\varepsilon_{t,\tau}$ are daily heat shocks. The $RR_{t,\tau}$ terms capture the effects of daily heat exposure on annual survival at a within-year temporal resolution. The vulnerability to heat exposure in any year t , given by g_t , will be specified as $g_t = b_5 \left(\frac{d_t}{d}\right)^\eta e^{-\kappa a_t}$, where $b_5, \eta, \kappa > 0$. Notice that an individual's vulnerability depends on health (measured by biological age, d_t) and on adaptation expenditures (a_t).

Because heat damages are convex in temperature and temperature varies substantially within a year, we do not rely on annual average temperature: by Jensen's inequality, damages evaluated at the annual mean understate the average damage from daily fluctuations. Temperature-driven mortality risk is in this sense inherently a high-frequency phenomenon. The model therefore has a mixed-frequency structure, with an inner daily index τ and an outer annual index t . This allows us to calibrate to empirical heat-mortality associations, typically estimated at daily frequency to avoid averaging out extremes, without requiring decision variables to be chosen daily, which would be computationally demanding. Each $\varepsilon_{t,\tau}$ is a realization from the intra-annual distribution of daily mean temperatures, assumed time-invariant absent climate change and evolving in moments and tail behavior under it. We consider only damages from warm temperatures, as explained in Section 1: $\varepsilon_{t,\tau}$ is the positive deviation from the minimum mortality temperature, taken as exogenous and detailed in Section 5.2.¹⁴ Cumulative survival up to year t for an agent born in $v = 0$ is $S_t = \prod_{v=0}^t s_v$.

Budget constraint. Agents have access to the capital market. The intertemporal budget constraint is given by

$$w_t + R_{t-1} k_{t-1} = c_t + a_t + h_t + k_t, \quad (10)$$

where $R_{t-1} = (1 + r + m_{t-1})$.¹⁵ The interest rate r is exogenous and constant over time. The wage rate w_t is exogenous and time-varying. It will capture empirically plausible life-cycle income profiles. There is no initial wealth: $k_{-1} = 0$. Agents are subject to a no-Ponzi game condition.

Optimization problem. The agent maximizes expected lifetime utility in the economic environment described above. For expositional clarity, we summarize the full

¹⁴For temperatures below the MMT, no heat-related damage occurs and $\varepsilon_{t,\tau} = 0$.

¹⁵The term $m_{t-1} k_{t-1}$ reflects actuarially fair, zero-profit insurance. While alive, agents receive transfers proportional to mortality risk and wealth; upon death, the insurer confiscates their wealth—unlike standard real-world insurance (Blanchard, 1985).

life-cycle model as a sequential dynamic optimization problem

$$\begin{aligned}
& \max_{\{a_t, h_t, k_t, c_t\} \geq 0} \mathbb{E}_0 \sum_{t=0}^T S_t \beta^t \underbrace{\left(\frac{c_t^{1-\sigma} - 1}{1-\sigma} + \bar{u} \right)}_{\text{annual utility}} \quad \text{s. t.} \\
& \underbrace{S_t}_{\text{cumulative survival}} = \prod_{v=0}^t \prod_{\tau=1}^{365} \exp\left(-\frac{b_1 d_v^\psi}{365} RR_{v,\tau}\right) \\
& \underbrace{d_{v+1} - d_v}_{\text{deficit accumulation}} = \mu [d_v - b_2(1 + b_3 d_v)^\alpha h_v^\gamma - b_4] \\
& \underbrace{RR_{v,\tau}}_{\text{daily relative risk}} = \exp\left(\underbrace{g_v}_{\text{vulnerability}} \underbrace{\varepsilon_\tau^\chi}_{\text{daily heat shocks}} \right) \\
& g_v = b_5 \underbrace{\left(\frac{d_v}{\bar{d}} \right)^\eta}_{\text{health term}} \underbrace{\exp(-\kappa a_v)}_{\text{adaptation term}} \\
& w_t + R_{t-1} k_{t-1} = c_t + a_t + h_t + k_t
\end{aligned} \tag{P1}$$

The discount factor is $\beta \in (0, 1)$. The agent lives for a maximum, exogenously given life span of $T + 1$ years. The expected life span is endogenous and, under the calibration, will be shorter than this upper bound. Notice that costly health expenditures introduce an intertemporal trade-off between consumption and life expectancy. There are four control variables (a_t, h_t, k_t, c_t) and two state variables: the health deficit stock d_t and predetermined capital k_{t-1} . All controls are restricted to be non-negative, so agents cannot borrow, and biological age cannot fall, $d_{t+1} \geq d_t$.¹⁶ Initial conditions are given by the initial health state $d_0 \geq 0$ and no initial wealth, $k_{-1} = 0$. The first-order conditions are provided in Section A.3.

Timing of events. Figure 1 illustrates the timing of events. At the beginning of each period, the agent receives labor income w_t and gross returns $(1 + r + m_{t-1})k_{t-1}$, where $m_{t-1} = 1 - s_{t-1}$, and chooses adaptation a_t , health expenditures h_t , and savings k_t (i.e. the purchase of one-period bonds). These choices determine consumption c_t , and hence utility $u(c_t)$, at the end of the period. Daily heat shocks $\varepsilon_{t,\tau}$ materialize within year t and determine the probability of surviving to the end of the period, consistent with $S_t = S_{t-1}s_t$ in (P1). Health expenditures affect biological age—a stock—and thus survival in all subsequent periods, whereas adaptation—a flow— reduces heat vulnerability only in the current period. All choices are forward-looking and depend on

¹⁶Only the constraint on k_t may bind, and only in some periods of the life-cycle. It prevents implausibly high debt when survival becomes unlikely, at the cost of ruling out borrowing at early ages (cf. also Böhm, Grossmann, & Strulik, 2021; De Nardi, French, & Jones, 2010). The restriction on biological age never binds in our parameter space.

expectations over the intra-annual distribution of daily temperatures, which is held fixed over the life-cycle within a given scenario but is shifted across scenarios. The shifted distribution in $t + 1$ illustrates that the probability distribution of daily heat shocks evolves over time due to climate change.

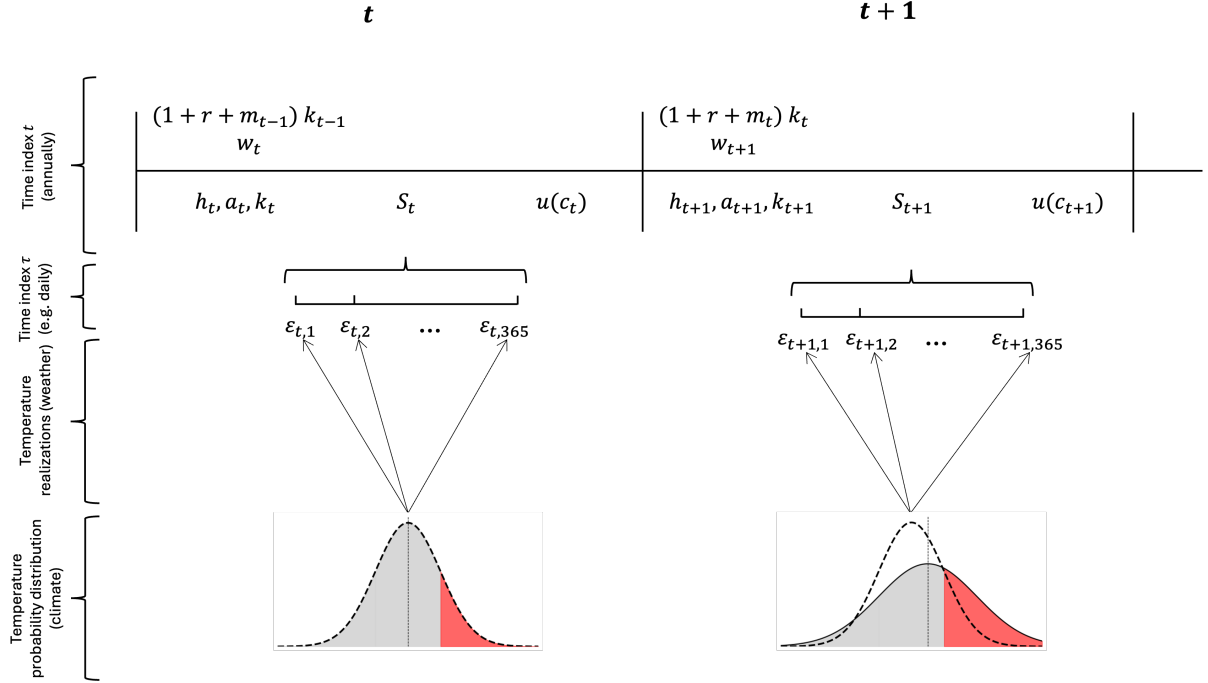


Figure 1: Timing of events

Notes. Qualitative illustration of the timing of events in the dynamic model. The upper two rows show the timing along the two time dimensions, years t and days τ . The lower two rows show that high-frequency temperature realizations are drawn from an intra-annual daily-mean temperature probability distribution, which represents climate in the model. The distribution may change over time: in the experiments below it differs across climate scenarios but remains stable within a given scenario.

5 Quantitative Implementation

This section brings the model to the data. We describe the numerical solution strategy, the exogenous income and temperature inputs that drive the experiments, and the calibration to U.S. data.

5.1 Solution Strategy

Two structural characteristics of the model make the numerical solution particularly tractable. First, daily heat shocks affect expected lifetime utility exclusively through survival probabilities and do not enter the laws of motion of the state variables (k_t, d_t) . Second, individual choices are made prior to the realization of daily heat shocks.

As a result, conditional on survival, the evolution of state variables is deterministic. Stochastic temperature therefore does not induce a branching tree of future histories over conditional state histories.¹⁷

The expected cumulative survival probability is computed by employing the probability distributions of positive deviations above the minimum mortality temperature (MMT), as explained in Appendix A.6:

$$\begin{aligned}\mathbb{E}_t(S_t) &= S_{t-1} \mathbb{E}_t(s_t) \\ &= S_{t-1} \left(\mathbb{E}_t \left(\exp \left(-b_1 d_t^\psi \frac{1}{365} \exp(g_t(a_t, d_t) \varepsilon_\tau^\chi) \right) \right) \right)^{365} \\ &= S_{t-1} \left(\sum_{n=1}^N \pi_n \exp \left(-b_1 d_t^\psi \frac{1}{365} \exp(g_t(a_t, d_t) x_n^\chi) \right) \right)^{365}\end{aligned}\tag{11}$$

with $\mathbb{P}(\varepsilon_{v,\tau} = x_n) = \pi_n$, $\vec{x} = (x_1, \dots, x_N)$, $\vec{\pi} = (\pi_1, \dots, \pi_N)$, where $n = 1, \dots, N$. The vectors $\vec{x}$ and $\vec{\pi}$ represent climate (temperature) scenarios, namely the discrete probability distribution of exceeding the MMT by x_n degrees in one-degree bins. We generate these distributions from climate scenario simulations (SP1-2.6, SSP2- 4.5, SSP3-7.0, and SSP5-8), as explained in greater detail in Section A.6.¹⁸

Notice that we do not replace $\varepsilon_{t,\tau}$ by $\mathbb{E}_0(\varepsilon_{t,\tau})$ in the objective function. This would result in the corresponding certainty-equivalent problem. But it would also ignore two important nonlinearities. First, the nonlinear dependence of the daily relative risk $e^{g_v \varepsilon_{v,\tau}^\chi}$ on heat exposure $\varepsilon_{v,\tau}^\chi$. Second, the convex dependence of heat exposure $\varepsilon_{v,\tau}^\chi$ on heat shocks $\varepsilon_{v,\tau}$.

