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Growth and adaptation to climate change in the long run[*]

Simon Dietz[†] Bruno Lanz[‡]

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Abstract

As the climate is changing, the global economy is adapting. We provide a novel method of estimating how much adaptation has taken place historically, how much it has cost, and how much it has reduced the impacts of climate change. The method is based on a structurally estimated, globally aggregated model of long-run growth, which identifies how household consumption and fertility preferences, innovation, and land use allow the economy to adapt to climate change. We identify the key role of agriculture, because it is especially vulnerable to climate change and food cannot be perfectly substituted. To compensate for declining crop yields, the world economy has shifted resources into agriculture and this has slowed down structural change. We also use the model to estimate optimal future carbon taxation. Adaptation is costly, so radically reducing future greenhouse gas emissions could improve welfare substantially. Uncertainty about climate damages remains substantial, particularly in agriculture, and this strongly affects optimal policy.

Keywords: agriculture; climate change; directed technical change; economic growth; energy; population growth; structural change; structural estimation; uncertainty

JEL Classification numbers: C51, O13, O44, Q54

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1 Introduction

Emissions of greenhouse gases since the industrial revolution have already warmed the planet by an estimated 1.1°C and, as the Intergovernmental Panel on Climate Change (IPCC) writes, "[t]he scale of recent changes across the climate system as a whole – and the present state of many aspects of the climate system – are unprecedented over many centuries to many thousands of years" (IPCC, 2021, Summary for Policymakers, p8).

Therefore, it is intuitive that climate change has already left an imprint on the world economy. Indeed, an emerging body of empirical research convincingly shows how mostly short-run fluctuations in climate affect a wide range of economic and social outcomes, including crop yields, GDP, mortality, and civil conflict (Dell et al., 2014; Carleton and Hsiang, 2016). The effects can be negative or positive. However, how climate change has shaped the *long-run* development of the world economy is much less well understood. The fundamental challenge is to estimate a counterfactual world without climate change and compare that world to the one we have. The aforementioned empirical literature provides ways of doing this, but a key concern is that short-run economic responses to climate variation are not the same as long-run responses to secular trends, because the capacity of households, firms and governments to adapt is limited over short timescales. While economists are increasingly studying local and micro adaptations to climate change (e.g. Barreca et al., 2016; Graff Zivin and Neidell, 2014), there remains a disconnect in scale with the global picture.

In this paper, we propose a new approach to estimating how climate change has affected the long-run development of the world economy, which is capable of identifying the role of adaptation mechanisms such as structural change, directed technical change, land-use change, and demographic change. The method revolves around building a structural model of the world economy, which has just enough structure to explicitly track the aforementioned adaptation mechanisms. While our approach could be extended and generalized to many model structures analysing different adaptation channels, our particular model structure has the following key features:

- Two sectors producing final goods, a climate-vulnerable sector (agriculture) and a less vulnerable sector (the rest of the economy). Consumer preferences over the agricultural good (i.e., food) and other goods are non-homothetic and imply imperfect substitution. This enables us to estimate how climate change mediates structural change out of agriculture into manufacturing and services, and how the special role of food in households' consumption bundle affects the welfare cost of climate change.

- An energy sector providing dirty (fossil) and clean inputs to final goods production. With this we can estimate how secular trends in final goods production and in the energy sector affect greenhouse gas (GHG) emissions.

- Endogenous technical change in both final goods sectors and in dirty and clean energy, driven by R&D labor in a Schumpeterian framework. This enables us to estimate how climate change induces innovation in different sectors, affects the direction of technical change, and how future pricing/taxation of carbon would do the same.
- Agriculture requires land as an input, so we can estimate how climate change affects the total stock of agricultural land.
- Endogenous fertility, whereby households derive utility from fertility and the utility their children achieve. This enables us to estimate how fertility and in turn demographic change are affected by climate change.
- A coupled climate system, which is warmed by GHG emissions from dirty energy use, deforestation from agricultural land expansion, and agricultural production, and which impacts productivity in the final goods sectors.

By coupling an aggregate model of long-run growth with a simple model of the climate, we essentially create an Integrated Assessment Model (IAM) of the type pioneered by Bill Nordhaus (e.g., Nordhaus, 1991; Golosov et al., 2014; Cai and Lontzek, 2019; Barrage, 2020), albeit with more structural complexity than is typical (e.g., two sectors, endogenous technical change and fertility, etc.). However, IAMs are traditionally used to simulate alternative futures. Our key innovation is to take the model to the data and use it to simulate the past, both actual and counterfactual. This is made possible by structurally estimating the model on time-series of observed data from 1960 to 2015, using a simulated method of moments. This ensures the estimated model replicates how key economic and climate variables have actually evolved over the last half century. We then "turn off" climate change and use the estimated model to simulate a counterfactual past in which the world economy was not affected by climate change. The difference between the actual and counterfactual pasts is the long-run impact of climate change.

Through this approach, we quantify how climate change has already left its imprint on the world economy. The underlying literatures on climate impacts tell us that climate change is likely to have had a large negative effect on productivity in the climate-vulnerable agriculture sector, and a small negative effect on productivity in the rest of the economy. However, with our model we estimate that the global economy has adapted to this downward pressure on productivity such that the eventual loss of agricultural output has been much reduced. Conversely, the eventual loss of output in the rest of the economy has been amplified. This is because resources have been shifted from the rest of the economy to agriculture, including capital, labor, and R&D. Therefore, while the global economy has been undergoing structural change away from agriculture towards manufacturing and services, our results imply that climate change has actually *slowed down* this process, drawing resources into agriculture to provide imperfectly substitutable food at the expense of the production of other goods. At the same time, climate change has marginally accelerated the demographic transition, because it has reduced households' demand for fertility through its implicit effect on children's prospects. Yet, while adaptation has significantly reduced climate damages in agriculture, together with residual climate damages it is likely to have come at a considerable cost – we estimate that the welfare cost of climate change between 1960 and 2020 is equivalent to a permanent reduction of consumption in 1960 of 6%. All these estimates are subject to large uncertainty, which comes principally from the still wide disagreement in the agronomic literature about how climate change affects crop yields. Our estimates range from very large negative effects of climate change on agriculture to very small positive effects, with a best estimate of a substantial negative effect.

We also use the estimated model to make future projections, a more conventional use of an IAM. Without a carbon tax, GDP and population keep increasing. The same adaptation mechanisms that we estimate have been at work in the past are also at work in the future, plus agricultural land also expands to compensate for increasingly negative yield effects from climate change. However, this adaptation comes at an increasing cost. Hence, it is optimal to tax global GHG emissions at a high rate, so that optimal warming is well below 2°C in 2100.

We conduct a further series of experiments to quantify the importance of different adaptation/adjustment channels in the economy, and we test the robustness of our results to a range of parametric assumptions. This leads to three main results. First, introducing constraints/frictions to the reallocation of resources in our model, we show that capital mobility is a key driver of the cost of the transition out of fossil energy. In our model, preventing the reallocation of fossil energy capital to other sectors eliminates most of the welfare gains of GHG abatement. Second, agricultural R&D is a particularly important mechanism in adapting to climate change. Third, our estimates are robust to variations in exogenous parameters, except for the pre-adaptation effect of climate change on agricultural productivity. This underscores the centrality of agricultural damages and food supply/demand to the welfare cost of climate change. Varying the pre-adaptation effect of climate change on the rest of the economy across the range of estimates has minimal effect on optimal GHG taxes, but varying the corresponding effect on agriculture across the range of estimates in the agronomic literature has a large effect.

1.1 Related literature

The structure of our growth model builds on a number of fundamental theories. We extend the model of Barro and Becker (1989), which endogenizes population growth through households' inter-temporal preferences over consumption and fertility. Food preferences build on an important recent contribution to the literature on structural change (Comin et al., 2021), which proposes non-homothetic constant-elasticity-of-substitution (CES) preferences as the best representation of data on income elasticities across sectors. We build on endogenous growth theory. Productivity growth is driven by R&D in the Schumpeterian tradition (Aghion and Howitt, 1992). In particular, productivity growth depends on the share of labor allocated to R&D, so our model belongs to the class of endogenous growth models that do not exhibit a population scale effect (e.g. Dinopoulos and Thompson, 1998; Young, 1998). Since we differentiate between clean and dirty energy, and technical change is endogenous in both sectors, GHG emissions abatement is subject to directed technical change (Acemoglu et al., 2012). It also means that innovation is a mechanism to compensate for climate damages, i.e., to adapt to climate change (Fried, 2018). This turns out to be important in agriculture.

We also contribute to quantitative research on how climate change and economic growth interact. As mentioned above, our structural model can be viewed as an IAM and hence owes a debt to the IAM literature. Our work is largely complementary to reduced-form econometric studies, which use exogenous variation in past climate and weather as a natural experiment (Dell et al., 2014; Carleton and Hsiang, 2016). Most of this work uses plausibly exogenous variation in climate over the short run (mostly year to year) for identification.[1] We make some use of this work to calibrate the pre-adaptation climate impact on productivity in the rest of the economy, since short-run responses leave little time for adaptation, but then we depart from it by taking a structural approach to estimating long-run effects.

In taking a structural approach, this paper has an affinity with other recent work on climate change using structural models, such as Costinot et al. (2016), Desmet and Rossi-Hansberg (2015), and Nath (2022). These papers major on the geographical dimension. They build on the heterogeneity of climatic conditions to explore how climate change will affect the location of economic activities, and how spatial processes such as migration and trade will mediate climate impacts. While spatial heterogeneity is unquestionably a feature of climate change, our focus is different. Building on the IAM tradition, we aggregate over space so that we can focus more fully on long-run economic dynamics at the global level, including capital accumulation, demographic change, innovation, land-use change, and sectoral reallocation.

The remainder of the paper is set out as follows. Section 2 presents the model and discusses our structural estimation strategy. Section 3 evaluates how well the model is able to track the evolution of the economy, population, agriculture, energy and GHG emissions historically. In Section 4, we construct counterfactual estimates of climate impacts over the 1960-2020 period,

[1] A subset of the empirical literature attempts to estimate longer-run effects, for example, Ricardian/cross-sectional studies (Mendelsohn et al., 1994; Nordhaus, 2006), and panel studies using long differences or using short-run differences but specifying interactions and lagged effects to capture longer-run impacts (Dell et al., 2012).

i.e., we ask, what has the impact of climate change already been? In Section 5, we turn to the future and make projections over the 21st century, both in a laissez faire scenario and when the GHG externality is optimally internalized. In Section 6, we assess what role adjustment constraints might play in our analysis. This includes both constraints in the transition to a low-carbon economy, and constraints in reallocating resources to adapt to climate change. Section 7 reports on our sensitivity analysis. Section 8 provides a discussion and concludes. We provide several appendices that explore issues such as structural parameter identification and calibration of exogenous parameters.

2 Model structure and estimation

2.1 Structure

One of our main interests is in how climate change has affected structural change in the global economy away from agriculture towards manufacturing and services. The minimum structure we require for this is two final goods sectors, agriculture and the rest of the economy.

Agricultural production

Agricultural output $Y_{t,ag}$ is subject to constant returns to scale and produced by combining land X_t and non-land inputs with CES:

$$Y_{t,ag} = A_{t,ag}\left[(1-\theta_X)\left(K_{t,ag}^{\theta_K}E_{t,ag}^{\theta_E}L_{t,ag}^{1-\theta_K-\theta_E}\right)^{\frac{\sigma_X-1}{\sigma_X}} + \theta_X X_t^{\frac{\sigma_X-1}{\sigma_X}}\right]^{\frac{\sigma_X}{\sigma_X-1}} \cdot \exp(-\Omega_{ag}\left[S_t-\overline{S}\right]), \quad (1)$$

where the non-land inputs, capital $K_{t,ag}$, labor $L_{t,ag}$ and energy $E_{t,ag}$, are Cobb-Douglas. $A_{t,ag}$ is an endogenous, Hicks-neutral gross agricultural TFP index and θ_i, $i \in \{K, E\}$ are technology parameters satisfying $\theta_i \in (0,1)$ and $\Sigma_i\theta_i < 1$. In our main specification, we assume the elasticity of substitution between land and the capital-energy-labor composite σ_X is below unity, reflecting long-run empirical evidence (Wilde, 2013).[2]

Agricultural output is also a function of the climate state variable S_t, the atmospheric GHG concentration. This is a reduced-form simplification of the concentration-temperature-damages relationship that was introduced by Golosov et al. (2014) and made possible by the fact that temperature responds almost instantaneously to GHG emissions (Dietz and Venmans, 2019). GHG emissions from energy, agricultural production and land use increase S_t and this in turn

[2] The Cobb-Douglas ($\sigma_X = 1$) formulation is used in applied work (e.g. Mundlak, 2000; Hansen and Prescott, 2002). However, it implies land is asymptotically inessential for agricultural production, which is problematic for long-run analysis.

affects TFP in agriculture, most likely negatively, although positive impacts are not ruled out *a priori*. The scale of climate damages in agriculture is measured by the parameter Ω_{ag}. This is an estimate of the biophysical impact of climate change on global crop yields and below we discuss how we calibrate it using results from the literature on crop modeling.

Production in the rest of the economy

Output in the rest of the economy $Y_{t,mn}$ (*mn* stands for manufacturing, but all sectors minus agriculture are included here) is produced using capital $K_{t,mn}$, labor $L_{t,mn}$, and energy $E_{t,mn}$ with constant returns and scale and Cobb-Douglas substitution:

$$Y_{t,mn} = A_{t,mn} K_{t,mn}^{\vartheta_K} E_{t,mn}^{\vartheta_E} L_{t,mn}^{1-\vartheta_K-\vartheta_E} \cdot \exp(-\Omega_{mn} \left[S_t - \overline{S}\right]) , \tag{2}$$

where $A_{t,mn}$ is the corresponding gross technology index and $\vartheta_i \in (0,1)$, $i \in \{K, E\}$, are technology parameters again satisfying $\Sigma_i \vartheta_i < 1$.[3] Similar to agriculture, climate change affects aggregate productivity through the parameter Ω_{mn}. We use estimates of the short-run impact of climate change on aggregate productivity, *excluding* agriculture, to calibrate this. The use of short-run responses for calibration should ensure that Ω_{mn} is not biased by implicitly including the adaptation mechanisms we later model explicitly. We provide further details of the calibration below.