Once the expected annual survival probabilities are computed, optimal policies can be determined by solving an appropriately formulated deterministic problem (cf. also Blanchard, 1985, p. 226). The Lagrangian of (P1) and the associated system of FOC can be found in A.3. We solve for the optimal policies that fulfill the system of FOCs by applying the relaxation algorithm (Trimborn, Koch, & Steger, 2008). The numerical solution procedure is implemented in Python and available upon request.

¹⁷Most of the literature on stochastic life-cycle models employs a recursive approach to solve these models (De Nardi et al., 2010; Scholz, Seshadri, & Khitatrakun, 2006), since uncertainty enters the laws of motion of state variables.

¹⁸We simplify by assuming that draws from these distributions are i.i.d. Alternatively, one could model daily temperature as an autoregressive process, which would result in additional complexity in the computation of expectation without adding much additional insights as the consecutive effect of heat days is rather small (Gasparrini & Armstrong, 2011).

5.2 Experimental Setup

The wage income per decile and the intra-annual daily mean temperature distribution are exogenous to the model. For the wage income per decile, we use US life-cycle wage income profiles as described in Appendix A.5. The probability distribution of intra-annual daily mean temperatures that generates the daily heat shocks $\varepsilon_{t,\tau}$ is constructed from the Coupled Model Intercomparison Project Phase 6 (CMIP6). These distributions provide a high-frequency representation of global warming, with the right-hand tail being of particular interest, as it captures the probability of extreme heat days. Appendix A.6 details how the temperature probability distributions are derived from CMIP6.

These shock distributions constitute the exogenous source of variation in our main experiment. We compare a moderate-climate benchmark to climate scenarios associated with higher greenhouse-gas concentrations and radiative forcing, which exhibit more frequent and more intense heat periods, that is, increases on both the extensive and intensive margins. Since heat damages are convex and intra-annual temperature variation is substantial, we use daily rather than annual average temperatures, as discussed above.

A moderate climate is represented by climate-model simulations associated with SSP1-2.6, for which the intra-annual daily mean temperature probability distribution remains approximately stationary over time. A hot climate is represented by the late-century (2096–2100) intra-annual daily mean temperature probability distribution associated with SSP5-8.5. The left-hand panel of Figure 2 illustrates the evolution of the temperature distribution over time.

The analysis is restricted to the effects of warm temperatures, excluding cold temperatures. Accordingly, we extract the portion of the temperature probability distribution lying above the MMT for the USA. Resulting heat distributions associated with SSP1-2.6 and SSP5-8.5 are illustrated in the right-hand panel of Figure 2. The quantitative analysis further includes the intermediate scenarios SSP2-4.5 and SSP3-7.0. Holding wage income fixed, we compute equilibrium life-cycle trajectories under both heat distributions to identify the consequences of a shift in the probability distribution of daily heat shocks on our outcome variables (expected lifetime and LTU) driven by climate change.

5.3 Calibration

As in Strulik and Grossmann (2025), agents enter the model at $t = 0$ with a chronological age of 20 years, where t denotes model time and chronological age is given by $t + 20$. We calibrate the model in several steps. First, we fix a set of parameters determined outside the calibration procedure. Second, we estimate the remaining pa-

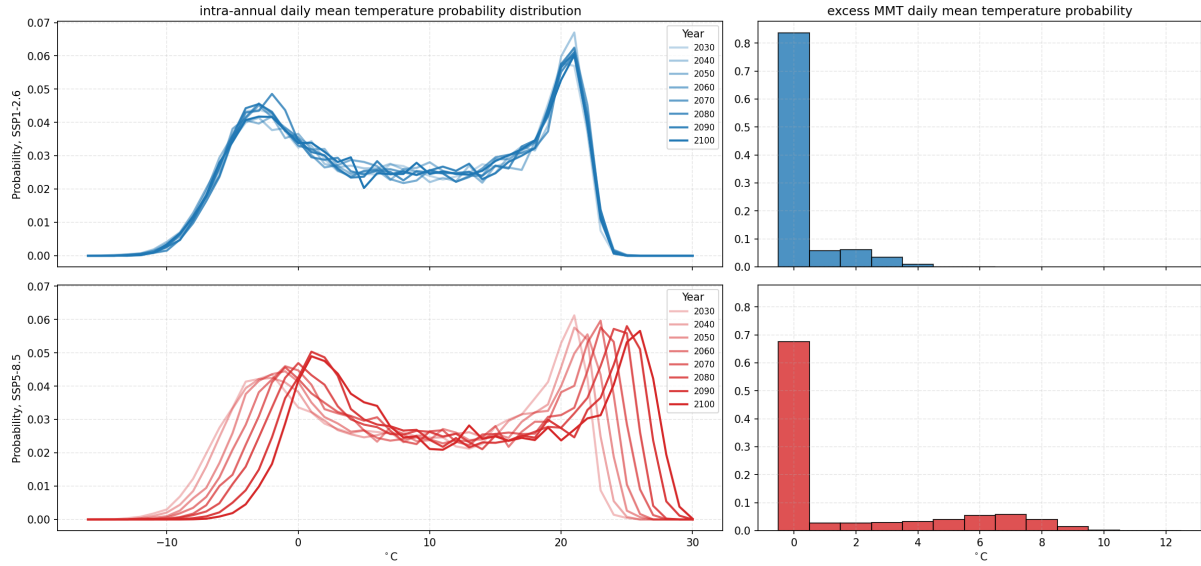


Figure 2: Daily mean temperatures and climate change

Notes. Left panel: intra-annual daily-mean temperature probability distributions for the USA associated with SSP1-2.6 and SSP5-8.5, shown evolving over time in ten-year increments and derived from the MPI-ESM1-2-LR climate model. The experiments below use late-century (2096–2100) daily heat-shock distributions. Right panel: binned probability distribution of exceeding the MMT in year 2100.

rameters using the Simulated Method of Moments (SMM). We target life expectancies across income groups, health expenditures, and accumulated deficits for the average agent, as well as the relative mortality risk as a function of income, age, and health expenditures, given U.S. income and temperature data. A detailed description of all calibration steps, a complete list of calibration targets, and the estimated parameters are provided in Appendix A.7.

6 Quantitative Results

How large are the life-expectancy and welfare losses from heat-induced mortality, and who bears them? We first report the outcomes, then identify the underlying mechanisms.

6.1 Outcomes

We compute life-expectancy and welfare losses, conditional on income and allowing for adaptation, under the higher-emissions scenarios SSP2-4.5, SSP3-7.0, and SSP5-8.5 relative to a low-emissions SSP1-2.6 benchmark.¹⁹

¹⁹For brevity, we index scenarios in the formulas by the numerical suffix of the SSP label: for example, SSP1-2.6 is denoted by 2.6, and 8.5 denotes SSP5-8.5.

Life expectancy. Figure 3 shows the life-expectancy losses. Under SSP5-8.5, the average agent loses about 0.07 years of life expectancy, and the loss falls with income: 0.26 years for the poorest decile against 0.04 years for the richest. These magnitudes are of the same order as those in the climate-demographic literature, e.g. [Hauer and Santos-Lozada \(2021\)](#), who compute changes in life expectancy due to extreme weather events based on disaster databases. Milder scenarios imply smaller and less regressive losses, a pattern that recurs in the welfare results below. The life-expectancy losses may look modest, but the welfare losses are substantial, since survival is only one of the two channels through which heat operates.

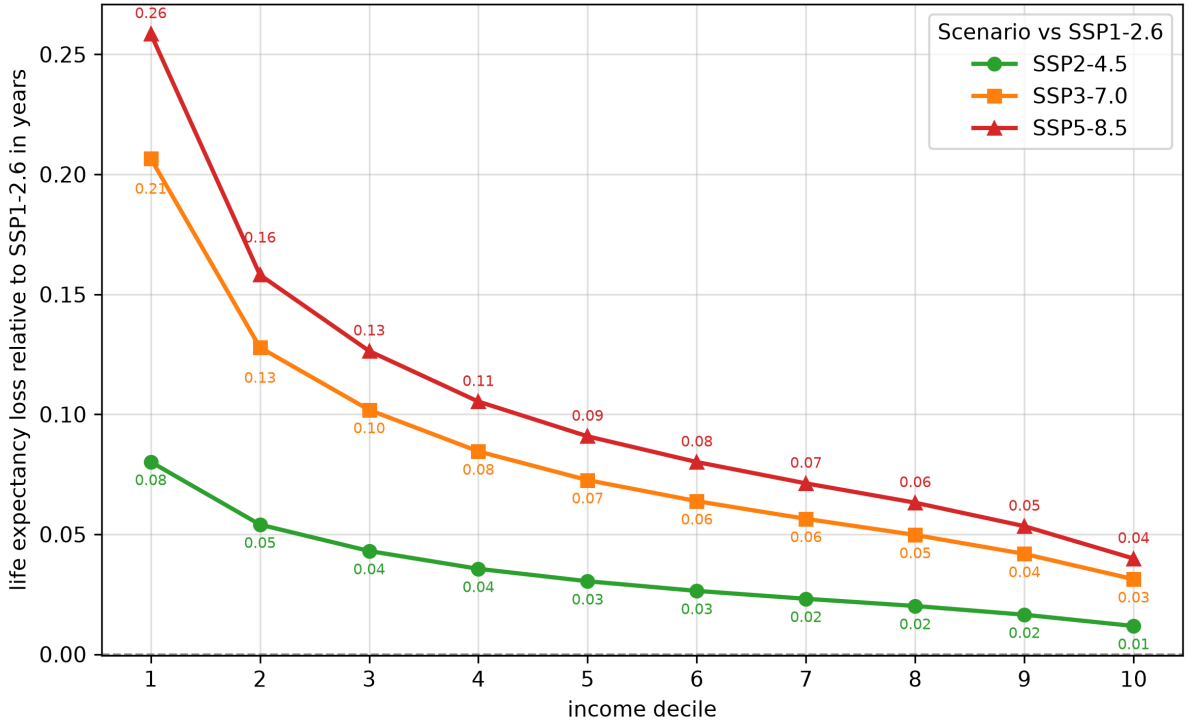


Figure 3: Life expectancy losses of additional heat

Notes. Life-expectancy losses, measured in years relative to the SSP1-2.6 benchmark, for intra-annual temperature probability distributions associated with high- (red, triangle markers), medium- (orange, square markers), and low-emissions scenarios (green, dotted), by income decile. Larger values indicate a lower life expectancy.

Welfare. How do losses in expected lifetime utility vary with income? We address this question by computing the consumption-equivalent variation (CEV) from:

$$\mathbb{E}_0 \left[\sum_{t=0}^T \beta^t S_t^{2.6} u((1-\lambda)c_t^{2.6}) \right] = \mathbb{E}_0 \left[\sum_{t=0}^T \beta^t S_t^Z u(c_t^Z) \right]. \quad (12)$$

The CEV (λ) indicates the permanent proportional change in the SSP1-2.6 benchmark consumption stream required to equalize expected lifetime utility across heat

scenarios $Z \in \{4.5, 7.0, 8.5\}$. Since welfare is lower under high temperatures, $\lambda > 0$.

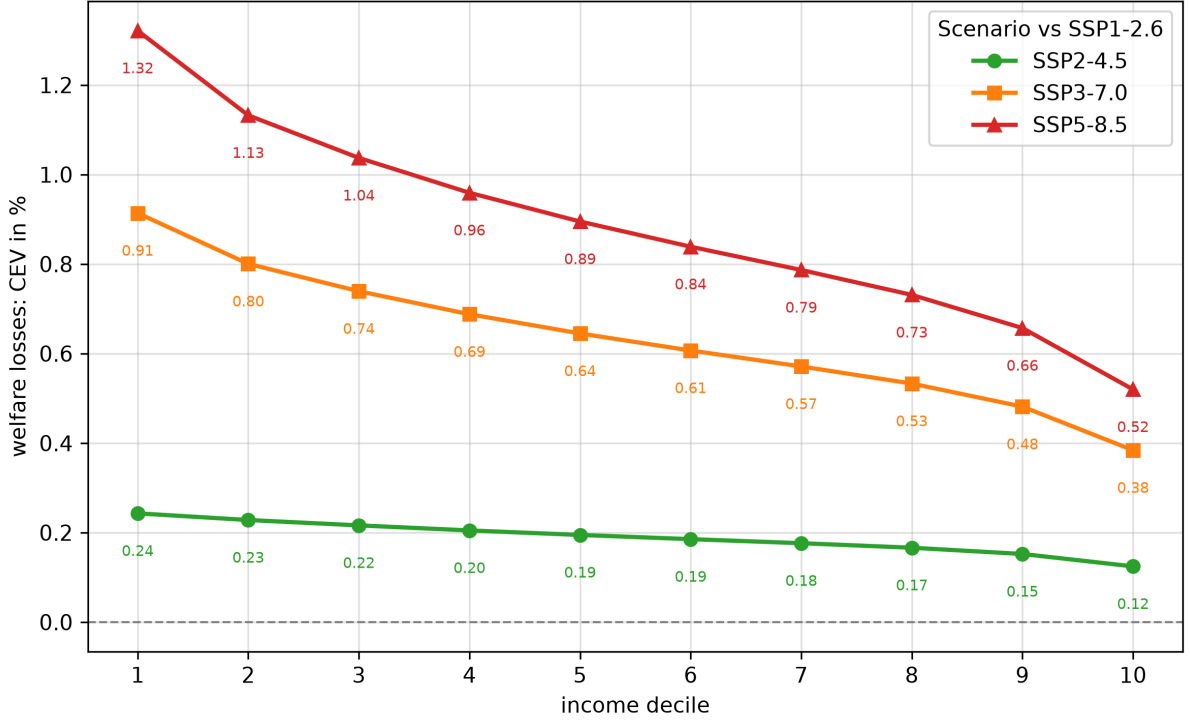


Figure 4: Welfare losses of additional heat

Notes. Welfare losses relative to the SSP1-2.6 benchmark, expressed as $\lambda \times 100$, for intra-annual temperature probability distributions associated with high- (red, triangle markers), medium- (orange, square markers), and low-emissions scenarios (green, dotted), by income decile. Larger values indicate larger welfare costs.

Figure 4 summarizes the results by showing the CEV for each income decile. Higher emissions climate scenarios (SSP2-4.5, SSP3-7.0, SSP5-8.5) generate welfare losses for all agents. The average agent loses about 0.80%. However, the magnitude of these losses differs markedly along the income distribution. While the lowest-income agent experiences a welfare loss of approximately 1.32%, the highest-income agent loses only about 0.52%. The welfare burden associated with rising heat-induced mortality risk is clearly regressive, driven by differences in protective capacity—both adaptation and health investment—across income groups.

Age- j -conditional welfare. Given that the welfare costs of heat-induced mortality increase substantially over the life-cycle, discounting period utility obscures somewhat the welfare effects beyond a chronological age of, say, 50 years. To make this pattern visible, we turn to the age- j -conditional expected lifetime utility, as opposed to the ex ante welfare of a 20-year-old individual at $j = 0$. To this end, we compute expected lifetime utility at each age j over the remaining lifetime (continuation value) of the agent as follows:

$$\mathbb{E}_j \left[\sum_{t=j}^T \beta^{t-j} \frac{S_t^{2.6}}{S_j^{2.6}} u((1 - \lambda_j) c_t^{2.6}) \right] = \mathbb{E}_j \left[\sum_{t=j}^T \beta^{t-j} \frac{S_t^Z}{S_j^Z} u(c_t^Z) \right]. \quad (13)$$

The CEV multiplier λ_j can be computed at each age j . Technically, the welfare results shown in Figure 4 represent λ_0 . By evaluating (13) at each age j , we can trace how welfare losses are distributed throughout the life-cycle. Figure 5 shows that the welfare burden increases over large parts of the life-cycle, driven by three mechanisms: i) higher vulnerability at advanced biological ages, ii) lower consumption due to rising adaptation expenditures, iii) poorer health status due to adaptation increasingly crowding out health investment. This measure indicates that the regressivity of the welfare effects of heat intensifies over the life-cycle. For example, conditional on survival to age 50 rather than measured at age 20, losses are substantially larger and more dispersed, ranging from 6.65% for the poorest decile to 1.11% for the richest.

Moreover, Figure 5 shows that welfare losses after age 50 are not necessarily monotonic in j but may instead exhibit a hump-shaped pattern, declining later in the life-cycle. Two forces counteract. Vulnerability rises with biological age, which raises the per-year loss. But λ_j captures all remaining years of life. As remaining life expectancy shortens, smaller continuation value losses might dominate losses from higher vulnerability. Which force dominates depends on income and heat exposure.

Taken together, the three measures point the same way: heat-induced mortality reduces welfare for every income group, and the burden falls disproportionately on the poor and on the old. The life-expectancy losses may appear modest in absolute terms while the welfare losses of this single damage channel are substantial, because survival is only one of the two channels through which heat operates; the other is consumption forgone to protection. The next subsection separates the two and then asks what generates the income gradient in the first place.

6.2 Mechanisms

Survival and consumption. Which mechanisms shape the welfare effects across income groups? Equation (12) indicates that two channels affect expected lifetime utility: changes in consumption and changes in survival probabilities. To disentangle these two channels, we compute specific CEV measures, denoted by λ_S and λ_c . The CEV λ_S isolates the survival effect induced by more heat exposure, while holding consumption fixed at the low-emissions benchmark (at $c_t^{2.6}$):

$$\mathbb{E}_0 \left[\sum_{t=0}^T \beta^t S_t^{2.6} u((1 - \lambda_S) c_t^{2.6}) \right] = \mathbb{E}_0 \left[\sum_{t=0}^T \beta^t S_t^Z u(c_t^{2.6}) \right]. \quad (14)$$

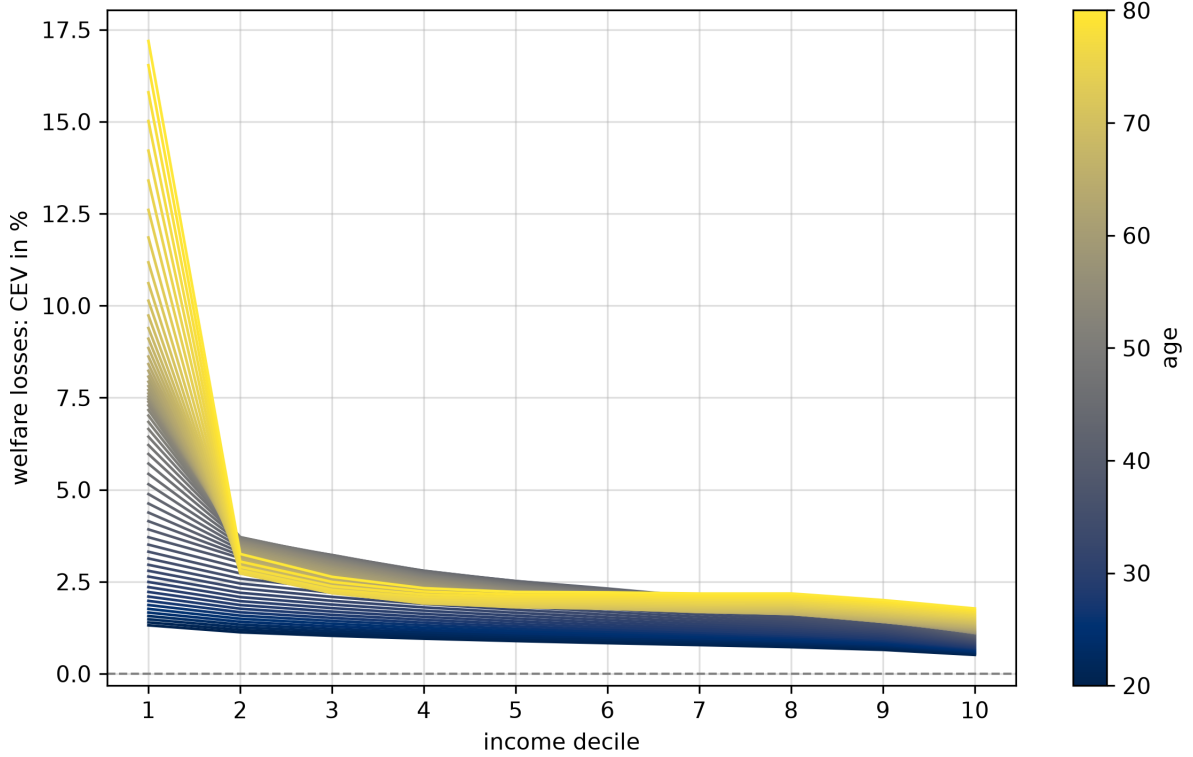


Figure 5: Age- j -conditional welfare of additional heat

Notes. Expected utility loss over the remaining lifetime, expressed in CEV $\lambda_j \times 100$, conditional on being alive at chronological age j , for each income decile under the SSP5-8.5 heat distribution. The lowest (darkest) line, representing chronological age 20 (model age 0), corresponds to the red line with triangle markers in Figure 4.