Clean and dirty energy

The climate footprint of economic development comes mostly but not exclusively from dirty/fossil energy use. In our model, final energy E_t is used in both final goods sectors and the energy sector produces E_t by combining dirty (dt) and clean (cl) energy intermediates. Dirty energy comprises coal, natural gas and oil. Clean energy comprises, e.g., biofuels, hydroelectric power, nuclear, solar, wind, and even fossil energy if combined with carbon capture and storage. The functional relationship is CES,

$$E_t = \left[E_{t,cl}^{\frac{\sigma_E - 1}{\sigma_E}} + E_{t,dt}^{\frac{\sigma_E - 1}{\sigma_E}} \right]^{\frac{\sigma_E}{\sigma_E - 1}} , \tag{3}$$

[3] This is a plausible representation of substitution patterns in the long run (conditional on Hicks-neutral technological progress; see Antràs, 2004). For short- and medium-run analyses, it may be more appropriate to use a CES function, in which the elasticity of substitution between energy and other inputs is less than unity (Fried, 2018; Hassler et al., 2016b). Baqaee and Farhi (2018) show that complementarity between energy and non-energy inputs in the short run can be used to explain the disproportionate macroeconomic impact of the 1970s oil shock.

where σ_E is the elasticity of substitution, wihch is assumed to be greater than unity (Stern, 2012; Papageorgiou et al., 2017).

The production of clean and dirty energy intermediates is a Cobb-Douglas function of capital and labor:

$$E_{t,cl} = A_{t,cl} K_{t,cl}^{\alpha} L_{t,cl}^{1-\alpha} \qquad \text{and} \quad E_{t,dt} = A_{t,dt} K_{t,dt}^{\alpha} L_{t,dt}^{1-\alpha}, \tag{4}$$

where $A_{t,cl}$ and $A_{t,dt}$ are endogenous technology indices. The dirty intermediate is a Leontief (fixed proportion) composite of energy and a fossil resource in finite supply R_t, so that $E_{t,dt} = R_t$, with the constraint that

$$\overline{R} \geq \sum_{0}^{T} R_t , \tag{5}$$

where $\overline{R}$ is the reserves of fossil resources and T is the time at which resources are exhausted. See Acemoglu et al. (2019) for a similar formulation.

Land

Land used in agriculture has to be converted from a finite reserve stock of natural land $\overline{X}$ and slowly reverts back to its natural state if left unmanaged. Thus, we can simulate the gradual expansion of global agricultural land and how climate change has affected that. Below, we also show how agricultural land expansion produces GHG emissions through deforestation.

As in Lanz et al. (2017), the evolution of land available for agricultural production is given by

$$X_{t+1} = X_t(1 - \delta_X) + \psi_t , \quad X_0 \text{ given}, \tag{6}$$

where $\delta_X > 0$ is a (very low) depreciation rate and ψ_t represents additions to the agricultural land area (subject to the constraint that $X_t \leq \overline{X}$, $\forall t$). Land conversion is a function of labor $L_{t,X}$:

$$\psi_t = \psi \cdot L_{t,X}^{\epsilon}, \tag{7}$$

where ψ and $\epsilon \in (0, 1)$ are productivity parameters.

Linear depreciation, which allows agricultural land to revert back to its natural state over time, together with decreasing labor productivity in land conversion as measured by ϵ, implies that the marginal cost of land conversion increases with the total agricultural land area, in the spirit of Ricardo.

Innovation

Innovation drives the evolution of TFP in both final goods sectors and in clean and dirty energy. We formulate a simple discrete-time version of the Schumpeterian model of Aghion and Howitt (1992, 1998), in which the use of labor determines the arrival rate of new innovations. In each sector $j \in \{ag, mn, cl, dt\}$, TFP evolves according to

$$A_{t+1,j} \;=\; A_{t,j} \cdot (1 + \lambda \cdot \rho_{t,j}) \;, \tag{8}$$

where $\rho_{t,j}$ is the endogenous arrival rate of innovations in the sector and represents the fraction of maximum growth λ that is achieved over the course of each time period.

This arrival rate of innovations is assumed to be an increasing function of labor employed in sectoral R&D, L_{t,A_j},

$$\rho_{t,j} \;=\; \left(\frac{L_{t,A_j}}{N_t}\right)^{\mu_j} \;, \tag{9}$$

where $\mu_j \in (0,1)$ is a labor productivity parameter that captures the duplication of ideas among researchers (Jones and Williams, 2000). One important feature of this representation is that we dispose of the population scale effect by dividing the labor force in R&D by total population N_t (Chu et al., 2013). In particular, along a balanced growth path on which the share of labor allocated to each sector is constant, the size of the population does not affect the growth rate of output.[4] As shown by Laincz and Peretto (2006), the R&D employment share can be interpreted as a proxy for average employment hired to improve the quality of a growing number of product varieties, a feature that is consistent with micro-founded firm-level models by Dinopoulos and Thompson (1998), Peretto (1998), and Young (1998), among others.

Population dynamics

The evolution of population is given by

$$N_{t+1} \;=\; N_t(1 + n_t - \delta_N)\,, \quad N_0 \text{ given}\,, \tag{10}$$

where n_t is the endogenous fertility rate, determined by household preferences (see below), and δ_N is the exogenous mortality rate.[5] Raising children requires labor, the aggregate cost of which

[4] Although economic growth has been positively associated with the level and growth of world population on a millennial time-scale (Kremer, 1993), it is harder to find evidence of scale effects in more contemporary data (Jones, 1995) and our question is contemporary in nature.

[5] Given that we equate total population with the total workforce, $1/\delta_N$ can be interpreted as the expected working lifetime and calibrated to match data on average working lifetimes.

is given by

$$n_t N_t \;=\; \overline{\chi}_t \cdot L_{t,N} \,. \tag{11}$$

Labor productivity in fertility is determined by the coefficient $\overline{\chi}_t$, which in turn is given by

$$\overline{\chi}_t = \chi L_{t,N}^{\zeta-1} \,, \tag{12}$$

where χ and $\zeta \in (0,1)$ are labor productivity parameters. In this way, $\overline{\chi}_t$ is inversely proportional to the opportunity cost of time spent raising children. This opportunity cost will increase, the higher are wages elsewhere in the economy. Since technological progress elsewhere in the economy drives up labor productivity and wages, the cost of fertility increases over time together with technology (Galor, 2005). Consequently, the model produces a demographic transition as incomes rise.

Capital dynamics

Agricultural output is just for food consumption in the same period,

$$Y_{t,ag} = C_{t,ag}, \tag{13}$$

however output of the non-agricultural part of the economy can be consumed or invested to accumulate capital:[6]

$$Y_{t,mn} \;=\; C_{t,mn} + I_t \,. \tag{14}$$

The equation of motion for capital is

$$K_{t+1} \;=\; K_t(1-\delta_K) + I_t \,, \quad K_0 \text{ given} \,, \tag{15}$$

where δ_K is the depreciation rate.

Preferences

The representative household has preferences over (i) own consumption of food and other goods, (ii) family size, which is increased by the number of children it produces, and (iii) the total future utility of these children.

[6] See Ngai and Pissarides (2007) for a similar treatment of savings and capital accumulation in a multi-sector model.

(i) Following Comin et al. (2021), the household has non-homothetic CES preferences over food and the composite non-agricultural good. This preference structure conforms to Engel's law, while also allowing food and other goods to be imperfect substitutes.[7] Consumption preferences are characterized by a utility function that is implicitly defined by the constraint

$$\kappa_{ag}^{\frac{1}{\sigma_c}} \left(\frac{c_{t,ag}}{g(U_t)^{\varepsilon_{ag}}} \right)^{\frac{\sigma_c - 1}{\sigma_c}} + \kappa_{mn}^{\frac{1}{\sigma_C}} \left(\frac{c_{t,mn}}{g(U_t)^{\varepsilon_{mn}}} \right)^{\frac{\sigma_c - 1}{\sigma_c}} = 1, \tag{16}$$

which simply says that the sum of expenditure shares on food and other goods equals one. The parameter σ_c is the elasticity of substitution between food and other goods, the utility elasticities ε_i, $i \in \{ag, mn\}$ control the degree of non-homotheticity, and the parameters κ_i represent tastes. $g(U_t)$ must be positive-valued, continuously differentiable and monotonically increasing. The simplest special case is $g(U_t) = U_t$ and we use this. Note that the income elasticity of demand for good i is given by

$$\frac{\partial \log c_i}{\partial \log E} = \sigma_c + (1 - \sigma_c) \frac{\varepsilon_{ag}}{\bar{\varepsilon}}, \tag{17}$$

where E denotes total expenditure and $\bar{\varepsilon}$ is the expenditure-weighted average non-homotheticity parameter across the two sectors (Comin et al., 2021). This is relevant for calibration.

Intertemporal preferences over own consumption of the two goods are then described by an isoelastic utility function

$$v(U_t) = \frac{U_t^{1-\gamma} - 1}{1 - \gamma}, \tag{18}$$

where γ is the intertemporal elasticity of substitution.

(ii) Preferences over family size are represented by

$$b(\tilde{n}_t) = \tilde{n}_t^{-\eta}, \tag{19}$$

where $\tilde{n}_t = (1 - \delta_N) + n_t$, and $\eta \in (0, 1)$ determines how fast marginal utility declines as n increases. For the special case of $\delta_N = 0$, where individuals survive for just one period, these preferences are identical to Barro and Becker (1989). Thus, like Jones and Schoonbroodt (2010), we generalise Barro-Becker fertility preferences to preferences over family size, but since mortality is fixed and exogenous in our model, the only way to express a preference for increasing family size is indeed by increasing fertility.

(iii) All children k are assumed identical, so that the future overall utility of a household's children $\sum_k W_{k,t+1} = n_t W_{t+1}$. We also assume parents care equally about their own future

[7] Comin et al. (2021) find a stable relationship between income and relative expenditure shares on agriculture, manufacturing and services in panel data from OECD countries, and that the slopes of relative Engel curves do not level off rapidly as income grows. They show these patterns are better captured by their non-homothetic CES preferences than generalized Stone-Geary preferences.

utility (conditional on survival probability $1 - \delta_N$) and the future utility of their children. The overall utility function in period t is then

$$W_t \;=\; v(U_t) + \beta \tilde{n}_t^{1-\eta} W_{t+1}\,, \tag{20}$$

where $\beta \in (0,1)$ is the discount factor, and recursively we derive the intertemporal welfare function of a dynastic household head:[8]

$$W_0 = \sum_{t=0}^{\infty} \beta^t \, N_t^{1-\eta} \, \frac{U_t^{1-\gamma} - 1}{1-\gamma}\,. \tag{21}$$

Allocation of capital, labor and energy

Within each period, capital is allocated between agriculture, the rest of the economy, clean and dirty energy,

$$K_t \;=\; K_{t,ag} + K_{t,mn} + K_{t,cl} + K_{t,dt}\,. \tag{22}$$

Energy is allocated between the two final goods sectors,

$$E_t = E_{t,ag} + E_{t,mn}\,. \tag{23}$$

Labor is allocated between the two final goods sectors, the two energy sectors, the four corresponding R&D sectors, land conversion, and fertility:

$$N_t \;=\; L_{t,ag} + L_{t,mn} + L_{t,cl} + L_{t,dt} + \sum_j L_{t,A_j} + L_{t,X} + L_{t,N}\,. \tag{24}$$

The allocation of capital, labor and energy across activities is driven by relative marginal productivities and constrained by feasibility conditions. For all three inputs, we take a long-run perspective and assume they can be moved from one sector to another at no cost. However, in Section 6 we explore various scenarios in which constraints are introduced to resource reallocation.

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[8] This is obtained though sequential substitution in $W_0 = v(U_0) + \beta \tilde{n}_0^{1-\eta} W_1$, yielding $W_0 = \sum_{t=0}^{\infty} \beta^t v(U_t) \Pi_{\tau=0}^{t} \tilde{n}_\tau^{1-\eta}$. Further, noting that Equation (10) can be rewritten as $N_{t+1} = N_t \tilde{n}_t$, we have $\Pi_{\tau=0}^{t} \tilde{n}_\tau^{1-\eta} \tilde{n}_\tau = (N_t/N_0)^{(1-\eta)}$.

GHG emissions and climate

Most IAMs focus on CO_2 emissions from energy, but studying the changing role of agriculture as an emissions source requires more, since land-use change is a major source of CO_2, and agricultural production (per unit area) mainly results in methane and nitrous oxide emissions, rather than CO_2. Thus, we include three GHGs – CO_2, CH_4 and N_2O – which have four sources:

1. CO_2 emissions from burning fossil fuels;
2. CH_4/N_2O emissions associated with burning fossil fuels (primarily CH_4 emissions as a waste product of fossil-fuel extraction and distribution);
3. CO_2 emissions from expanding agricultural land (principally deforestation);
4. CH_4/N_2O emissions from agricultural production.