Analogously, λ_c isolates the consumption effect induced by more heat exposure, while holding survival probabilities fixed at the low-emissions benchmark (at $S_t^{2.6}$):

$$\mathbb{E}_0 \left[\sum_{t=0}^T \beta^t S_t^{2.6} u \left((1 - \lambda_c) c_t^{2.6} \right) \right] = \mathbb{E}_0 \left[\sum_{t=0}^T \beta^t S_t^{2.6} u \left(c_t^Z \right) \right]. \quad (15)$$

The result of this decomposition is displayed in Figure 6. The figure shows that welfare losses among low-income agents are driven primarily by the survival channel. The reason is that heat vulnerability depends on biological age d_t and adaptation a_t . Income shapes both: low-income agents spend less on health and adaptation, so they accumulate more health deficits and remain less protected against heat. Their survival losses are therefore larger, which is the force pushing the welfare burden toward the poor. Richer agents, who can afford protection, bear relatively more of the burden through forgone consumption.²⁰

²⁰This decomposition is incomplete. The interaction effect is, however, so small that the bars in Figure 6 almost add up to the numbers shown in Figure 4.

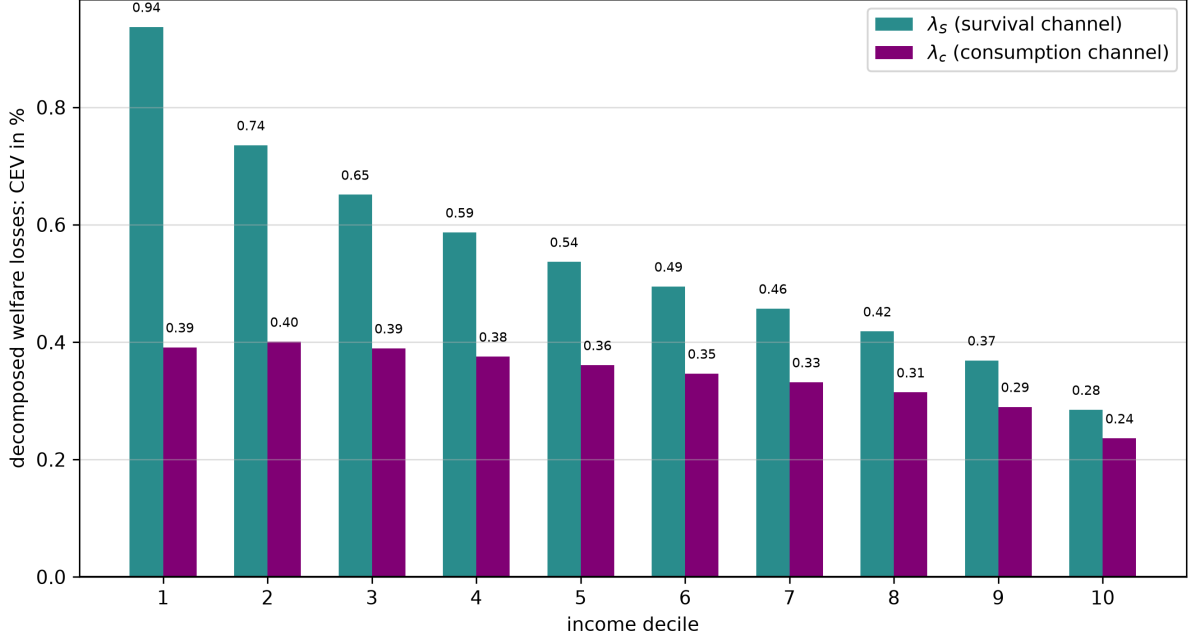


Figure 6: Decomposition

Notes. Decomposition of welfare losses under the SSP5-8.5 temperature distribution into mortality impacts (survival channel; teal bars) and forgone consumption (consumption channel; purple bars), expressed in CEV $\lambda_s \times 100$ and $\lambda_c \times 100$, by income decile. The survival channel decreases monotonically along the income distribution, while the consumption channel follows a hump-shaped pattern.

Adaptation. To see the differential effect of adaptation, we assume that adaptation is ineffective ($\kappa = 0$), holding all other parameters fixed to ensure comparability. The behavioral consequence is, of course, that agents do not engage in adaptation. Panel B in Figure A.4 shows that, absent adaptation, life-expectancy losses are larger and rise with heat, but their regressivity nearly vanishes, driven only by the biological-age gradient across income levels. Adaptation therefore accounts for essentially all of the income gradient in mortality damages: under the SSP5-8.5 heat distribution, it averts about 0.64 years of life expectancy for the poorest decile (from roughly 0.90 to 0.26 years) but about 0.78 years for the richest (from roughly 0.82 to 0.04 years). Because protection rises so steeply with income, it turns an almost income-neutral welfare burden into a markedly regressive one.

The same pattern holds for welfare. Panel A in Figure A.4 illustrates the welfare analysis in the absence of adaptation. Overall welfare losses of additional heat are larger, but the distributional consequence switches from regressive to slightly hump-shaped. High-income agents are still less vulnerable to heat due to their lower biological age, but welfare losses are mildly progressive along the bottom 30% of the income distribution.

Climate denial. So far, we have assumed rational expectations, implying optimal adaptation. We now allow for climate denial to capture the role of (irrational) expectations. We again compute a CEV, denoted by λ^* , which measures the welfare loss when agents face greater heat exposure but continue to form expectations based on the baseline scenario (SSP1-2.6). Agents do not re-optimize their behavior in response to a shifted temperature probability distribution. Instead, they continue to believe in the baseline temperature distribution while being exposed to greater heat in the higher-emissions scenarios. Specifically, λ^* is calculated from:

$$\mathbb{E}_0 \left[\sum_{t=0}^T \beta^t S_t^{2.6} u \left((1 - \lambda^*) c_t^{2.6} \right) \right] = \mathbb{E}_0 \left[\sum_{t=0}^T \beta^t S_t(a_t^{2.6}, h_t^{2.6}, \varepsilon^{8.5}) u \left(c_t^{2.6} \right) \right]. \quad (16)$$

Figure 7 shows that all agents are worse off under irrational expectations compared to rational expectations, which is intuitive. In this experiment, welfare losses arise solely from the survival channel, as no consumption is forgone for additional adaptation. In absolute terms, the welfare losses are relatively similar across income levels, with the difference in CEV ranging from 0.5% to 0.8%. Interestingly, however, richer agents are proportionally more strongly affected by climate denial: the loss of the highest income decile increases by 120%, compared with roughly 40% for the poorest income decile. Thus, climate denial exhibits a progressive incidence in terms of relative welfare losses.

7 Conclusion

We developed a stochastic life-cycle model to quantify the effects of heat-induced mortality along the income distribution. The framework combines uncertain death, endogenous biological aging through health-deficit accumulation, and costly private adaptation, and features a mixed-frequency structure in which agents choose annually while heat exposure operates at a daily frequency. This structure preserves the nonlinear, upper-tail nature of heat damages that annual averages would obscure, and can be applied more broadly to intensive-margin extreme events.

Comparing the daily heat-shock distribution associated with SSP5-8.5 to the SSP1-2.6 benchmark, we find substantial and regressive losses in both life expectancy and lifetime welfare. The average agent loses about 0.07 years of life expectancy, with the poorest decile losing 0.26 years. In welfare terms, the average agent loses about 0.80% in consumption-equivalent terms, ranging from 1.32% for the poorest decile to 0.52% for the richest. Shutting down adaptation raises both losses considerably and renders them almost flat in income, so that the income gradient is generated essentially by

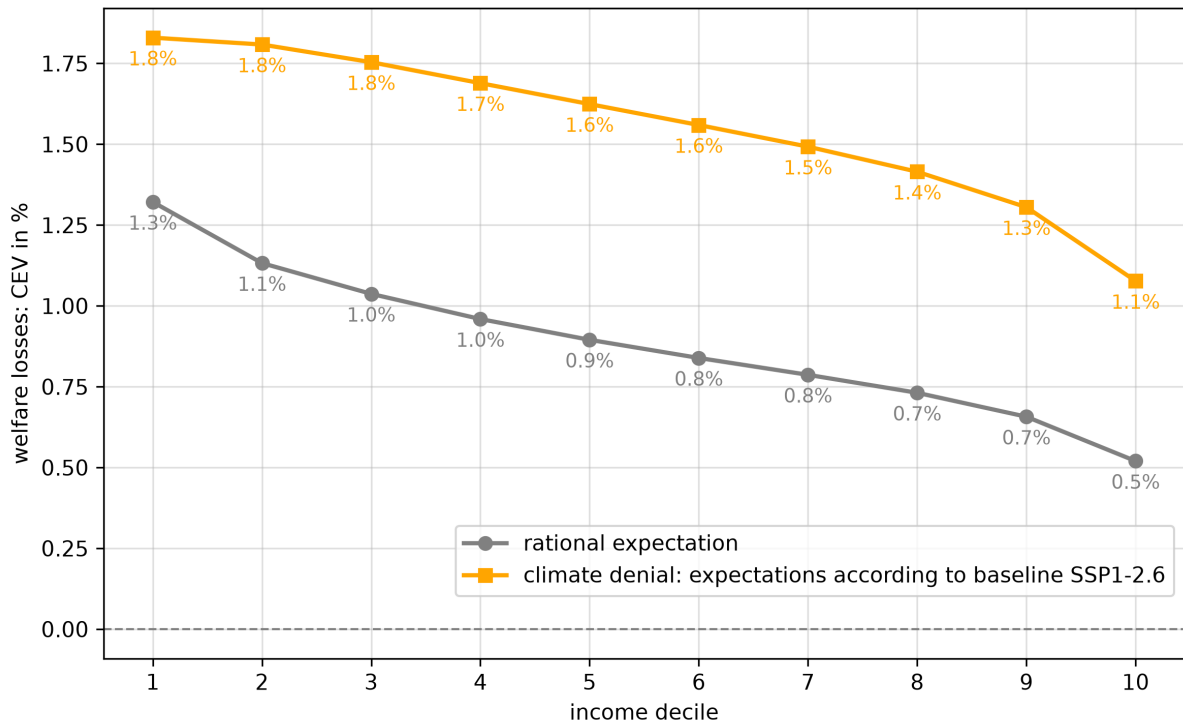


Figure 7: Burden of disbelief in climate change

Notes. The optimized SSP5-8.5 scenario (gray, dotted) from Figure 4 is compared with welfare costs under the SSP5-8.5 temperature distribution when agents do not re-optimize life-cycle policies (orange, square markers), expressed in CEV $\lambda \times 100$ and $\lambda^* \times 100$. The ratio of welfare costs is larger for higher income deciles.

differential adaptation rather than by differences in health status. Decomposing the welfare effect, poorer agents lose primarily through reduced survival, as they devote fewer resources to health expenditure and adaptation, whereas richer agents bear the burden relatively more as forgone consumption. The regressivity intensifies over the life-cycle: conditional on survival to age 50 rather than measured at age 20, losses are considerably larger and more dispersed, ranging from 6.65% for the poorest decile to 1.11% for the richest. Climate denial hurts high-income agents relatively more, because they forgo protection they could easily afford.

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A Appendix

A.1 Stylized Model

This appendix collects the derivations for the stylized model of Section 1. The agent lives at most one period, consumes $c = w > 1$ under $u(c) = \ln c$ with $u(\text{death}) = 0$, and faces mortality risk m . Expected utility is $V(w) = (1 - m) \ln w$.

Two welfare measures. The utility loss from introducing the risk is

$$\Lambda(w) \equiv u(w) - V(w) = m \ln w. \quad (17)$$

The consumption equivalent λ solves $u((1 - \lambda)w) = V(w)$, i.e. $\ln(1 - \lambda) = -\Lambda(w)$, so

$$\lambda = 1 - e^{-\Lambda(w)} = 1 - w^{-m} \in (0, 1). \quad (18)$$

The two measures carry the same information: Λ states the loss in utils, λ rescales it to an income share. Because $x \mapsto 1 - e^{-x}$ is strictly increasing,

$$\text{sgn}\left(\frac{d\lambda}{dw}\right) = \text{sgn}\left(\Lambda'(w)\right), \quad (19)$$

and the incidence can be read off the simpler object Λ . We call the burden *progressive* if λ rises with w and *regressive* if it falls; since λ is already an income share, this is the usual incidence convention.

A general criterion. Let mortality depend on income, $m = m(w)$, and define the income elasticities of the value of a statistical life and of mortality risk,

$$\varepsilon_{\text{VSL}}(w) \equiv \frac{d \ln \text{VSL}(w)}{d \ln w}, \quad \text{VSL}(w) \equiv \frac{u(w)}{u'(w)}, \quad \varepsilon_m(w) \equiv -\frac{w m'(w)}{m(w)} > 0, \quad (20)$$

so that ε_m measures the strength of protection: a one percent higher income buys an ε_m percent lower risk. For any increasing u with $u(\text{death}) = 0$, a first-order expansion of $u((1 - \lambda)w) = (1 - m(w))u(w)$ gives

$$\lambda(w) \approx \frac{m(w)}{w} \text{VSL}(w), \quad (21)$$

hence $d \ln \lambda / d \ln w = \varepsilon_{\text{VSL}}(w) - 1 - \varepsilon_m(w)$ and

$$\text{the burden is regressive} \iff \varepsilon_m(w) > \varepsilon_{\text{VSL}}(w) - 1. \quad (22)$$

Both forces of Section 1 are special cases of (22): the utility scale operates through ε_{VSL} , protection through ε_m .

Benchmark: exogenous mortality is progressive by construction. With m constant, $\varepsilon_m = 0$ and (22) states that exogenous mortality is progressive iff $\varepsilon_{\text{VSL}}(w) > 1$. Log utility with the value of death set to zero delivers $\text{VSL}(w) = w \ln w$ and

$$\varepsilon_{\text{VSL}}(w) = 1 + \frac{1}{\ln w} > 1, \quad (23)$$

consistent with $\Lambda'(w) = m/w > 0$ from (17) and $\partial \lambda / \partial w = m w^{-m-1} > 0$ from (18). The homothetic CRRA case $u(c) = c^{1-\gamma}/(1-\gamma)$ with $\gamma < 1$ and death at zero gives $\text{VSL}(w) = w/(1-\gamma)$, $\varepsilon_{\text{VSL}} = 1$, and a λ independent of income. Progressivity in the benchmark is therefore a property of the preference specification, not a general law, and we do not read it as a result. The restriction $w > 1$ ensures $u(w) = \ln w > 0$, i.e. that life is worth living; below it (17) is negative and the exercise degenerate.

Endogenous mortality can reverse the sign. Let $m'(w) < 0$. From (17),

$$\Lambda'(w) = \underbrace{\frac{m(w)}{w}}_{\text{utility scale}} + \underbrace{m'(w) \ln w}_{\text{protection}}, \quad (24)$$

and the burden is regressive iff

$$\varepsilon_m(w) > \frac{1}{\ln w}, \quad (25)$$

which is (22) evaluated at $\varepsilon_{\text{VSL}} = 1 + 1/\ln w$; under log utility the condition is exact rather than a first-order approximation. If ε_m is non-decreasing and bounded away from zero, the left side of (25) rises and the right side falls in w , so a unique threshold $w^* > 1$ separates a progressive region ($w < w^*$) from a regressive one ($w > w^*$). For the constant-elasticity case $m(w) = \bar{m} w^{-\alpha}$ with $\alpha > 0$ we have $\varepsilon_m = \alpha$ and $\Lambda'(w) = \bar{m} w^{-\alpha-1}(1 - \alpha \ln w)$, so

$$w^* = e^{1/\alpha}. \quad (26)$$

Stronger adaptation gradients (higher α) push w^* down and widen the regressive region.

Two caveats. First, w^* is not invariant to the normalization of the utility of death. Under $u(c) = b + \ln c$ the subsistence point moves to $w = e^{-b}$, $\varepsilon_{\text{VSL}} = 1 + 1/(b + \ln w)$, and $w^* = e^{1/(\alpha-b)}$: the qualitative pattern—progressive below a threshold, regressive above—survives, but the threshold is pinned down only jointly with b . Quantitative statements about where an economy sits relative to w^* therefore require the life-cycle model of Section 4, where the flow value of life is calibrated rather than normalised. Second, $m(w)$ is a reduced form: the resource cost of adaptation is suppressed, so consumption remains w . Making that cost explicit adds a third, negative term to (24) through the consumption of the protected, which the life-cycle model accounts for.

A.2 Reduced-form Model

This appendix collects the derivations for the reduced-form model of Section 3.2. Throughout, take the shock deterministic at $\bar{\varepsilon}$ and write $\rho \equiv g\bar{\varepsilon}^\chi$ for the log relative risk, $H_0 \equiv b_1 d^\psi$ for the hazard without heat, and $H_1 \equiv H_0 e^\rho$ for the hazard with heat, so that $\vartheta = e^{-(H_1-H_0)}$.²¹

²¹With the binary shock, $\vartheta = 1 - \omega + \omega e^{-(H_1-H_0)}$, so $1 - \vartheta$ is expected heat mortality and the first two terms of (5)—which follow from the envelope theorem and the budget constraint alone—are unchanged. Only the biological-age coefficient differs: ϑ is replaced by $\omega e^{-(H_1-H_0)} < \vartheta$, which scales the term down but leaves every sign intact.

First-order condition. Since $\ln \vartheta = -H_0(e^\rho - 1)$ and $\partial_a \rho = -\kappa \rho$,

$$\partial_a \ln \vartheta = -H_0 e^\rho \partial_a \rho = \kappa \rho H_1. \quad (27)$$

The interior condition for (3), $\vartheta_a u(c^*) = \vartheta u'(c^*)$ with $u'(c) = 1/c$, gives the sufficient statistic

$$\kappa \rho^* H_1^* c^* u(c^*) = 1. \quad (28)$$

At low income the marginal cost $u'(w) = 1/w$ exceeds the marginal benefit $\kappa \rho H_1 u(w)$ evaluated at $a = 0$, so no interior solution exists and $a^* = 0$: the poorest are at a corner, where (28) holds as a strict inequality.²²

Envelope and the incidence condition. Differentiating $\Phi(w) = \max_a \vartheta(a, d(w)) u(w - a)$ and applying the envelope theorem,

$$\Phi'(w) = \vartheta u'(c^*) + \vartheta_d d'(w) u(c^*). \quad (29)$$

For the first term, $w = c^* + a^*$ gives

$$w [u'(w) - \vartheta u'(c^*)] = 1 - \vartheta \frac{w}{c^*} = (1 - \vartheta) - \vartheta \frac{a^*}{c^*}, \quad (30)$$

which uses only the budget constraint and therefore holds at the corner as well. For the second term, $\partial_d \ln \vartheta = -\frac{1}{d} [\psi(H_1 - H_0) + \eta \rho H_1]$ and $d'(w) = -\nu d/w$ give the biological-age channel. Substituting both into $\Lambda'(w) = u'(w) - \Phi'(w)$ and multiplying by w yields (5), which is exact and valid at every w .

A collapsed condition. Daily heat mortality is small, so $H_1 - H_0 = H_0(e^\rho - 1) \approx \rho H_0 \approx \rho H_1$, the bracket in (5) reduces to $(\psi + \eta)(H_1 - H_0)$, and $1 - \vartheta \approx H_1 - H_0$. Dividing (5) by $1 - \vartheta$ and setting $\vartheta \approx 1$, $c^* \approx w$, heat is regressive at w iff

$$\frac{a^*/w}{1 - \vartheta} + \nu u(w) (\psi + \eta) > 1. \quad (31)$$

Both protective forces are now expressed relative to the mortality they act on. At $\nu = 0$ this is exactly $\frac{a^*}{w} > 1 - \vartheta$; at the corner $a^* = 0$ it states that heat is progressive at the bottom iff $\nu u(w)(\psi + \eta) < 1$, replacing the informal requirement that ν be small by a checkable threshold. With the exponents of Table A2 and Table A3, $\psi + \eta \approx 3.87$, so progressivity at the bottom requires $\nu u(w) \lesssim 0.26$.

²²At an interior optimum, (28) allows $u'(c^*)$ to be replaced by $\kappa \rho H_1 u(c^*)$, so that the adaptation channel can equivalently be written as the marginal hazard reduction $\kappa \rho H_1$ rather than as an income share. The two forms coincide wherever adaptation is interior; (5) is the more useful one, since it remains valid at the corner.

Corner, threshold, and uniqueness. At $a^* = 0$ the adaptation term in (5) is identically zero and $w\Lambda'(w) = (1 - \vartheta) - \nu\vartheta u(w)[\psi(H_1 - H_0) + \eta\rho H_1]$, positive under the condition just stated: heat is progressive at the bottom. Because $a^*(w)$ is continuous, so are c^* , ϑ , and Λ' ; the adaptation channel therefore switches on continuously—with a kink, not a jump—at the income where (28) first holds with equality.