Total GHG emissions at time t are given by

$$GHG_t = \left(\pi_{E,CO2} + \pi_{E,NCO2}\right) E_{t,dt} + \pi_X \left(X_t - X_{t-1}\right) + \pi_{ag} \left(K_{t,ag}^{\theta_K} E_{t,ag}^{\theta_E} L_{t,ag}^{1-\theta_K-\theta_E}\right) , \tag{25}$$

where $\pi_{E,CO2}$ is CO_2 emissions per unit of dirty energy, $\pi_{E,NCO2}$ is non-CO_2 emissions per unit of dirty energy (i.e., CH_4/N_2O), π_X is CO_2 emissions per unit of agricultural land expansion, and π_{ag} is CH_4/N_2O emissions per unit input of the capital-labor-energy composite in agriculture.[9] $\pi_{E,NCO2}$ and π_{ag} are expressed in units of CO_2-equivalent.

The state variable S_t represents the atmospheric GHG concentration. The evolution of S_t is based on the carbon-cycle model of Joos et al. (2013) used extensively by IPCC. This model was built to replicate the behavior of more complex carbon-cycle models. In the model, atmospheric CO_2 is divided into four reservoirs, indexed by r, with $S_t = \Sigma_r S_{t,r}$, each of which decays at a different rate:

$$\begin{aligned}
S_t &= \sum_{i=0}^{3} S_{t,i} && (26)\\
S_{t,0} &= a_0 \left[\pi_{E,CO2} E_{t,dt} + \pi_X \left(X_t - X_{t-1}\right)\right] + (1-\delta_{S,0}) S_{t-1,0} && (27)\\
S_{t,i} &= a_i \left[\pi_{E,CO2} E_{t,dt} + \pi_X \left(X_t - X_{t-1}\right)\right] \\
&\quad + \frac{a_i}{\sum_{i=1}^{3} a_i} \left[\pi_{E,NCO2} E_{t,dt} + \pi_{ag} \left(K_{t,ag}^{\theta_K} E_{t,ag}^{\theta_E} L_{t,ag}^{1-\theta_K-\theta_E}\right)\right] \\
&\quad + (1-\delta_{S,i}) S_{t-1,i},\ i = 1,2,3, && (28)
\end{aligned}$$

where $\sum_{i=0}^{3} a_i = 1$. The decay rate of the first reservoir S_0 is almost zero and this represents

[9] We assume net radiative forcing from other GHGs and aerosols is zero, which has been approximately true in recent years (IPCC, 2013).

geological re-absorption of CO_2. Carbon in the second reservoir S_1 decays somewhat faster, but still takes centuries to exit the atmosphere. This represents uptake by the deep oceans. The remaining two, faster-decaying reservoirs represent, respectively, slower (S_2) and faster (S_3) uptake of carbon by the biosphere and surface oceans. Since CH_4 and N_2O emissions are converted into CO_2-equivalent using their 100-year Global Warming Potential, we exclude them from the first reservoir. Doing so ensures these two gases are approximately completely removed from the atmosphere 100 years after their emission.[10]

Optimization and solution concept

The model is a discrete-time planning problem. The intertemporal welfare function (21) is maximized by selecting aggregate consumption, as well as the allocation of capital (22), energy (23), and labor (24), subject to the various constraints. Given the parameter restrictions, the problem is convex. Appendix A contains a formal statement of the primal optimization problem and discusses some further computational issues. When we estimate the model and use it to quantify past climate impacts, we assume the climate externality was not internalized.[11] When we use the model to make future projections, we study both the optimal path that internalizes the climate externality and the laissez faire path that does not.

Besides being a natural way of simulating optimal paths, a planning framework helps make our problem computationally tractable. For structural estimation, we need to solve a model with a large number of stock variables using many vectors of candidate estimates. A planner formulation affords a number of simplifications, including reducing the number of state variables to be computed.[12] Yet, while it is natural to quantify optimal allocations using a planning framework, this is not so for sub-optimal allocations. The use of a planning framework to simulate sub-optimal climate policies was pioneered by Nordhaus (1993). In his DICE model, a laissez faire future is simulated using a social planner who does not control CO_2 emissions. Although it is straightforward to show that a planning solution corresponds to a decentralized equilibrium in an economy with complete and perfect markets, the existence of myriad market imperfections in reality means that the planning solution is an approximation. Consequently, our structural

[10] A more complete model would have fully independent climate dynamics for CH_4 and N_2O, but this would add excessive complexity. We also omit carbon-cycle feedbacks (Dietz et al., 2021) for simplicity. This will have little effect on our historical analysis but may have an effect on our long-run projections, such that the atmospheric GHG concentration may not respond enough to emissions in the model in the long run.

[11] Towards the end of the historical period, prototypical climate policies such as the Kyoto Protocol and the European Union Emissions Trading System were introduced. However, these attempts had a trivial effect on total global GHG emissions pre-2020.

[12] We use a primal formulation, so that we only compute quantities, and prices are implicitly given by Lagrange multipliers and can be retrieved at the solution point. This formulation allows us to exploit efficient solvers for non-linear mathematical programs.

parameter estimates come to embody market imperfections present in the observations, as these are the free parameters that permit the model to closely reproduce the past in multiple dimensions. This has two implications. First, our structural parameter estimates will be different to those of a representative household or firm operating in an economy with complete and perfect markets. Second, we need to make the following assumption: society's (in)ability to correct non-climate market imperfections is scenario-invariant, so we can use the same set of structural parameter estimates retrieved from fitting the model on the observed past to simulate a counterfactual past without climate change, as well as different futures. For example, we must assume the absence of climate change in the counterfactual world would not have made the world materially better or worse at internalizing positive innovation externalities. We cannot directly test this assumption, but in Appendix E we provide encouraging evidence that our endogenous, structural parameter estimates are consistent across many variations in exogenous parameters and to changing the period over which the structural estimation is done.

2.2 Estimation

Our approach to model estimation proceeds in two steps.

Step 1. Exogenous parameters

The first step is to impose a subset of exogenous model parameters (Table 1). Most of these are parameters whose values are fairly standard in the literature and/or well pinned down by external sources. Appendix C provides further details, discusses how we calibrate initial values of the eleven state variables, and reports the parametrization of the emissions/climate module.

Here we focus on the crucial exogenous parameters Ω_{ag} and Ω_{mn}, which give the pre-adaptation effect of climate change on productivity in agriculture and the rest of the economy, respectively. We calibrate Ω_{ag} on the latest synthesis of the crop modeling literature provided by IPCC in its *Sixth Assessment Report* (IPCC, 2022, chapter 5). We obtained the underlying IPCC database of results from the crop modeling literature, containing 8,703 separate estimates of crop responses to increasing atmospheric carbon dioxide and temperature from 202 studies published between 1984 and 2020 (Hasegawa et al., 2022). We use near-term estimates (i.e., roughly the response today to climate change since pre-industrial) to maximize the precision of our historical calibration and, after filtering out studies using old climate scenarios, studies ignoring the carbon dioxide fertilization effect on crops, and studies including adaptation by farmers, we are left with 571 estimates for one of the four main crop types, i.e., maize, wheat, rice, and soybean. Collectively, these four crops contribute c. 90% of today's global caloric production of all cereals and soybean (FAO, 2022). We estimate Ω_{ag} for each crop type separately and then construct a weighted average using the average share of each crop type in the total production of all four crop types over the period 1960-2018. Our central parameter estimate implies that the 1.1°C warming since pre-industrial has reduced global aggregate crop yields by approximately 10% relative to a world without climate change, with an upper bound of a 28% reduction and a lower bound of a 2% increase. Thus, the uncertainty is large and our analysis carries that through.

We calibrate Ω_{mn} on empirical estimates of the short-run impact of annual temperature fluctuations on global industrial value added reported in Dell et al. (2012). Although various estimates are now available of the impact of annual temperature fluctuations on aggregate GDP (e.g. Burke et al., 2015), the key benefit of the estimates in Dell et al. (2012) is that they exclude agriculture. Therefore, agricultural impacts are not double-counted. We use the 95% confidence interval reported in Dell et al. (2012) to estimate lower and upper bounds.

Table 1: Parameters imposed for estimation

Parameter value	Definition	Source
Preferences and population		
$\beta = \{0.99, 0.97\}$	Discount factor	Giglio et al. (2015)
$\gamma = 2$	Intertemporal elasticity of substitution	Guvenen (2006)
$\varepsilon_{ag} = 0.42$	Elasticity of utility wrt. food	Calibrated
$\delta_N = \{0.022, 0.0166\}$	Mortality rate	Calibrated
Rest of the economy and capital accumulation		
$\vartheta_K = 0.3$	Capital share	Various
$\vartheta_E = 0.04$	Energy share	Golosov et al. (2014)
$\delta_K = 0.1$	Capital depreciation	Various
$\Omega_{mn} = \{1.23\text{E-}05, 9.11\text{E-}07, 2.37\text{E-}05\}$	Rest-of-economy damage intensity	Dell et al. (2012)
Agricultural sector		
$\sigma_X = \{0.6, 0.2\}$	Substitutability of land in agriculture	Wilde (2013)
$\theta_K = 0.25$	Capital share	Various
$\theta_X = 0.3$	Land share	Lanz et al. (2017)
$\theta_E = 0.04$	Energy share	Golosov et al. (2014)
$\delta_X = 0.02$	Land depreciation	Calibrated
$\overline{X} = 3$	Land reserves (billion ha)	Alexandratos and Bruinsma (2012)
$\Omega_{ag} = \{2.35\text{E-}04, -4.15\text{E-}05, 7.04\text{E-}04\}$	Agricultural damage intensity	IPCC (2022, chapter 5)
Energy sector and R&D activities		
$\sigma_E = 1.5$	Substitutability of energy intermediates	Stern (2012)
$\alpha = 0.6$	Capital share	Barrage (2020)
$\overline{R} = \{5000, \infty\}$	Dirty energy (Gt oil eq)	Rogner (1997)
$\lambda = 0.05$	Innovation size in R&D	Fuglie (2012)

Notes: this table reports model parameters imposed prior to structural estimation of the model. For parameters considered in the sensitivity analysis, we report multiple values, starting with our baseline assumption. See Appendix C for a discussion of parameter selection.

Step 2. Simulated method of moments

Given imposed parameter values and initial conditions, we then use an SMM procedure to identify the vector of remaining parameters: $\Theta = \{\psi, \epsilon, \mu_{mn}, \mu_{ag}, \mu_{cl}, \mu_{dt}, \chi, \zeta, \sigma_c, \kappa_{ag}, \eta\}$. This method selects values for the elements of the vector that jointly minimize the distance between (log-transformed) targeted, observed variables over the estimation period and their simulated counterparts. More specifically, for a given candidate vector of parameter estimates Θ_v, we solve the model to obtain simulated trajectories for k targeted quantities $Z_{\tau,k}^{model\,;\,\Theta_v}$, where τ indexes years over which the estimation is performed. Denoting the observations of each targeted quantity by $Z_{\tau,k}^{data}$, we then measure the error $e_k^{\Theta_v}$ associated with Θ_v as the relative squared deviation summed over the estimation period:

$$e_k^{\Theta_v} = \sum_{\tau} \left[\log(Z_{\tau,k}^{model\,;\,\Theta_v}) - \log(Z_{\tau,k}^{data}) \right]^2 , \tag{29}$$

The vector of estimated parameters $\hat{\Theta}$ is chosen to minimize weighted model error:

$$\min_{\hat{\Theta}} \sum_{k} \omega_k \, e_k^{\Theta} , \tag{30}$$

with weights ω_k inversely proportional to the volatility of the observations of k.[13] In order to find a solution to Equation (30), we use an iterative procedure. We start with a vector Θ_1 of parameters that coarsely approximates the observed trajectories, and solve the model for 10,000 vectors randomly drawn from a uniform distribution around Θ_1. This allows us to identify a subset of parameter values that improves the objective function, and we repeat the sampling process for a vector of estimates Θ_2, leading us to gradually update the distribution of parameters considered until we converge to the set of estimates reported in Table 2. The following observed variables are targeted: (i) world population (United Nations, 2019); (ii) agricultural output and (iii) output in the rest of the economy (World Bank, 2020); TFP in (iv) agriculture and (v) the rest of the economy (Martin and Mitra, 2001; Fuglie, 2012); (vi) cropland area (FAO, 2022); (vii) fossil and (viii) clean energy use (BP, 2017).

The uniqueness of the solution to Equation (30) cannot be formally proved, a well-known issue with the estimation of non-linear models (see Gourieroux and Monfort, 1996). We note, however, that our estimation procedure targets multiple moments jointly identifying the parameters of interest, which makes the convergence criterion highly demanding. Moreover, using a primal formulation allows us to solve the model for a very large number of parameter combinations, which gives confidence that alternative combinations cannot further improve the objective function. Appendix D reports the elasticity of total model error with respect to each structural parameter, as well as the elasticity of the error for each target variable, thus providing evidence about identification of each individual parameter.

[13] Volatility is measured as the sum of the residuals around the time trend for each observed series. This weighting prevents the fitting criterion being unduly influenced by series that are simply more volatile.

Table 2: Parameters estimated with SMM

Parameter estimates	Definition
$\mu_{mn} = 0.905$	Elasticity of labor productivity in rest-of-economy R&D
$\mu_{ag} = 0.763$	Elasticity of labor productivity in agricultural R&D
$\mu_{cl} = 0.204$	Elasticity of labor productivity in clean energy R&D
$\mu_{dt} = 0.454$	Elasticity of labor productivity in dirty energy R&D
$\psi = 0.052$	Labor productivity in agricultural land conversion
$\epsilon = 0.139$	Elasticity of labor productivity in agricultural land conversion
$\eta = 0.157$	Elasticity of intergenerational altruism
$\chi = 0.187$	Labor productivity in fertility and education
$\zeta = 0.303$	Elasticity of labor productivity in fertility and education
$\sigma_c = 0.126$	Elasticity of substitution between food and other goods
$\kappa_{ag} = 0.231$	Food taste parameter

Notes: this table reports parameters estimated for the baseline model.