Setting $\nu = 0$ to isolate the adaptation channel, heat is regressive at w iff

$$\frac{a^*(w)}{w} > 1 - \vartheta(a^*(w), d). \quad (32)$$

The right-hand side falls with income, since richer agents are better adapted—and, once $\nu > 0$ is restored, biologically younger as well. A unique threshold w^* therefore exists whenever the adaptation share a^*/w is non-decreasing over the relevant range. This sufficient condition is not global: a^*/w is hump-shaped, so at high incomes both sides of (32) decline and single crossing requires residual heat mortality to fall faster than the adaptation share. This holds at the parameter values implied by our quantitative calibration, but we do not claim it in general.

Mean-preserving spread. Adaptation responds to expected conditional heat-induced mortality $\mathbb{E}\phi(\varepsilon)$, where $\phi(\varepsilon) = 1 - e^{-H_0(e^{g\varepsilon^\chi} - 1)}$ and $\phi(0) = 0$. For the small daily heat-induced mortality relevant here, $\phi(\varepsilon) \approx H_0(e^{g\varepsilon^\chi} - 1)$, which is convex in ε for every $\chi \geq 1$; convex temperature damages ($\chi > 1$) strengthen the convexity. A mean-preserving spread therefore raises $\mathbb{E}\phi$, and with it a^* , by Jensen's inequality. It also raises residual heat-induced mortality $1 - \vartheta$, so both sides of (32) rise and the net effect on w^* is ambiguous; w^* falls whenever the induced rise in the adaptation share outweighs the rise in residual mortality, which is the case at our parameter values.

Adaptation rises with biological age. The sign of da^*/dd equals that of the cross-partial $\partial^2 \ln \vartheta / \partial a \partial d$, since the second-order condition is negative. With $\rho H_1 \propto d^{\psi+\eta} e^\rho$ and $\rho \propto d^\eta$,

$$\frac{\partial^2 \ln \vartheta}{\partial a \partial d} = \frac{\kappa}{d} \rho H_1 [(\psi + \eta) + \eta\rho] > 0, \quad (33)$$

so $da^*/dd > 0$: frailer agents adapt more, because worse health raises both the hazard scale d^ψ and the loading d^η and hence the absolute survival gain from protection.

A.3 Life-Cycle Model with Daily Heat Shocks and Adaptation

The Lagrangian function of (P1) and the associated FOCs are given by

$$\begin{aligned} \mathcal{L} = \mathbb{E}_0 \left\{ \sum_{t=0}^T \beta^t \left[S_t u(c_t) \right. \right. \\ + \lambda_t^k (w_t + (1 + r + m_{t-1})k_{t-1} - c_t - h_t - k_t - a_t) \\ + \lambda_t^s (S_t - S_{t-1}s_t) \\ \left. \left. + \lambda_t^d (\mu (d_t - b_2(1 + b_3d_t)^\alpha h_t^\gamma - b_4) - d_{t+1} + d_t) \right] \right\} \end{aligned} \quad (34)$$

$$\frac{\partial \mathcal{L}}{\partial c_t} = 0 = \mathbb{E}_t(S_t) u_c(c_t) - \lambda_t^k \quad (35)$$

$$\frac{\partial \mathcal{L}}{\partial h_t} = 0 = -\lambda_t^k - \lambda_t^d \mu b_2 \gamma (1 + b_3d_t)^\alpha h_t^{\gamma-1} \quad (36)$$

$$\frac{\partial \mathcal{L}}{\partial a_t} = 0 = -\lambda_t^k - \lambda_t^s S_{t-1} \mathbb{E}_t(s_a(a_t, d_t)) + \beta \lambda_{t+1}^k \mathbb{E}_t(m_a(a_t, d_t) k_t) \quad (37)$$

$$\frac{\partial \mathcal{L}}{\partial k_t} = 0 = -\lambda_t^k + \beta \lambda_{t+1}^k (1 + r + \mathbb{E}_t(m_t)) \quad (38)$$

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial d_{t+1}} = 0 = & -\lambda_t^d + \beta \lambda_{t+1}^d (\mu [1 - b_2 \alpha b_3 (1 + b_3 d_{t+1})^{\alpha-1} h_{t+1}^\gamma] + 1) \\ & - \beta \lambda_{t+1}^s S_t \mathbb{E}_t[s_d(d_{t+1}, a_{t+1})] \\ & + \beta^2 \lambda_{t+2}^k k_{t+1} \mathbb{E}_t[m_d(d_{t+1}, a_{t+1})] \end{aligned} \quad (39)$$

$$\frac{\partial \mathcal{L}}{\partial \mathbb{E}_t(S_t)} = 0 = u(c_t) + \lambda_t^s - \beta \lambda_{t+1}^s \mathbb{E}_t(s_{t+1}) \quad (40)$$

With $k_T = 0$, $h_T = 0$, $\lambda_T^d = 0$ and the constraints in (P1). We differentiate with respect to $\mathbb{E}_t(S_t)$ rather than S_t because, under the model's ex ante timing, S_t is not realized until after the period- t controls (including c_t) are chosen, so the first-order condition is expressed in terms of the conditional expectation that is actually known at the time those choices are made.

A.4 Health Expenditures and Adaptation: Complements or Substitutes?

The model features two coping mechanisms that operate at different horizons: health expenditures h_t slow biological aging and improve survival in all future periods, while adaptation a_t directly lowers current vulnerability g_t . We isolate the technological interaction analytically and let the calibration resolve the net effect. Collapsing intra-

annual exposure into a scalar ε , consider the per-period hazard

$$H(d_t, a_t, \varepsilon) = d_t^\psi \exp \left[\underbrace{b_5 \left(\frac{d_t}{d} \right)^\eta e^{-\kappa a_t} \varepsilon^\chi}_{\equiv q_t} \right],$$

which suppresses the baseline scaling and daily averaging in (P1) without affecting the signs below. The marginal hazard reduction from adaptation, $\text{MHR}_{a_t} \equiv -\partial H / \partial a_t = \kappa q_t H$, rises with biological age, $\partial \text{MHR}_{a_t} / \partial d_t = \kappa q_t H (\psi + \eta + \eta q_t) / d_t > 0$, so worse health raises the effectiveness of adaptation. Its value need not rise with d_t , however: it equals MHR_{a_t} weighted by the shadow value of survival λ_t^S , and higher d_t shortens remaining life and depresses λ_t^S . In the calibrated model, optimal adaptation still rises with age. Across margins, health investment lowers future deficits, $\partial d_{t+1} / \partial h_t < 0$, so—holding a_{t+1} fixed—it lowers tomorrow’s marginal hazard reduction: h_t and a_{t+1} are substitute margins. This is incomplete, since a_{t+1}^* rises in d_{t+1} ; the induced response has sign $(-)(+)(-) = (+)$ and offsets it, so that the cross-effect cannot be identified analytically. The calibration settles it: greater heat exposure triggers more adaptation but slightly less health investment. Since a more severe heat environment raises the overall value of protection—which alone would raise both margins—the fall in h_t shows that substitution toward the more direct margin dominates.

A.5 Life-Cycle Labor Income Profiles

The experimental setup described in Section 5.2 uses heterogeneous life-cycle wage income profiles as an exogenous source of variation. These profiles are constructed as follows: We extract average post-tax life-cycle income profiles for each income decile from the Consumer Expenditure Survey (CES) of the U.S. Bureau of Labor Statistics’ 2023 interview dataset.²³ While there are datasets on income data with larger population sizes, this dataset provides post-tax income as well as detailed data on consumption and health expenditures. We filter for households with an age higher than 20 years of the reference person and an average income of \$500 during the previous year to exclude students and all kinds of unemployed consumption units that received substantial government transfers to survive. We apply the given CE weights and divide the household income by the square root of household size to approximate the individual income. Next, we calculate the average income per income group and the household’s reference person’s age. Thus, we obtain a snapshot of income per age and not the longitudinal income development of specific consumption units. We smooth the life-cycle income profile by applying a spline approximation, starting model-consistent with the age of 20 years and leaving the income of the 75+ age cohort constant. The resulting

²³ Accessible via https://www.bls.gov/cex/pumd_data.htm

income profiles are displayed in Figure A.1.

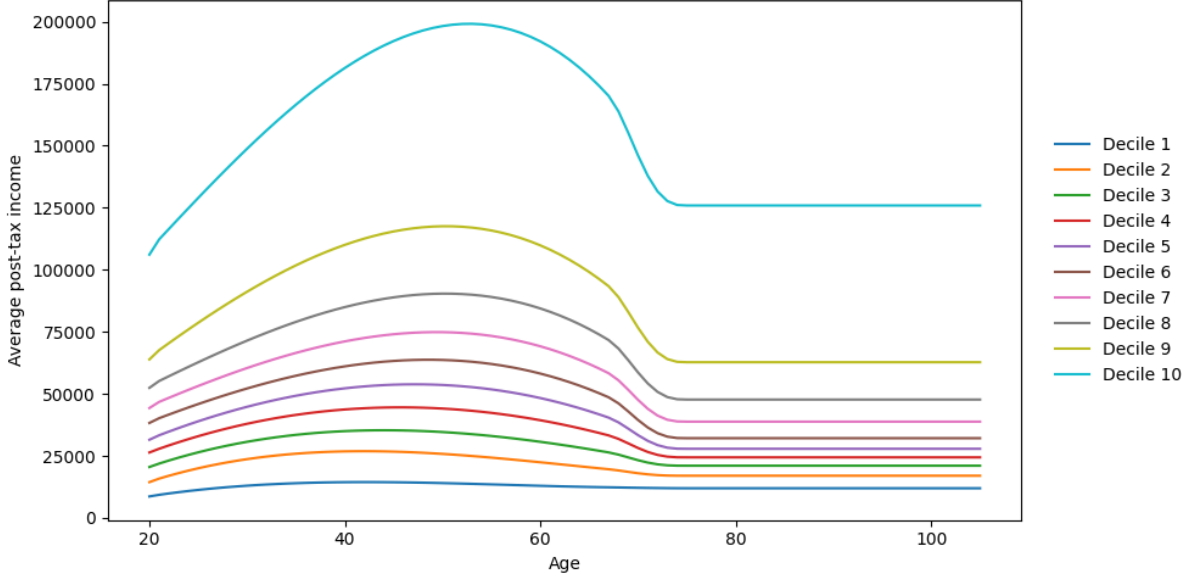


Figure A.1: Life-cycle labor income profiles

Notes. Average post-tax life-cycle labor income profiles by income decile based on the 2023 Consumer Expenditure Survey (CES) of the U.S. Bureau of Labor Statistics. Income profiles are smoothed, adjusted to single-person households, and kept constant after age 75.