Importantly, we follow the same empirical strategy when we investigate alternative assumptions about the exogenous/imposed parameters as part of a sensitivity analysis (see Section 7). For example, we know from previous research that changing the discount factor will affect optimal carbon taxation in the future. However, an alternative assumption about the discount factor will affect the ability of the model to fit 1960-2015 data. Our approach to this problem is to find the set of structural parameters $\hat{\Theta}$ that minimizes total model error under alternative values of the discount rate, so that the model fits past data under all the alternative parameter values considered in the sensitivity analysis.[14]

3 Goodness of fit, and the joint evolution of the world economy and climate

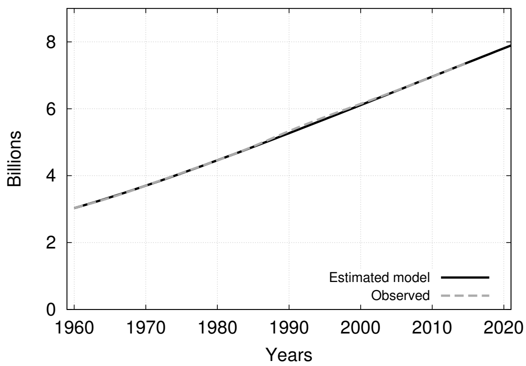
This section documents how well the model fits the data. In the process, it sets the scene for our main results by illustrating many of the key trends in the joint evolution of the world economy and climate over the past half century.

Figure 1 plots model trajectories of six economic variables that we target in our structural estimation and compares them with observed trajectories over the period 1960 to 2015: (a)

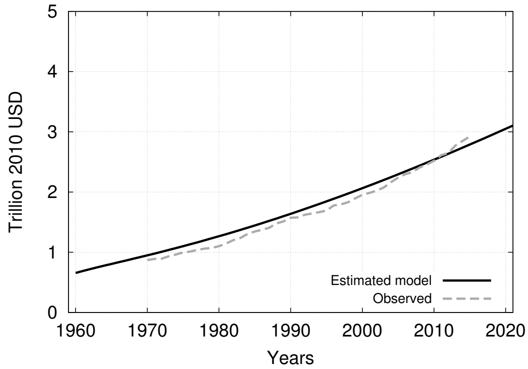
[14] Because we need to re-estimate the model each time an exogenous parameter value is changed, we can only change one exogenous parameter at a time, keeping all the other exogenous parameters at their standard values. Adopting a structural estimation approach means that global sensitivity analysis methods (see e.g. Harenberg et al., 2019) are infeasible.

Figure 1: Estimation results for population, output, productivity and land

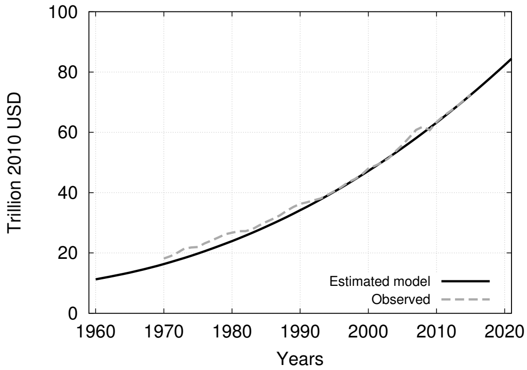
(a) World population



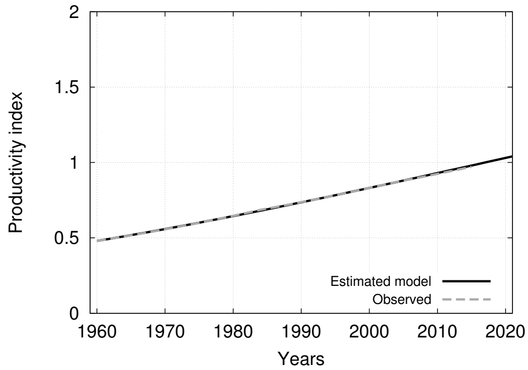
(b) Agricultural output



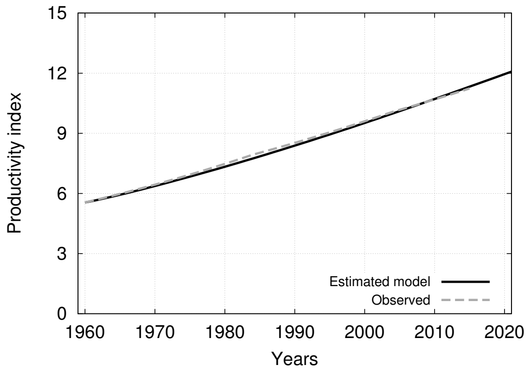
(c) Rest of the economy output



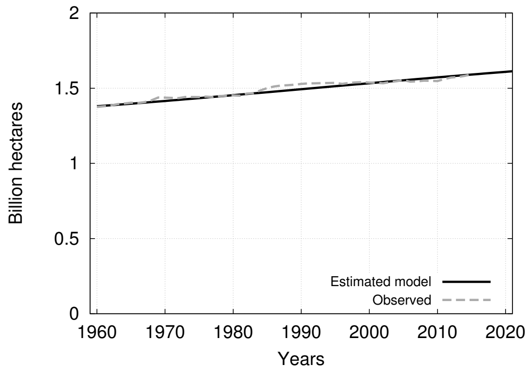
(d) TFP in agriculture including climate



(e) TFP in rest of economy including climate



(f) Arable land and permanent crops



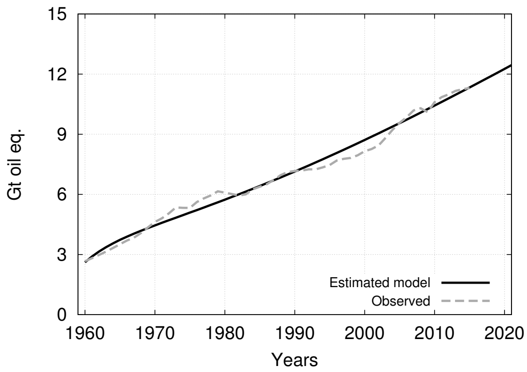
population; (b) agricultural output; (c) output in the rest of the economy; (d) agricultural TFP net of climate damages (i.e. $A_{t,ag} \cdot \exp(-\Omega_{ag}\left[S_t - \overline{S}\right])$); (e) TFP in the rest of the economy net of climate damages; and (f) cropland area. The comparison shows that the model fits the data closely, particularly the long-run trends it is intended to simulate. The plots also illustrate well-known trends. World population and GDP have expanded hugely. Population has grown slightly more than arithmetically, while GDP has grown exponentially, driven by output in the rest of the economy. Agricultural output has also grown (more than fourfold, indeed), but still its share of GDP has fallen. TFP has grown at a declining rate in both sectors, with the decline greater in agriculture, while cropland has slowly expanded as part of the growth of world food supply.

Figure 2 compares model estimates of six key energy/emissions/climate variables with their corresponding observations: (a) fossil energy use; (b) non-fossil energy use; (c) agricultural GHG emissions; (d) GHG emissions from fossil-fuel burning; (e) total GHG emissions; and (f) the atmospheric GHG stock. Fossil and non-fossil energy use are targeted by our structural estimation, thus the comparison is another test of goodness of fit. The remaining emissions/climate variables are not directly targeted by the estimation procedure, however. Thus, the comparison serves as a limited test of prediction out of sample. Again, the model closely tracks the observations. The huge expansion of world GDP has led to a similarly huge expansion in global energy use. Fossil energy use was much greater than non-fossil energy use throughout the period, although non-fossil energy use grew more quickly. Total GHG emissions roughly doubled between 1970 and 2010, agricultural GHG emissions grew by about one third over the same period, the share of GHG emissions from burning fossil fuels rose slightly, and the rising atmospheric GHG stock is tracked particularly closely.

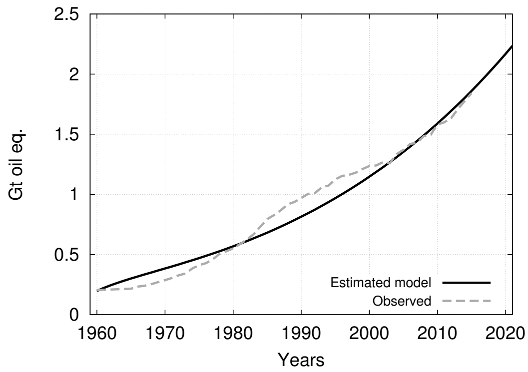
In Appendix B, we report further tests of the robustness of our estimation procedure. In particular, we split the estimation period into 1960-1990 and 1990-2015, and we compare the resulting model projections with each other, with the model estimated on the full period 1960-2015, and with the observations. Overall, the different model estimates are highly consistent. Comparing the model estimated on 1960-1990 with observations post-1990 provides a proper out-of-sample prediction test, even if ultimately there is no good reason to ignore post-1990 data for our purposes. This model closely predicts observed population, land, and dirty energy use, but it overestimates GDP and clean energy use, intuitively due to the slowdown observed in GDP and clean energy growth post-1990.

Figure 2: Estimation results for energy, emissions and climate variables

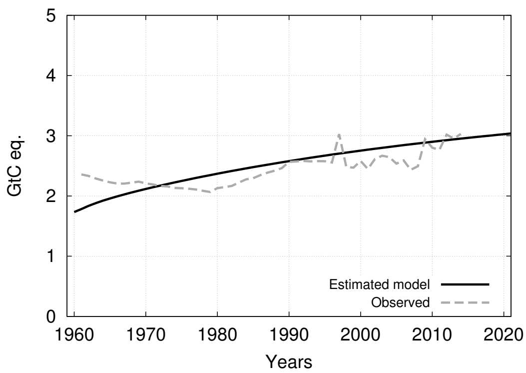
(a) Global fossil energy use



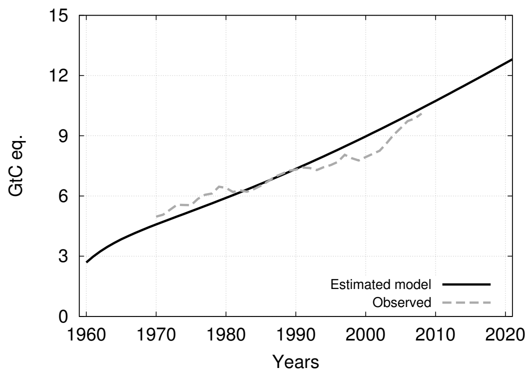
(b) Global non-fossil energy use



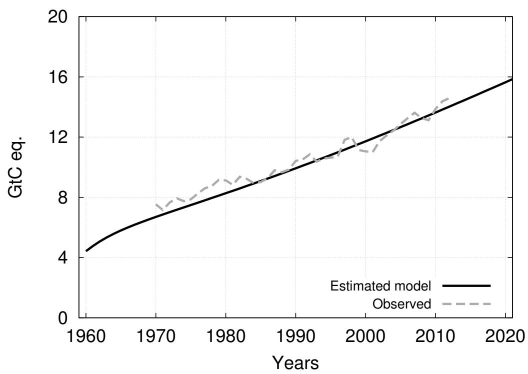
(c) Agricultural GHG emissions



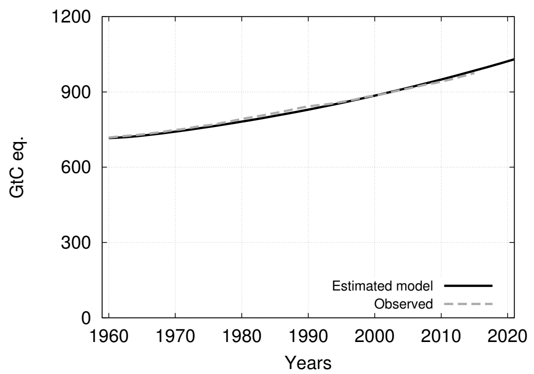
(d) Fossil GHG emissions



(e) Total GHG emissions



(f) GHG stock



4 Counterfactual analysis: global climate impacts and adaptation over recent decades

In this section, we use our structural model to provide novel evidence on how much climate change has affected world agriculture and the rest of the economy in the past half century, and we quantify the role of adaptation channels such as structural change, agricultural land expansion, innovation and fertility in reducing climate damages. To do so, we leverage the fact that our SMM approach allows us to simulate a counterfactual economy in the absence of climate change. The counterfactual equilibrium is computed by solving the model with climate damages 'turned off', i.e., setting $\Omega_{ag} = \Omega_{mn} = 0$, without re-estimating the structural parameters.

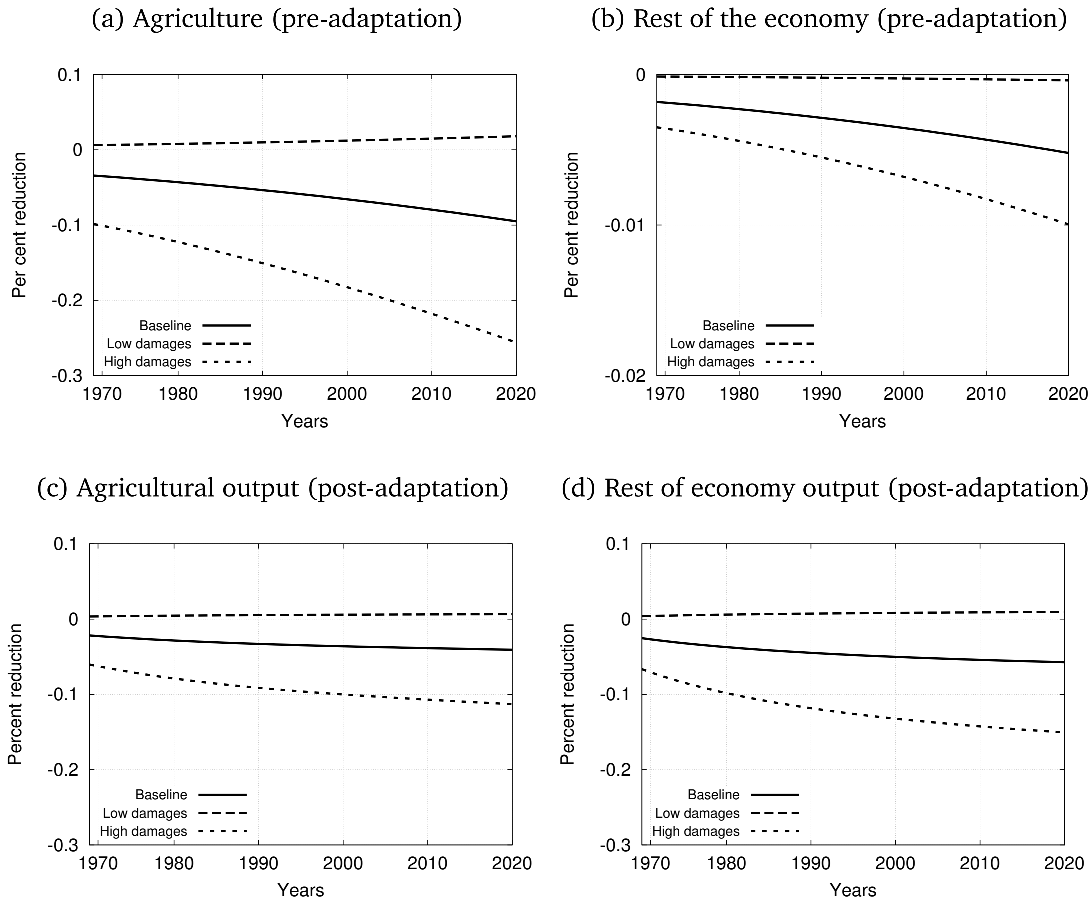
In Figure 3, we quantify overall climate damages and how much they have been reduced by adaptation. The top two panels plot the *pre-adaptation* productivity effect on agriculture and the rest of the economy, respectively. These are obtained simply by taking the atmospheric GHG stock estimated by the model and plugging it into the sectoral damage multipliers, i.e., $\exp(-\Omega_{ag}\left[S_t - \overline{S}\right])$ and $\exp(-\Omega_{mn}\left[S_t - \overline{S}\right])$, respectively.

Thus, the top two panels represent the distribution of productivity effects estimated in the underlying literatures we use for calibration. Absent any adaptation, climate damages would already have reduced agricultural output/productivity by 3.5% in 1970, relative to a counterfactual world without climate change.[15] This is within a sensitivity range from a 0.6% increase in agricultural output to a 10.1% decrease, estimated by running the model with the damage coefficient Ω_{ag} set to its lower/upper bounds. By 2020, rising temperatures would have caused agricultural damages to rise to 9.7% of output, within a range from a 1.8% increase to a 26% decrease. Thus, these results reflect the large uncertainty in crop yield effects from climate change that exists in the crop modeling literature (IPCC, 2022), and a null effect is not ruled out. However, the best estimate is a significant decrease in output. In the rest of the economy, climate damages would have been lower, reducing output by 0.2% in 1970 if no adaptation had taken place, within a sensitivity range of 0.0% to 0.4% (also obtained by setting Ω_{mn} to its lower/upper bounds). By 2020, damages in the rest of the economy would have risen to 0.5% (range 0.0-1.0%).

In comparison, the bottom two panels of Figure 3 plot lost output in agriculture and the rest of the economy after macroeconomic adjustments, i.e. *post-adaptation*. To do this, we solve the estimated model with climate damages, solve it again for a counterfactual world without climate damages, and calculate the relative difference in sectoral output between the two solutions.

[15] Although the model is structurally estimated on data from 1960, our comparison here focuses on the period from 1970 onwards, because we want the effect of initial conditions on variables such as land, output and population to be eliminated.

Figure 3: Estimated climate change impacts since 1970, before and after adaptation



Output will be different in this situation, because the economy adjusts to the raw productivity losses from climate change by changing factor inputs, innovating to increase the productivity index, etc.

The results show that adaptation has substantially reduced climate damages in agriculture. In 1970, post-adaptation agricultural output was 2.2% lower than the counterfactual world without climate change, within a range from 0.4% higher to 6.3% lower. In 2020, we estimate post-adaptation agricultural output was 4.1% lower, within a range from 0.7% higher to 11.4% lower. By contrast, in the rest of the economy we estimate that the loss of output due to climate change was *higher* post-adaptation than pre-adaptation. Output in the rest of the economy was 2.7% lower than the counterfactual in 1970, within a range from 0.4% higher to 7% lower. In 2020, we estimate that post-adaptation output in the rest of the economy was 5.8% lower than the counterfactual, within a range from 1.0% higher to 15.1% lower. As we now show, this reversal is the result of diverting resources from the rest of the economy towards agriculture in a bid to produce enough food to meet demand.

Table 3: Historical adaptation to climate change

	1970	1980	1990	2000	2010	2020
Ag. innovation rate (% diff)	+7.7	+8.5	+9.8	+11.3	+13.3	+15.6
Population (% diff)	-1.0	-1.5	-1.9	-2.1	-2.2	-2.3
Cropland (% diff)	0.0	0.0	-0.1	-0.1	-0.2	-0.2
Shares of capital (ppts.)						
Agriculture	+0.53	+0.42	+0.34	+0.29	+0.28	+0.29
Rest of economy	-0.53	-0.42	-0.34	-0.29	-0.28	-0.29
Shares of labor (ppts.)						
Agriculture	+0.18	+0.11	+0.07	+0.06	+0.06	+0.08
Rest of economy	-0.25	-0.23	-0.20	-0.17	-0.14	-0.11
Agriculture R&D	+2.06	+2.10	+2.18	+2.31	+2.45	+2.59
Rest of economy R&D	-0.82	-0.59	-0.44	-0.34	-0.27	-0.21
Fertility	-1.17	-1.39	-1.62	-1.86	-2.11	-2.36

Notes: this table reports estimates of adaptation through alternative channels (best damage coefficient estimates). For each quantity in the table, we report the difference between our estimated model with climate change and a counterfactual simulation in which productivity impacts of climate change are turned off ($\Omega_{ag} = \Omega_{mn} = 0$).

In Table 3, we document several adaptation mechanisms that the world economy has used to reduce the damaging effects of climate change. The mechanisms identified by our model include agricultural innovation, population change, cropland area, and reallocation of capital and labor. For each quantity, we report the difference between the estimated model with climate impacts and the counterfactual simulation without climate change. For brevity, we only report results for the central damage coefficients (baseline) here.

Our results suggest that climate change has induced an increase in agricultural innovation, as measured by the growth rate of the gross technology index $A_{t,ag}$. We estimate that by 2020 the agricultural TFP growth rate was 16 percent higher than in the absence of climate change. The consistently higher agricultural innovation rate up to 2020 resulted in a *level* of agricultural technology that was 7.9% higher than the counterfactual in 2020. We further estimate that world population is slightly lower as a result of climate change. By 2020, world population was 2.3% lower than in the counterfactual world without climate change. By reducing output, especially in agriculture, climate change reduces the utility of a household's children. Since households value their children's utility, they prefer marginally lower fertility. Underpinning – and in addition to – these changes are adjustments in the allocation of capital and labor. Capital has been shifted from the rest of the economy to agriculture, while more labor has been allocated to agricultural R&D and agricultural production, and less less labor has been allocated to fertility.[16] We estimate that in 2020 the share of the world labor force in agricultural R&D was 2.6 percentage points higher than in the counterfactual without climate change. We do not find a significant response of cropland area to climate change, rather the world economy has adjusted on other margins. In summary, we find that by diverting capital and labor back into agriculture, climate change has been a countervailing force to the wider macroeconomic forces driving structural change out of agriculture.

What has the welfare cost of climate change been so far? To calculate this, we first convert consumption of the two goods into a non-homothetic CES index of real consumption (Comin et al., 2021), using the composite good as the base good.[17] This gives the level of consumption of the composite good that would give the same utility as consumption of the two goods separately under non-homothetic CES preferences. We then compute the change in the stationary equivalent of the index (Weitzman, 1976), i.e., the initial consumption index value that, if held constant, gives the same welfare as the actual stream of the index.[18] This welfare measure has the advantage of working for non-marginal changes. We estimate that the welfare cost of climate change between 1960 and 2020 is equivalent to a loss of stationary consumption of the composite good of 6.2% in 1960, relative to the counterfactual world without climate change. This is within a sensitivity range of -0.9% (low damages in both sectors) to 20% (high damages in both sectors). Therefore, while adaptation has significantly reduced climate damages in agriculture, the cost of adaptation, together with residual damages from climate change, is likely to have produced a non-trivial deadweight loss globally. Again, however, the uncertainty is large, driven by uncertainty about climate effects on global crop yields.

5 Optimal future policy

As an IAM, our model can naturally also be used to make future projections, not only under a continued, laissez faire emissions scenario, but also under a welfare-maximizing policy that internalizes climate damages through a Pigouvian carbon price/tax. We simulate the introduction of a GHG tax[19] in 2016, the year following the United Nations Paris Agreement on Climate

[16] We see negligible effects on the capital and labor shares in clean and fossil energy production, and on the labor shares in clean and fossil energy R&D.

[17] The non-homothetic CES index of real consumption $\log C_t = \varepsilon_{mn} \log U_t + \frac{1}{1-\sigma_c} \log \kappa_{mn}$, where the base good is the composite non-agricultural good. See Comin et al. (2021), p321, Eq. (12).

[18] In our setting, with endogenous population, we need to ensure population is the same on both paths being compared. Thus, for these calculations we set population to the baseline path and solve for the 1960 consumption index value that, if held constant, gives the same welfare as the actual consumption/population path being evaluated.

[19] This tax is implicitly levied not only on CO_2, but also on CH_4 and N_2O in proportion to their CO_2-equivalence. Formally, it is derived as the marginal rate of substitution between GHG emissions and consumption of the composite good.

Change.

Figure 4 projects the Pigouvian GHG tax (panel a) and the resulting optimal paths of total energy use (b), agricultural GHG emissions (c), fossil GHG emissions (d), the atmospheric GHG stock (e), and temperature (f). Despite finding in the previous section that the world economy adapts to climate change on several margins, we estimate a high Pigouvian GHG tax. The tax rate is \$151/tCO_2eq in 2020 (in 2010 US dollars). This increases in real terms to \$283/t in 2050 and \$557/t in 2100. The GHG tax significantly reduces total energy use and GHG emissions, particularly fossil GHG emissions which are 81% lower in 2050. Agricultural GHG emissions are 9% lower in 2050, illustrating that emissions in agriculture are more costly to abate given the food preferences of a growing world population. The large reduction in GHG emissions slows growth in the atmospheric stock of GHGs and, in turn, the global mean temperature. The optimal policy reduces the atmospheric stock of GHGs by 21% in 2050 and 41% in 2100. Although temperature plays no explicit role in our model, here we use the IPCC's two-box temperature model (Geoffroy et al., 2013) to estimate what temperature increase these GHG stocks would lead to.[20] The optimal policy reduces warming from 3.2°C in 2100 to 1.7°C. This means optimal warming in 2100 according to our model is in agreement with the goal of the UN Paris Agreement on climate change to hold "the increase in the global average temperature to well below 2°C above pre-industrial levels".

In Table 4, we compare the laissez faire and optimal scenarios on pre-adaptation climate damages, post-adaptation output, as well as several adaptation channels investigated in the previous section. Since optimal GHG emissions are much below the laissez faire level, pre-adaptation climate damages to agriculture are also much lower, particularly by the end of the century, when damages on the laissez faire scenario are projected to be 26% relative to the counterfactual without climate change, compared to 11% on the optimal path. The laissez faire economy continues to adapt to climate change. The post-adaptation loss in agricultural output, relative to the counterfactual without climate change, is much lower than its pre-adaptation counterpart. For example, it is just 6% in 2100. Post-adaptation damages are lower still on the optimal path, at only 3% in 2100. GHG abatement is prevention while adaptation is the cure. Thus, on the optimal path agricultural innovation is lower, population is higher, and cropland is lower. While we estimate that cropland expansion was not a significant adaptation mechanism at the global level in the past, our future projections imply that it could become significant in the second half of the century. By 2100, 500 million hectares more cropland is in use in the

[20] As we feed not only CO_2 emissions into the model of Geoffroy et al. (2013), but also CH_4 and N_2O (in tCO_2eq), we make a bias correction of -0.372°C to the level of temperature in all years, which corresponds to the difference between the model projection of warming in 2005 relative to the 1850/1900 average, and observations obtained from IPCC (2013). The 2005 temperature in the model is obtained by feeding historical emissions of CO_2, CH_4 and N_2O through our carbon cycle and the temperature model of Geoffroy et al. (2013), starting in 1765.