A.6 Intra-Annual Daily Mean Temperature Probability Distribution

The intra-annual probability distributions of daily mean temperatures represent the climate and constitute the second source of exogenous variation in the experimental setup introduced in Section 5.2. We construct these distributions for the United States as follows. First, we retrieve daily mean temperature time series from 50 runs of the MPI-ESM1-2-LR climate model under the CMIP6 experiments SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5, which are identified by their nominal 2100 radiative forcing levels of 2.6 W m^{-2} , 4.5 W m^{-2} , 7.0 W m^{-2} , and 8.5 W m^{-2} , respectively. Second, we average daily mean temperature across all regions associated with the United States. Third, we sort daily mean temperatures into 1°C bins; for example, the 15°C bin is in $[14.5^\circ\text{C}, 15.5^\circ\text{C})$. Fourth, we aggregate all bin entries across models and runs for a pooled five-year interval from 2096 to 2100 in the experiment distributions. In Figure 2, we only pooled every tenth single year to show the evolution of the distribution. Finally, we count the number of observations in each bin and divide by the total number of observations to obtain a probability mass function.

To construct the right-hand panel of Figure 2, we aggregate the probability of all bins below the MMT. To construct an area-weighted MMT for the USA, we rely on the estimates reported in the appendix of [Gasparrini et al. \(2015\)](#) and compute the average

minimum mortality percentile across all U.S. locations included in that study, which yields an MMT of 19°C for the average U.S. distribution. Note that a population-weighted MMT might be higher for the USA. Also note that we keep the MMT constant and exogenous in the modeling framework.

A.7 Calibration

This section of the appendix describes the construction of calibration targets and the numerical calibration procedure.

Calibration Targets

We retrieve life-cycle mortality data from the Human Mortality Database²⁴ (HMD) and data on accumulated health deficits as a measure of biological age for U.S. males from the appendix of [Abeliansky, Erel, and Strulik \(2020\)](#). Following [Strulik and Grossmann \(2025\)](#), we use mortality data for males in 2010 and estimate an exponential relationship between annual survival and annual deficits to obtain the parameters b_1 and ψ . Average health expenditures over the life-cycle are calculated using the same method as the wage income profiles from the CES. We take life expectancies by income percentile from the publicly available dataset of [Chetty et al. \(2016\)](#) and average them by income decile. Because life expectancies in [Chetty et al. \(2016\)](#) are calculated across many calendar years and expressed for 40-year-old individuals, they differ from the HMD figures for U.S. males in 2010. We therefore use only the life-expectancy spread along the income distribution in [Chetty et al. \(2016\)](#), computing each decile’s deviation from the average agent, while taking the average agent itself from the HMD data. This procedure yields the income–life-expectancy distribution shown in Figure A.2, which is purely descriptive.

For the heat-mortality association, we draw on the climate epidemiology literature, which provides estimates of relative risk that have been explicitly incorporated into the model structure. Note that $RR_{t,\tau}$ depends on exogenous temperature realizations as well as endogenous model variables a and d and therefore indirectly on income and expectations about future weather. To the best of our knowledge, there are no studies providing estimates of heat-related relative mortality risk by income groups within regions of the same temperature exposure. We therefore target relative risks for the average income as expressed in the climate epidemiological literature ([Ballester et al., 2023](#); [Gasparrini et al., 2015](#); [Lee & Dessler, 2023](#)) assuming the past is in line with the SSP1-2.6 temperature probability distribution. Then we draw on [Carleton et al. \(2022\)](#) for the variation with respect to income and the temperature distribution by

²⁴<https://www.mortality.org>

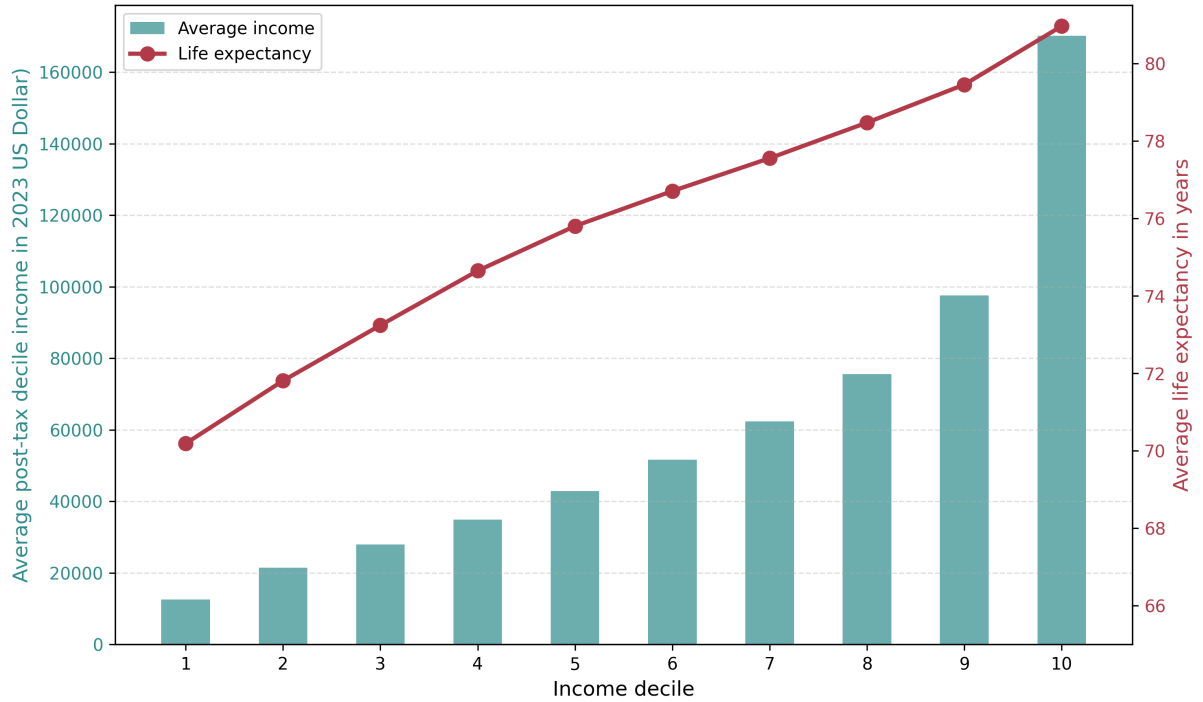


Figure A.2: Average income and life expectancy per decile

Notes. The teal bars show average annual post-tax income in the cross-section, scaled to single households, in U.S. dollars. As in Section A.5, the source is the CES. The red dotted line shows the within-country Preston Curve for the USA.

using their replication code under a constant annual mean temperature as proxy for the temperature distribution and income levels from the different income groups in the US. We then convert the reported number of deaths to RR values relative to the average agent, assuming a constant baseline mortality risk. This procedure relies on the assumption that relative mortality differences between regions in Carleton et al. (2022) provide informative guidance for mortality heterogeneity within countries. The following table lists all calibration targets.

Calibration Procedure

We estimate the model using a two-step Method of Simulated Moments, following the literature on stochastic life-cycle models (De Nardi et al., 2010; Gourinchas & Parker, 2002). First, we fix a set of parameters that are determined outside the estimation procedure. Second, we estimate the remaining parameters using the Simulated Method of Moments.

Exogenous parameters. We build on a number of predetermined or exogenously set parameters from comparable studies.

Description	Details	Value
Health expenditure share of labor income in percent	Age 30	3.72
	Age 50	5.45
	Age 60	6.63
	Age 70	10.78
Life expectancy in years per income decile	Decile 1	70.19
	Decile 2	71.81
	Decile 3	73.24
	Decile 4	74.65
	Decile 5	75.81
	Decile 6	76.71
	Decile 7	77.56
	Decile 8	78.48
	Decile 9	79.46
	Decile 10	80.97
Cumulated deficits of the average agent	Age 20	0.036
	Age 30	0.047
	Age 40	0.062
	Age 50	0.082
	Age 60	0.111
	Age 70	0.152
	Age 80	0.209
	Age 90	0.288
	Age 100	0.400
Cumulated survival probability of the average agent	Age 20	0.986
	Age 30	0.973
	Age 40	0.957
	Age 50	0.923
	Age 60	0.851
	Age 70	0.718
	Age 80	0.478
	Age 90	0.145
	Age 100	0.006
Relative risk of the average agent	SSP1-2.6 Age 40 MMT + 5	1.05
	SSP1-2.6 Age 85 MMT + 5	1.1
	SSP1-2.6 Age 40 MMT + 7	1.1
	SSP1-2.6 Age 85 MMT + 7	1.2
High income (9th decile) relative risk	SSP1-2.6 Age 85 MMT + 7	1.09
Low income (2nd decile) relative risk	SSP1-2.6 Age 85 MMT + 7	1.61
Relative risk of the average agent under the SSP5-8.5 temperature distribution	SSP5-8.5 Age 85 MMT + 7	1.16

Table A1: Empirically observed moments (ζ_N^{data})

Simulated method of moments. By $\theta = (b_2, \gamma, b_3, \alpha, b_4, \chi, b_5, \kappa, \eta)$ we denote the vector of parameters that cannot be determined outside the model. To identify θ structurally, we employ the Simulated Method of Moments (SMM). As a special case of the Generalized Method of Moments, SMM is typically applied in stochastic modeling environments in which recursive solution methods are required and optimal policies cannot be derived analytically. However, [Acemoglu, Akcigit, Hanley, and Kerr \(2016\)](#) and [Dietz and Lanz \(2025\)](#) provide examples of applying SMM in deterministic modeling contexts, while [Schünemann, Strulik, and Trimborn \(2020\)](#) describe a related procedure motivated by SMM. Let $\hat{\theta}_N$ denote the SMM estimator, defined as

$$\hat{\theta}_N = \arg \min_{\theta} \left[\ln \frac{\zeta_i^{model}(\theta)}{\zeta_i^{data}} \right]' W_N \left[\ln \frac{\zeta_i^{model}(\theta)}{\zeta_i^{data}} \right] \quad (41)$$

where ζ_N^{data} denotes empirically observed moments, $\zeta_N^{model}(\theta)$ denotes model-implied moments as functions of θ , N is the number of observations or targeted moments and W_N is a weighting matrix. Following [Dietz and Lanz \(2025\)](#), we choose a scaled iden-

Parameter	Value	Source
σ	1.01	Strulik and Grossmann (2025)
β	0.94	Strulik and Grossmann (2025)
r	0.06	Strulik and Grossmann (2025)
d_0	0.036	Strulik and Grossmann (2025)
μ	0.034	Strulik and Grossmann (2025)
$\bar{u}$	-0.2	Set to target VSL of 10 million \$ at age 40 as in Hall and Jones (2007)
T	90	Maximum lifespan of 110 years
k_{-1}	0	Assumption
b_1	3.3842	Fitted to capture the association between d and S
ψ	2.5629	Fitted to capture the association between d and S
$\bar{d}$	d_0	

Table A2: Parameters set outside of estimation

tity matrix for W_N . While Dietz and Lanz (2025) model moments and scale squared deviations of time trends by their variances, we set each diagonal element of W_N equal to $\frac{1}{B_N}$, yielding

$$\hat{\theta}_N = \arg \min_{\theta} \left[\sum \frac{1}{B_N} \left(\ln \frac{\zeta_i^{model}(\theta)}{\zeta_i^{data}} \right)^2 \right] \quad (42)$$

where B_N denotes the block size associated with each block of moments. For example, the block size of life expectancy targets is 10 as we have one target per decile. We apply this scaling, because our calibration targets comprise moments of very different structure. Some targets take the form of life-cycle time series with multiple observations, while others summarize entire life-cycle trajectories in a single statistic, such as life expectancy across income groups, or capture cross-sectional relationships, such as relative heat-related mortality risks across heat scenarios and ages. Without block-size normalization, moment categories represented by many observations would mechanically receive greater weight in the objective function than targets summarizing life-cycle outcomes with only one or a few observations. In addition to block-size scaling, we normalize deviations by relative percentage differences to account for differences in magnitude across target moments. Accordingly, we depart from the optimal variance-covariance weighting matrix commonly used in the econometrics literature for two reasons. First, the targeted moments are heterogeneous in nature and do not consist exclusively of time series data. Second, higher-order moments and covariances of the empirical targets are not available.