Figure 4: laissez faire (baseline) and optimal GHG taxation, energy, emissions and climate outcomes over the 21st century

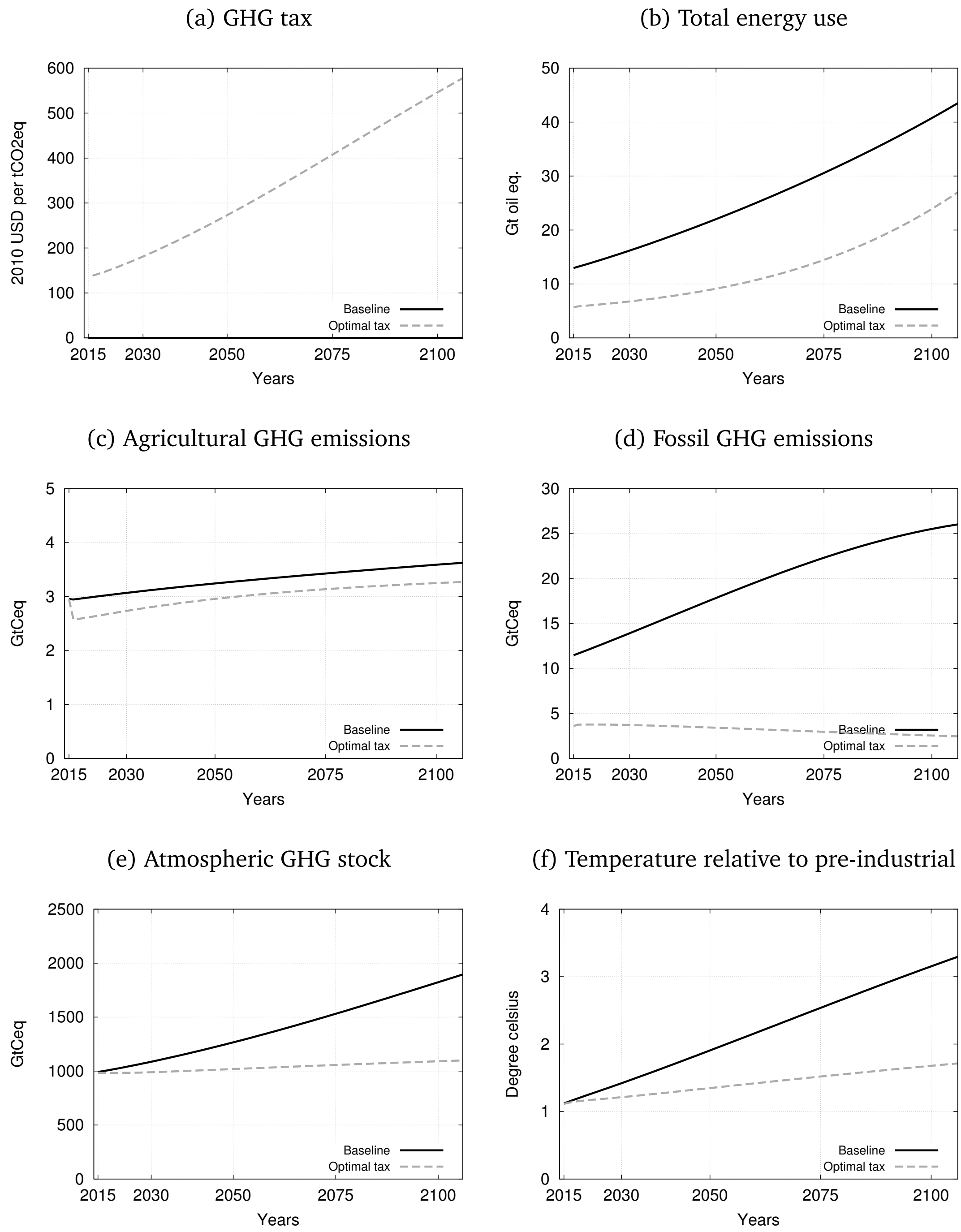


Table 4: Laissez faire and optimal climate damages and adaptation

	2025	2050	2075	2100
Pre-adaptation climate damages to agriculture (% change in output/productivity)				
Baseline	-10.51	-15.09	-20.27	-25.59
Optimal	-8.88	-9.66	-10.45	-11.16
Post-adaptation agricultural output (% diff. with counterfactual)				
Baseline	-4.25	-4.70	-5.15	-5.58
Optimal	-4.38	-4.14	-3.40	-3.09
Post-adaptation output in the rest of the economy (% diff. with counterfactual)				
Baseline	-5.93	-6.45	-6.74	-6.85
Optimal	-8.77	-8.33	-6.78	-6.07
Agricultural innovation (gross TFP index in agriculture)				
Baseline	1.17	1.52	1.91	2.33
Optimal	1.16	1.48	1.80	2.11
Population (billions)				
Baseline	8.13	10.11	11.91	13.45
Optimal	8.15	10.18	12.02	13.61
Cropland (billion hectares)				
Baseline	1.62	1.70	1.76	1.81
Optimal	1.61	1.67	1.72	1.76

Notes: this table compares model simulations under the baseline scenario (laissez faire) with those under optimal GHG taxation, focusing on climate damages, post-adaptation output, and various adaptation mechanisms. All results are for the central damage specification.

laissez faire scenario compared to the optimal scenario. Post-adaptation output also includes the cost of emissions abatement. That is why optimal post-adaptation output is initially lower in both sectors compared to laissez faire, but by the end of the century it is higher. This reflects the well-known intergenerational trade-off that climate policy presents.

Overall, our analysis shows that – despite anticipating further, widespread adaptation to climate change – it is optimal to significantly curb GHG emissions. Following a laissez faire strategy would come with a larger welfare cost, as resources are diverted from their most productive uses to manage the impacts of climate change, and despite the costs of GHG abatement themselves. We estimate that the welfare gain from optimal emissions abatement is 8.7% (i.e., the change in stationary consumption in 2015), relative to the laissez faire path.

6 Decomposition analysis: adjustment constraints

In this section, we provide evidence on the importance of different adjustment channels in the presence of GHG taxes and climate change. We compare the optimal policy solution discussed in the previous section with constrained optimal paths, where a set of key adjustment margins are fixed to their respective laissez faire trajectories. The comparison serves two purposes. First, it provides further insight into which adjustment margins are most important, for example in relation to climate adaptation is it land expansion, innovation or fertility/population? Second, since our model simplifies by assuming that capital, labor and energy are shifted between sectors without adjustment costs, it provides insight into how the presence of frictions might change our results. By fixing certain variables at their laissez faire levels, we implement an extreme form of adjustment constraint and thereby 'stress-test' our findings from above. Results are reported in Table 5, focusing on welfare, GHG tax rates, cropland, agricultural innovation and population.

The first three rows of the table focus on different frictions in the low-carbon transition, i.e., the shift from a fossil-fuel economy to one based on clean energy. We start by fixing fossil energy capital at its laissez faire trajectory. In this scenario, GHG abatement costs increase significantly, which results in higher optimal GHG taxes but lower total emissions abatement, so the world economy has to undertake more adaptation to climate change, here apparent in the form of more agricultural land expansion than the unconstrained optimum, more agricultural innovation (higher values of the gross agricultural TFP index), and lower population. The results for agricultural R&D are particularly striking, with the gross agricultural TFP index 12% higher than the unconstrained optimum by the end of the century. This constraint imposes the largest welfare cost, unsurprisingly so given the desirability of reducing the dirty capital stock in the future. However, fixed fossil energy capital is a particularly extreme assumption, as it requires continued investment in fossil energy even in the presence of high GHG taxes. Therefore, the second scenario explores a milder form of this constraint, in which the stock of fossil energy capital is allowed to depreciate after 2015 (we use $\delta_k = 0.1$), but no conversion of fossil energy capital into clean energy capital is allowed. With this constraint, the welfare loss relative to the unconstrained optimum is much smaller. We also observe that the GHG tax path is flatter, starting higher than the unconstrained optimum but ending lower. This is consistent with the trajectory of fossil energy capital itself, which starts higher than the unconstrained optimum, due to the inability to convert it to clean capital, but ends up lower to compensate. Changes in cropland, agricultural R&D and population are similar to the unconstrained optimum. Lastly, we consider scenarios where energy R&D is fixed to its laissez faire trajectory, first clean and dirty energy R&D together, then clean energy R&D alone. Imposing these constraints does not have a significant impact on model outcomes, implying that in the energy sector capital investment is more important as an adjustment margin than R&D. This is consistent with the energy systems

Table 5: Optimal paths with adjustment constraints

	Welfare (% diff.)	GHG tax ($/tCO2eq and % diff.)				Cropland (million ha. and % diff.)				Gross agricultural TFP (index value and % diff.)				Population (billions and % diff.)			
		2025	2050	2075	2100	2025	2050	2075	2100	2025	2050	2075	2100	2025	2050	2075	2100
Unconstrained optimum	-	169.19	283.11	418.57	556.79	1.61	1.67	1.72	1.76	1.16	1.48	1.80	2.11	8.15	10.18	12.02	13.61
Frictions in the low-carbon transition																	
Fixed fossil capital	-7.4	+8.2	+11.0	+13.6	+16.0	0.0	+0.1	+0.3	+0.6	+0.9	+3.8	+7.6	+11.9	-0.2	-0.6	-0.9	-1.1
No fossil to clean capital	-1.2	+3.7	-4.2	-7.6	-7.8	0.0	0.0	0.0	-0.1	0.0	0.0	-0.3	-0.7	-0.1	-0.2	-0.2	-0.2
Fixed energy R&D	-0.1	0.0	+0.1	+0.1	+0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Fixed clean energy R&D	0.0	0.0	+0.1	+0.1	+0.2	0.0	0.0	0.0	0.0	0.0	0.0	+0.1	+0.1	0.0	0.0	0.0	0.0
Frictions in adaptation to climate change																	
Fixed cropland	0.0	+0.2	+0.1	0.0	0.0	Fixed at baseline				-0.1	-0.5	-0.8	-1.1	0.0	0.0	0.0	0.0
Fixed agricultural R&D	-1.7	-8.2	-12.8	-17.5	-21.6	-0.2	-0.8	-1.6	-2.4	Fixed at baseline				-0.1	-0.3	-0.5	-0.5
Fixed population	-0.5	+0.2	-0.1	+0.3	+1.7	+0.1	+0.3	+0.3	+0.4	-0.1	-0.1	0.0	+0.3	Fixed at baseline			
Fixed ag. prod. capital	-0.1	-0.1	+0.2	+0.6	+0.8	0.0	0.0	0.0	0.0	-0.1	-0.3	-0.5	-0.6	0.0	0.0	-0.1	0.0

Notes: this table reports estimates of welfare impacts and optimal trajectories for GHG taxes, cropland, agricultural innovation and population (central damage specification). Aside from the unconstrained optimum discussed in Section 5, we report optimal policy results for models in which alternative variables are constrained to follow their baseline/laissez faire trajectory.

modeling literature, which invariably finds that ambitious climate goals can be met through deployment of existing technologies (IPCC, 2018), but a caveat is that our use of long-run historical trends in energy use to identify labor productivity in energy R&D may underestimate the future potential of clean energy R&D.

In the bottom four rows, we consider frictions in adapting to climate change by fixing cropland, agricultural R&D, population and agricultural capital to their respective laissez faire trajectories and solving for the optimal GHG tax given these constraints. Two main findings emerge. First, the differences between the unconstrained optimum and these constrained optima are generally small. This suggests that our conclusions above are robust to the inclusion of these individual adaptation frictions. Second, the constraint with the largest effect and by inference the most important adaptation mechanism is agricultural innovation. Fixing agricultural innovation to its laissez faire trajectory implies allocating too much labor to agricultural R&D, resulting in a sub-optimally high gross agricultural TFP index. As a consequence, GHG taxes are significantly lower. Put another way, the economy is 'over-built' to withstand climate change in this scenario, so it is optimal to allow higher GHG emissions. With sub-optimally high agricultural innovation, cropland area is sub-optimally low, as is population.

7 Sensitivity analysis

In this section, we document the robustness/sensitivity of our optimal policy results to varying a number of exogenous parameters. We pay particular attention to the damage intensity parameters Ω_{ag} and Ω_{mn}, in light of the results above. Given the model is structurally estimated, changing exogenous parameters is not a trivial step, as it may result in the model no longer fitting observations over the estimation period. Therefore, the model must be re-estimated whenever a parameter is varied, keeping the distance between the model estimates and our targeted variables to a minimum. In Appendix E, we report the structural parameter estimates accompanying the sensitivity analysis.[21] Table 6 summarizes the results, reporting the sensitivity of five variables: the welfare gain from the laissez faire equilibrium, the GHG tax, total GHG emissions, and, as two examples of adaptation to climate change, we include the differences in cropland and population from the laissez faire equilibrium.

We analyze three pairs of variations of the damage intensity parameters. In the first pair of variations, we set both Ω_{ag} and Ω_{mn} to their lower- and upper-bound estimates, respectively. In the second pair, we vary only Ω_{ag}, leaving Ω_{mn} at its best estimate ('low damages ag' and 'high

[21] Changing the carbon cycle parameters has no significant impact on trajectories over the estimation period, so the structural parameters remain at their baseline level. However, alternative parametrizations of the carbon cycle do affect the ability of the model to match observed atmospheric GHG concentrations. The base parametrization matches them best.

Table 6: Sensitivity of optimal paths to variations in exogenous parameters

	Δ welfare (%)	GHG tax ($/t$CO_2$eq)			Total GHG emissions (GtCeq)			Δ cropland from laissez faire (mn. ha.)			Δ population from laissez faire (mn.)		
		2020	2050	2100	2020	2050	2100	2020	2050	2100	2020	2050	2100
Main specification	+8.7	150.90	283.11	556.79	6.4	6.4	5.8	-5.1	-27.6	-50.5	+7.8	+58.2	+161.9
Low damages	+0.5	-25.42	-49.17	-96.68	18.6	29.5	41.9	+0.6	+3.2	+4.3	-1.3	-3.1	+4.4
High damages	+49.9	399.43	770.84	1527.64	2.9	3.5	3.7	-18.5	-95.7	-164.5	+34.9	+269.6	+686.6
Low damages ag	+0.2	-17.05	-31.84	-59.02	17.6	26.7	37.5	+0.4	+2.2	+2.8	-0.9	-2.5	+0.8
High damages ag	+49.8	398.20	768.33	1524.60	2.9	3.5	3.7	-18.5	-95.7	-164.5	+34.9	+269.3	+686.3
Low damages mn	+8.1	143.93	269.47	527.85	6.6	6.6	6.0	-4.8	-26.5	-48.8	+7.5	+55.4	+152.8
High damages mn	+9.1	157.66	296.17	584.42	6.3	6.2	5.7	-5.3	-28.7	-52.2	+7.9	+60.4	+170.2
Slow CO_2 removal	+6.3	178.45	333.67	657.92	5.8	5.7	5.2	-5.8	-31.9	-58.0	+3.3	+35.4	+130.5
Fast CO_2 removal	+9.8	138.97	261.03	541.09	6.7	6.7	6.1	-4.7	-25.4	-47.0	+9.5	+67.8	+176.7
$\beta = 0.97$	+6.3	129.08	251.83	593.82	9.2	9.7	9.1	-5.4	-30.7	-58.9	+6.3	+49.9	+146.7
$\sigma_X = 0.2$	+8.8	148.83	265.84	482.74	5.6	4.9	3.9	-3.3	-18.4	-36.9	+7.2	+51.8	+134.5
$\overline{R} = \infty$	+8.7	150.96	283.45	557.32	6.4	6.4	5.8	-5.1	-27.6	-50.6	+8.2	+60.7	+165.3

Notes: this table reports estimates of welfare impacts and optimal trajectories for GHG taxes and emissions, as well as cropland and population relative to the laissez faire equilibrium (base damage specification).

damages ag'). In the third pair, we do the opposite, varying only Ω_{mn}, leaving Ω_{ag} at its best estimate ('low damages mn' and 'high damages mn'). Two key messages emerge from the analysis. The first is that, overall, the results are highly sensitive to the intensity of damages. Higher damages imply a larger welfare gain from controlling the climate externality, much higher GHG taxes, much lower GHG emissions, and more adaptation as exemplified by bigger differences in cropland and population relative to the laissez faire equilibrium. The opposite holds for lower damages. The second key result is that this sensitivity comes almost entirely from damages to agriculture. Compare, for example, the set of results for 'high damages' with those for 'high damages ag'. They are almost the same, whereas 'high damages mn', which has high damages to the rest of the economy but fixes agricultural damages to their best estimate, looks little different to our main specification. Therefore, this analysis underscores the centrality of agricultural damages and food supply/demand to the welfare cost of climate change. Under high agricultural damages, optimal GHG taxation would increase welfare by around 50% relative to a laissez faire future. Under low agricultural damages, the welfare gain is minimal and it would be optimal at this extreme of the parameter range to slightly subsidize GHG emissions, even if climate change reduces productivity in the rest of the economy.

Results are less sensitive to variations in the other parameters. We analyze sensitivity to the efficacy of the carbon cycle, specifically the speed of removal of CO_2 from the atmosphere via the parameters a_i and $\delta_{S,i}$. Slower CO_2 removal results in greater accumulation of CO_2 in the atmosphere for given emissions, so in this run of the model we see higher GHG taxes and lower emissions. The opposite is true of faster CO_2 removal. With less weight placed on future utility, a higher utility discount rate ($\beta = 0.97$) yields a somewhat smaller welfare gain from GHG taxation, lower optimal GHG taxes, higher optimal GHG emissions, and some differences in cropland and population. Results are insensitive to lowering the elasticity of substitution between land and the capital-labor-energy composite in agriculture, and removing the fossil-fuel resource constraint.

8 Discussion and conclusion

In this paper, we have formulated a structural model of the world economy as an empirical framework to study the relationship between economic growth, population growth, agriculture, and climate change, both in the past and in the future. Our approach integrates a number of seminal contributions to economic thought, including on fertility choice (Barro and Becker, 1989), consumer preferences/structural change (Comin et al., 2021), and technical change (Aghion and Howitt, 1992; Acemoglu et al., 2012). The model structure, combined with our estimation approach using more than half a century of data on key aggregates, constitutes a novel way of estimating the long-run impacts of secular climate change. First, our structural estimation approach allows us to construct a counterfactual past, in which temperatures did not rise. This allows us to study how the global economy has already been affected by long-run changes in climate. Second, our approach allows us to quantify adaptation to climate change through channels including factor reallocation between sectors, agricultural land expansion, and R&D investments. Our work complements recent empirical literature on the short-run productivity effects of climate change (e.g. Dell et al., 2012; Carleton and Hsiang, 2016). The intensity of damages in our model is captured by exogenous parameters that we calibrate in part on this literature. On the other hand, because our model emphasizes the long-run effects of climate change, it provides an alternative means of estimating this to the 'long differences' approach in the empirical literature (see Hsiang, 2016, for a discussion of how short- and long-run effects are handled in the empirical literature).

We estimate substantial impacts of climate change, both in the past and in the future. Agronomic evidence suggests that climate change has already depressed agricultural yields and would do so much more in a laissez faire future (IPCC, 2022). However, we estimate that this does not lead to equivalently large reductions in agricultural output due to general-equilibrium adjustments, moving resources out of the rest of the economy into agriculture to compensate for falling yields. Thus, market mechanisms allow the economy to adapt to climate change. This is not to say, however, that from the point of view of maximizing social welfare GHG emissions should be left uncontrolled. On the contrary, we estimate a relatively high optimal GHG tax, as the welfare cost of a laissez faire emissions path is high. It might be possible to allocate resources such that climate damages are apparently muted, but the opportunity cost of doing so is significant. Our estimates naturally rest to an extent on uncertain parameters. Qualitatively our results appear robust. Quantitatively they are also robust to many exogenous parameter variations, but they are especially sensitive to the intensity of pre-adaptation climate damages on agriculture, emphasizing the importance of further empirical work in that area.

As a sense-check, we can compare our model projections with others in the relevant literatures. Our population projections are higher than those of the United Nations (2019). Low population projections typically depend on assuming relatively rapid convergence to replacement fertility levels, which the data do not unambiguously support (Strulik and Vollmer, 2015). In our model, population growth slows down, but not as much. The primary mechanism driving falling fertility in our model is technological progress, which raises the opportunity cost of childrearing. We project that technological progress will itself slow down, such that fertility holds up. This economic approach to projecting population is fundamentally different to standard demographic projections, which make direct assumptions about fertility and mortality rates. We project GDP growth of 2.1% between now and 2060, which is close to the projection of 2.4% by OECD (2018). Our projection of global cropland in 2050 is almost identical to that of the FAO (Alexandratos and Bruinsma, 2012). Our laissez faire GHG emissions scenario closely tracks the

IPCC's RCP8.5 scenario, as does our estimated atmospheric GHG concentration. Our optimal GHG prices/taxes are high but representative of a trend in climate economics towards higher prices (Hänsel et al., 2020; Rennert et al., 2022), which has multiple sources including fast climate dynamics (which our model has) and higher damages.

A recent literature highlights that the impacts of climate change will be heterogeneous across space, and emphasizes the role of spatial reallocation of agriculture and economic activity (Costinot et al., 2016; Desmet and Rossi-Hansberg, 2015; Nath, 2022). In particular, growing conditions for crops may worsen in already hot climates, and improve in currently cold climates. Our model structure aggregates over space and we calibrate pre-adaptation agricultural damages by aggregating yield effects from the literature over space, so that our agricultural damage coefficient Ω_{ag} can be thought of as an average treatment effect. Spatial reallocation could reduce negative yield effects on average by directing more resources to production in cold climates at the expense of hot climates, thus constituting a potentially important adaptation mechanism, but only if trade is free enough to meet food demand everywhere. Nath (2022) provides important evidence to suggest that although the potential gains to spatial reallocation have been large, trade barriers have largely prevented them from being realised. This gives us some confidence in our historical estimates not conflating the effect of spatial reallocation on productivity with the effect of innovation. If trade barriers continue to prove difficult to overcome, then the adaptive response we attribute to innovation is likely to remain of first order importance.

There are several ways in which this work could be extended. One is into the area of population ethics and the social valuation of population, which has been identified as an important consideration for climate policy (Méjean et al., 2017; Scovronick et al., 2017). Our household's objective function (21) can be given a normative interpretation as an example of a number-dampened critical-level utilitarian social welfare function (Asheim and Zuber, 2014), which nests multiple important positions on population ethics and could be used to explore how they affect optimal GHG taxation/abatement. Because our goals in this paper have been empirical/quantitative, we chose to structurally estimate the parameter η that governs the social value of population. Further exploration of population ethics could be based on an alternative approach, where η is exogenous and the flexibility of the SWF is exploited. In the limit as $\eta \to 1$, the special case of discounted average utilitarianism is obtained, whereby social welfare depends only on average utility in the population. Conversely in the limit as $\eta \to 0$, the special case of discounted classical/total utilitarianism is obtained, whereby social welfare is the sum of the utilities of each member of the population and is increasing in population size.

Another extension is further study of the optimal carbon price trajectory. Previous work has examined the growth rate of the optimal carbon price. In a well-known result, Golosov et al. (2014) found the optimal carbon price grows at the same rate as GDP under certain assumptions, while other more recent work has suggested the optimal carbon price should grow faster than GDP (Rezai and van der Ploeg, 2016; Dietz and Venmans, 2019). Our results suggest the optimal carbon price grows slightly slower than GDP, of the order of 0.1 percentage points slower throughout the century. Further analysis of what factors drive this difference would be useful. These previous studies are based on one-sector models with exogenous population.

The structure of the model could be extended to take in a number of additional issues. We have assumed an exogenous, constant mortality rate and used fertility choice as the mechanism by which climate change affects population. Further work could link climate change with mortality. Although agricultural land expansion causes CO_2 emissions, the emissions intensity of land expansion is calibrated on past data and does not take into account any runaway effects of deforestation on carbon sequestration, nor does it take into account the effects of lost biodiversity. Doing so would constitute an interesting extension. It faces some extreme empirical challenges, but would be valuable as a form of stress test. Most of all, it seems important to begin attempting to combine/unify the globally aggregated, dynamic modeling approach exemplified by this paper with spatially disaggregated but less dynamic approaches such as Costinot et al. (2016); Desmet and Rossi-Hansberg (2015); Nath (2022).

To conclude, we suggest that structural estimation is a useful approach that could be adopted more widely in the literature building climate-economy models. Not only can it address concerns about the ability of such models to reproduce past trends (as highlighted by Millner and McDermott, 2016), it allows the construction of historical counterfactuals and opens up an alternative way of studying past impacts.

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Appendix A Optimization problem

Collecting terms, the optimization problem can be stated formally as:

$$
\begin{aligned}
\max_{C_t, K_{t,\cdot}, E_{t,\cdot}, L_{t,\cdot}} \quad W_0 = \quad & \textstyle\sum_{t=0}^{\infty} \beta^t N_t^{1-\eta} \frac{U_t^{1-\gamma}-1}{1-\gamma} \\
\text{s.t.} \quad & X_t \;=\; X_{t-1}(1-\delta_X) + \psi L_{t-1,X}^{\varepsilon}\,, \quad X_t \le \overline{X} \\
& A_{t,j} \;=\; A_{t-1,j}\left[1 + \lambda_j \left(\frac{L_{t-1,A_j}}{N_{t-1}}\right)\right]^{\mu_j}\,, \quad j \in \{mn, ag, cl, dt\} \\
& N_t \;=\; N_{t-1}(1-\delta_N) + \chi L_{t-1,N}^{\zeta} \\
& K_t \;=\; K_{t-1}(1-\delta_K) + I_{t-1} \\
& S_t = \textstyle\sum_{i=0}^{3} S_{t,i} \\
& S_{t,0} = a_0 \left[\pi_{E,CO2} E_{t,dt} + \pi_X \left(X_t - X_{t-1}\right)\right] + (1-\delta_{S,0}) S_{t-1,0} \\
& S_{t,i} = a_i \left[\pi_{E,CO2} E_{t,dt} + \pi_X \left(X_t - X_{t-1}\right)\right] \\
& + \frac{a_i}{\sum_{i=1}^{3} a_i}\left[\pi_{E,NCO2} E_{t,dt} + \pi_{ag}\left(K_{t,ag}^{\theta_K} E_{t,ag}^{\theta_E} L_{t,ag}^{1-\theta_K-\theta_E}\right)\right] \\
& + (1-\delta_{S,i}) S_{t-1,i},\ i = 1,2,3 \\
& \kappa_{ag}^{\frac{1}{\sigma_c}} \left(\frac{c_{t,ag}}{U_t^{\varepsilon_{ag}}}\right)^{\frac{\sigma_c-1}{\sigma_c}} + \kappa_{mn}^{\frac{1}{\sigma_C}} \left(\frac{c_{t,mn}}{U_t^{\varepsilon_{mn}}}\right)^{\frac{\sigma_c-1}{\sigma_c}} = 1 \\
& Y_{t,mn} \;=\; C_t + I_t \\
& Y_{t,ag} = C_{t,ag} \\
& E_t \;=\; E_{t,mn} + E_{t,ag}\,, \quad \textstyle\sum_0^T E_{t,dt} \le \overline{R} \\
& N_t \;=\; L_{t,mn} + L_{t,ag} + L_{t,cl} + L_{t,dt} + \textstyle\sum_j L_{t,A_j} + L_{t,X} + L_{t,N} \\
& K_t \;=\; K_{t,ag} + K_{t,mn} + K_{t,cl} + K_{t,dt} \\
& K_0, N_0, X_0, S_{0,i}, A_{0,j}\ \forall i\ \forall j \text{ given}
\end{aligned}
$$

This is an infinite-horizon, non-linear optimal control problem, which we solve using efficient mathematical programming methods. Such methods cannot explicitly accommodate an infinite horizon, because the problem would include both an infinite number of terms in the objective function and an infinite number of constraints.[22] We approximate the solution to the infinite-horizon problem using a finite horizon of T years, relying on the presence of a discount factor $\beta < 1$, which implies that only a finite number of terms matters for the numerical solution. We select a value for T that is large enough to avoid terminal-period effects influencing the solution

[22] A leading alternative formulation is dynamic programming, which uses a recursive formulation to accommodate infinite horizon problems (see e.g. Judd, 1998). This approach, however, also involves approximations to determine optimal transition rules, and computational requirements quickly increase with the number of state variables considered. In our case, we consider a problem with a large number of continuous state variables, and we need to solve the problem many times as part of our structural estimation procedure, which makes mathematical programming more attractive.

over the period of interest to us (i.e., up to 2100). We select $T = 300$ based on evidence that an increase in T does not affect relevant outcomes in 2100 by more than 0.1 percent.