When searching for parameters that minimize the loss, we face a global nonlinear optimization problem in nine dimensions that requires solving the underlying life-cycle model multiple times each iteration, corresponding to different combinations of wages and climate scenarios for each evaluation of the loss function. As such high-dimensional problems typically exhibit multiple local minima, we proceed step-wise. First, we calibrate a life-cycle deficit accumulation model as in Strulik and Grossmann

(2025) without any heat effect. Based on the resulting time series of consumption and health deficits, we calibrate the relative risk values per age as a static decision between given consumption and adaptation expenditures. This allows us to come up with plausible initial guesses for parameters that need to be estimated, where the interaction between adaptation and life-cycle decisions is not taken into account yet. Around these first-level parameter estimates, we define a plausible parameter space and employ multiple initial guesses within this range. The resulting parameter combination is listed in Table A3.

Parameter	Value
b_2	0.000807
γ	0.250537
b_3	0.014588
α	488.086637
b_4	0.000000
χ	1.988708
b_5	0.000953
κ	0.001178
η	1.304425

Table A3: Estimated parameters ($\hat{\theta}_N$)

Panel A in Figure A.3 shows the life-cycle trajectories of health expenditures, cumulative survival probability, and accumulated deficits for the average agent. As shown in Panel B of Figure A.3, the model delivers reasonable outcomes in terms of magnitude and qualitative patterns for endogenous relative heat risks. Note that the relative risk of dying due to heat is a daily, and therefore high-frequency, measure. Consequently, the values produced by the model are fairly small in absolute terms. Aligning with the calibration targets, it is visible that low-income agents face higher relative heat risks as a result of a lower engagement in adaptation, whereas the opposite holds for high-income agents. Agents calibrated under a high-temperature scenario invest substantially more in adaptation and therefore face lower relative heat risks because they expect more frequent and more intense heat days. While all other calibration targets are fairly close to model-generated values, the relative risk of the average agent under higher temperatures is lower than the corresponding empirical value. The within-country Preston Curve of life expectancy along the income distribution is shown in Figure Panel C of A.3. While being close to empirical targets of health expenditures, the Preston Curve is flatter compared to empirical targets. Life expectancy decreases under higher-emissions temperature distributions relative to the SSP1-2.6 benchmark. This difference gets smaller along the income distribution.

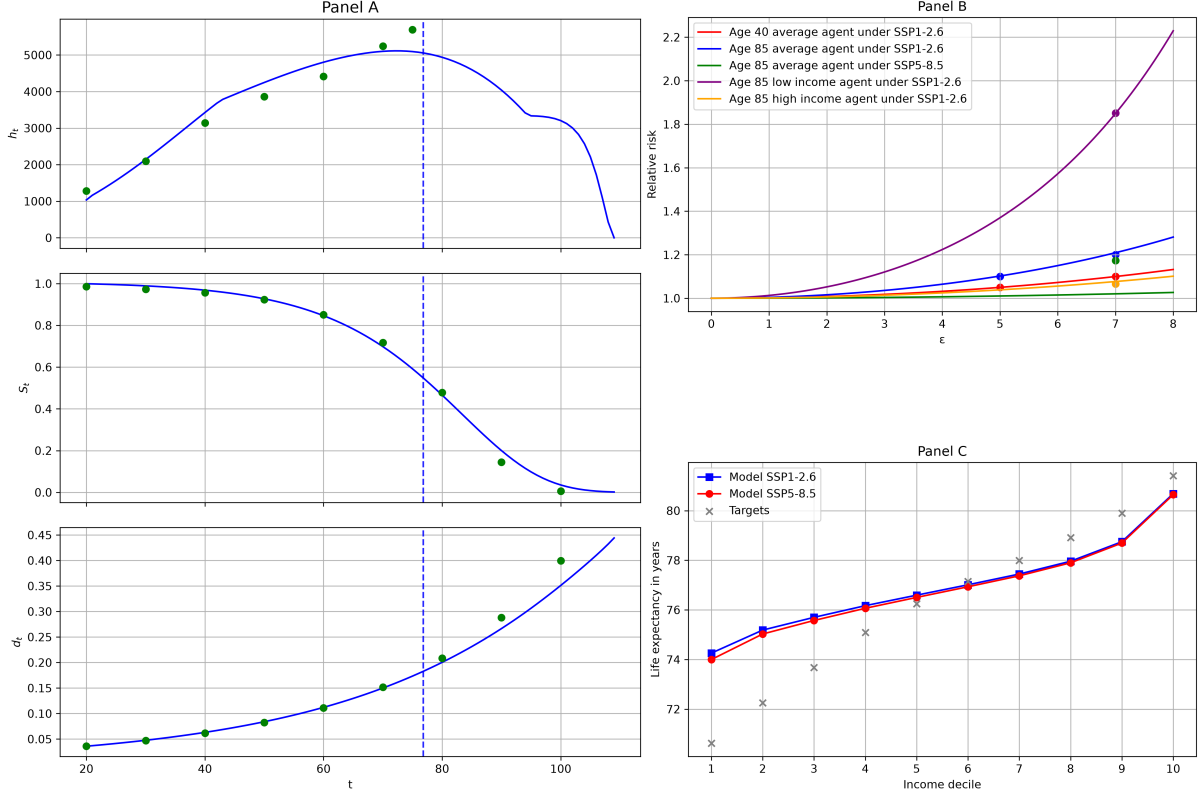


Figure A.3: Calibration results

Notes. Panel A: Calibration result of the life-cycle trajectories of health expenditures h_t , cumulative survival probability S_t , and accumulated deficits d_t for the average agent. Green dots show calibration targets and the dashed vertical line shows life expectancy. Panel B: Daily mortality relative risk as a function of a stochastic daily temperature realization, measured as ϵ degrees above the MMT. Colored dots denote calibration targets for different income levels, expectation regimes, and ages, while the corresponding solid lines show the model-implied mortality risk curves. Panel C: Life expectancy along the income distribution implied by the model's simulated life-cycle trajectories under the low-temperature scenario (blue) and the high-temperature scenario (red). Gray crosses denote the empirical target values shown in Figure A.2.

A.8 Results Absent Adaptation

Optimizing the LTU-maximizing level of adaptation at age t is a central feature of the model. How do the model results change when this channel is shut down and adaptation becomes ineffective against heat, i.e., when setting $\kappa = 0$? To address this question, we conduct a counterfactual model calibration in which all other parameters are held fixed and revisit both the baseline welfare analysis and the life expectancy losses presented in the main text.

Panel A in Figure A.4 presents the no-adaptation counterpart to Figure 4 in the main text. As shown analytically in Section 3, the distribution of welfare losses along the income distribution is not necessarily regressive or progressive. This theoretical result is reflected in the calibrated model: after re-optimizing under $\kappa = 0$, welfare losses exhibit a slightly hump-shaped pattern across all intra-annual temperature probability

distributions. Overall welfare losses increase for all income groups, with the difference relative to the baseline becoming larger further up the income distribution. Panel B extends the version shown in the main text by adding life expectancy losses in the absence of adaptation (dashed lines with the same color and marker). In contrast to the welfare analysis, the sign of the gradient does not flip: life expectancy losses still decline weakly with income, reflecting the lower biological age of higher-income agents. Overall losses are again larger than in a world where adaptation is effective, but the gradient is an order of magnitude smaller, so that virtually all income heterogeneity in mortality damages operates through adaptation rather than through health status.

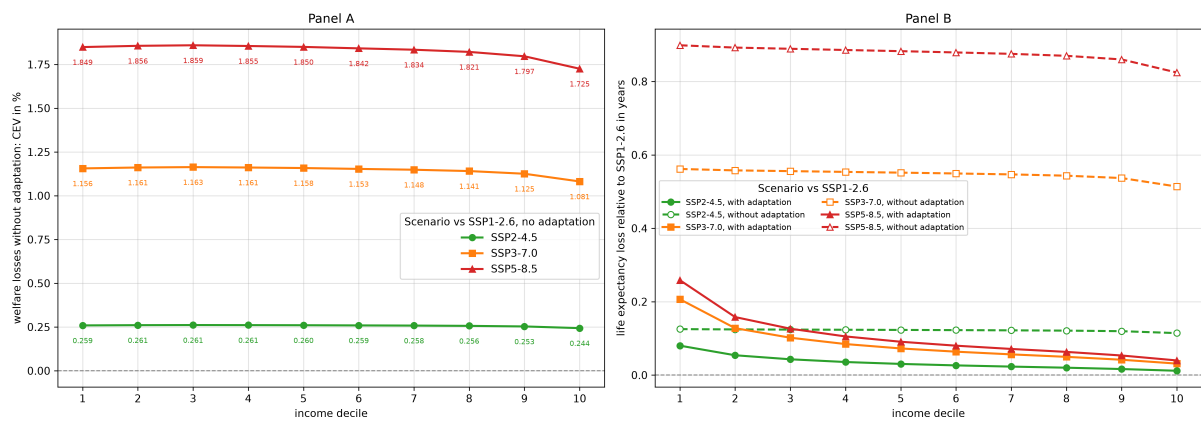


Figure A.4: Welfare and life expectancy losses absent adaptation

Notes. Panel A: Welfare losses absent adaptation, i.e., $\kappa = 0$, measured relative to the SSP1-2.6 benchmark and expressed as $\lambda \times 100$, for intra-annual temperature probability distributions associated with high- (red, triangle markers), medium- (orange, square markers), and low-emissions scenarios (green, dotted), by income decile. Larger values indicate larger welfare costs. Panel B: Life-expectancy losses, measured in years relative to the SSP1-2.6 benchmark, for intra-annual temperature probability distributions associated with high- (red, triangle markers), medium- (orange, square markers), and low-emissions scenarios (green, dotted), by income decile. Dashed lines show results absent adaptation in the model compared to the solid lines with the same color and marker, which are also shown in the main text. Larger values indicate a lower life expectancy.