To estimate the model and study past climate impacts, we initialize it to match observations in 1960, and solve it up to the year 2260. To compute the optimal future climate policy, the model estimated on 1960- data is re-initialized in 2015 and solved up to the year 2315. Once appropriately scaled, the nonlinear program solves in a matter of seconds, which is particularly important for the simulation-based estimation.

In order to make laissez faire projections, we set the stock of GHGs as exogenous. This exogenous stock affects the economy via the sectoral damage functions in Equations (1) and (2). However, this creates a potential inconsistency, as damages can change the level of emissions produced by the economy, in turn affecting the GHG stock. We resolve this following the iterative procedure of Böhringer et al. (2007). That is, we sequentially update the exogenous GHG stock using the GHG stock resulting from the laissez faire economy's emissions.[23] Our experience with the model suggests that, after one or two iterations, the exogenous GHG stock entering the climate damage functions converges to the GHG stock resulting from emissions with an accuracy of 0.1 percent.

We solve the numerical problem with the KNITRO package in GAMS (Byrd et al., 2006). This allows us to rely on analytical expressions for the Jacobian and Hessian matrices associated with the optimization problem, and use these in a solver that flexibly alternates between an interior point-type algorithm, looking for an optimum of the objective function in the feasible region defined by the constraints, and an active-set algorithm, which stays at the boundary of the feasible region.

[23] Note that this approach requires a first guess as to the trajectory of the exogenous GHG stock entering the damage function. For this purpose, we simply solve the model under an assumption of zero damages.

Appendix B Estimating the model on different time periods

This appendix provides further evidence on identification and the model's ability to fit the data, using data for alternative observation periods. Specifically, our main results are obtained by structurally estimating the model on data from the period 1960 to 2015. Here, we re-estimate the model on two subsets of these data: 1960-1990 and 1990-2015. In Table B1, we compare these three sets of estimates with each other and with the observed data that we target. As we compare the estimates obtained from 1960-1990 with observations post-1990, the analysis contains an out-of-sample prediction test.

Table B1: Comparison of model estimates and observations for models estimated on different time periods

	Estimation Period	Year 1970	1980	1990	2000	2010
Population (billion)	1960-1990	3.74	4.52	5.33	6.15	6.97
	1990-2015			5.33	6.11	6.90
	1960-2015	3.70	4.46	5.27	6.11	6.96
	Observed	*3.70*	*4.46*	*5.33*	*6.15*	*6.96*
GDP (trillion 2010 USD)	1960-1990	18.43	27.40	39.24	54.16	72.29
	1990-2015			36.70	49.15	64.88
	1960-2015	17.27	25.20	35.80	49.26	65.77
	Observed	*19.01*	*27.81*	*37.86*	*49.94*	*65.91*
Cropland (trillion ha)	1960-1990	1.43	1.48	1.53	1.58	1.62
	1990-2015			1.53	1.56	1.59
	1960-2015	1.42	1.45	1.49	1.53	1.57
	Observed	*1.44*	*1.45*	*1.53*	*1.54*	*1.55*
Clean energy (Gt oil eq.)	1960-1990	0.44	0.76	1.27	2.05	3.27
	1990-2015			0.90	1.23	1.58
	1960-2015	0.38	0.57	0.81	1.15	1.59
	Observed	*0.29*	*0.55*	*0.97*	*1.24*	*1.58*
Fossil energy (Gt oil eq.)	1960-1990	4.42	5.72	7.11	8.62	10.22
	1990-2015			6.92	8.73	10.42
	1960-2015	4.45	5.74	7.14	8.71	10.43
	Observed	*4.62*	*6.09*	*7.17*	*8.15*	*10.60*

Notes: This table provides the value of variables targeted in the estimation. We report predicted values for models estimated on data from 1960-1990, 1990-2015, and 1960-2015, as well as the corresponding observations.

Overall, the models estimated on the three different estimation periods are relatively close to each other and relatively close to the observations. This is most especially so for population, cropland, and fossil energy. Estimating the model on data from 1960-1990 does lead to overestimating GDP and clean energy in 2000 and 2010. In the case of GDP, there has been a well-documented slowdown in GDP growth, which the pre-1990 sample does not fully capture. Similarly, there was a less well-documented slowdown in clean energy expansion between 1990 and 2010, relative to the period from 1970-1990.

Table B2 compares the optimal future paths of the models estimated on different historical time periods. The paths show strong similarities. Using the period 1960-1990 for estimation results in slightly lower GHG taxes but also lower emissions, due to the projected faster expansion of clean energy in the absence of GHG taxation. Lower GHG emissions mean less adaptation is necessary, here in the form of cropland expansion and curtailed fertility. The opposite is true when the model is estimated on 1990-2015 data.

Table B2: Optimal paths for models estimated on different time periods

	Δ welfare (%)	GHG tax ($\$/tCO_2eq$)			Total GHG emissions (GtCeq)			Δ cropland from laissez faire (mn. ha.)			Δ population from laissez faire (mn.)		
		2020	2050	2100	2020	2050	2100	2020	2050	2100	2020	2050	2100
1960-1990	+7.7	138.74	247.52	430.10	6.3	5.9	4.7	-6.3	-35.1	-66.9	+6.3	+45.2	+120.1
1990-2015	+8.8	153.50	282.10	570.01	6.3	6.3	6.0	-4.8	-25.9	-46.3	+8.1	+60.8	+165.0
1960-2015	+8.7	150.90	283.11	556.79	6.4	6.4	5.8	-5.1	-27.6	-50.5	+7.8	+58.2	+161.9

Notes: this table reports estimates of welfare impacts and optimal trajectories for GHG taxes and emissions, as well as cropland and population relative to the laissez faire equilibrium (base damage specification).

Appendix C Selection of exogenous parameter values and initial conditions

This section provides a discussion of how we select the values of exogenous parameters in the model, all of which are reported in Table 1.

Starting with household preferences, the elasticity of utility with respect to the composite good, ε_{mn}, is normalized to one, as is the taste parameter κ_{mn}. The elasticity of utility with respect to food ε_{ag} is calibrated so that, given the structural estimate of σ_c, the income elasticity of demand for food as defined in Eq. (17) is 0.5 (Comin et al., 2021). This results in $\varepsilon_{ag} = 0.42$. We set the discount factor $\beta = 0.99$, which corresponds to a utility discount rate of 1%. This is consistent with empirical evidence on very long-run investments by Giglio et al. (2015), and with a recent survey of economists by Drupp et al. (2018). As an alternative, we also consider $\beta = 0.97$ in sensitivity analysis. The inverse of the elasticity of intertemporal substitution $\gamma = 2$ is consistent with the macroeconomic estimates reported in Guvenen (2006).

For the population dynamics, the mortality rate $\delta_N = 0.022$ is calibrated so that the expected working lifetime of agents in the model is 45 years (United Nations, 2013).

In the rest of the economy, the value of the capital share parameter is $\vartheta_K = 0.3$ and the depreciation rate of capital is $\delta_K = 0.1$, both standard values in the literature (see e.g. Hassler et al., 2016a). The share of energy is $\vartheta_E = 0.04$, which is taken from Golosov et al. (2014).

In agriculture, we take the elasticity of substitution between land and the capital-labor-energy composite from long-run econometric evidence reported in Wilde (2013), which suggests $\sigma_X = 0.6$. Because there is uncertainty about this parameter, and because land use is potentially an important adaptation channel in our model, we consider $\sigma_X = 0.2$ in sensitivity analysis. Share parameters for capital and land are respectively $\theta_K = 0.3$ and $\theta_X = 0.25$, consistent with the work of Ashraf et al. (2008), and we set $\theta_E = 0.04$ to be in line with Golosov et al. (2014). Taken together, this implies that our agricultural technology is broadly in line with factor shares reported in the aggregate database of Hertel et al. (2012). The reconversion rate for agricultural land $\delta_X = 0.02$ is set so that agricultural land reverts back to natural land over a period of 50 years (Lanz et al., 2017), and the stock of natural land that can be converted is $\overline{X} = 3$ billion hectares (as discussed in Alexandratos and Bruinsma, 2012).

In the energy sector, we set the elasticity of substitution between clean and fossil intermediates $\sigma_E = 1.5$, drawing on evidence from inter-fuel substitution by Stern (2012). This assumption is also consistent with empirical evidence for non-electric energy reported in Papageorgiou et al. (2017). The capital share $\alpha = 0.6$ is taken from Barrage (2020), and total reserves of fossil fuels are set to $\overline{R} = 5,000$ Gt of oil equivalent, in line with Rogner (1997). This takes into account all fossil fuels, as well as technological progress and new discoveries (this estimate is also used in Golosov et al., 2014; Acemoglu et al., 2016). In the sensitivity analysis, we consider a version of the model in which the total quantity of fossil fuels is unconstrained.

In the R&D sector, we set $\lambda = 0.05$, which can be interpreted as the maximum feasible rate of yearly TFP growth.

In Table C1, we report initial values for the stock variables and we also provide parameter values for the climate module of Joos et al. (2013). Initial values of the unobserved carbon stocks $S_{0,i}$ are obtained by feeding estimated CO_2 emissions from 1750 to 1960 (Boden et al., 2017; FAO, 2022; Janssens-Maenhout et al., 2017; Le Quéré et al., 2018; Meinshausen et al., 2011) into the carbon-cycle model under a pre-industrial parametrization (Millar et al., 2017). From 1960 onwards, the model is re-parametrized to match the contemporary response of carbon sinks to CO_2 accumulating in the atmosphere (again see Millar et al., 2017).

Table C1: Initial conditions and parameters for the climate module

Parameter value	Definition	Source
State variable: Initial values		
$N_0 = 3.03$	World population in 1960 (billion)	United Nations (2017)
$X_0 = 1.38$	Agricultural cropland in 1960 (billion ha)	FAO (2022)
$A_{0,mn} = 5.55$	Initial TFP in rest of economy	Calibrated on 1960 world GDP, estimated share of agricultural
$A_{0,ag} = 0.48$	Initial TFP in agriculture	output in 1960 world GDP, and assumed
$K_0 = 22.38$	Initial stock of capital (trillion 2010 USD)	capital depreciation
$A_{0,cl} = 0.29$	Initial TFP in clean energy	Calibrated on 1960 fossil and non-fossil
$A_{0,dt} = 2.31$	Initial TFP in fossil energy	energy use
$S_{0,0} = 28.115$	Stock of carbon in reservoir 0 in 1960 (GtC eq)	Obtained by initializing model in pre-industrial
$S_{0,1} = 54.826$	Stock of carbon in reservoir 1 in 1960 (GtC eq)	conditions and running forward to 1960 with
$S_{0,2} = 28.463$	Stock of carbon in reservoir 2 in 1960 (GtC eq)	reported parameters
$S_{0,3} = 10.451$	Stock of carbon in reservoir 3 in 1960 (GtC eq)	”
Parameters for the climate module		
$\overline{S} = 590$	Pre-industrial stock of atmospheric carbon (GtC eq)	IPCC (2013)
$\pi_{E,CO2} = 0.858$	Fossil energy CO_2 emissions factor (GtC eq. per Gt oil eq.)	Boden et al. (2017)
$\pi_{E,NCO2} = 0.171$	Fossil energy non-CO_2 emissions factor (GtC eq. per Gt oil eq.)	World Bank (2020)/EDGAR
$\pi_X = 348.859$	Land use change emissions factor (Gt C eq. per bn ha)	Le Quéré et al. (2018)
$\pi_{ag} = 0.435$	Agricultural emissions factor (Gt C eq. per unit of input)	FAO (2022)
$a_0 = \{0.217, 0.285, 0.178\}$	Share of CO_2 going to geological re-absorption	Joos et al. (2013)
$a_1 = \{0.224, 0.294, 0.165\}$	Share of CO_2 going to deep ocean	“
$a_2 = \{0.282, 0.238.0.380\}$	Share of CO_2 going to biospheric uptake / ocean thermocline	“
$a_3 = \{0.276, 0.183, 0.277\}$	Share of CO_2 going to rapid biospheric uptake / ocean mixed layer	“
$\delta_{S,0} = 1E^{-6}$	Geological re-absorption rate	“
$\delta_{S,1} = \{0.00254, 0.0022, 0.0026\}$	Deep ocean invasion/equilibration rate	“
$\delta_{S,2} = \{0.0325, 0.04, 0.0271\}$	Biospheric uptake/ocean thermocline invasion rate	“
$\delta_{S,3} = \{0.232, 0.4965, 0.2686\}$	Rapid biospheric uptake/ocean mixed layer invasion rate	“

Notes: For parameters considered in the sensitivity analysis, we report multiple values, starting with our baseline assumption.

Appendix D Parameter identification and model error

In Table D1, we report the elasticity of total model error with respect to each structural parameter, and we also report the elasticity of the error in predicting each target variable. To obtain these elasticities, we increase each parameter value by one percent, simulate the model and compute the percentage change in the estimation error/fit. This provides evidence on the sensitivity of the model to different parameters, as well as evidence on which target variables contribute to identification of which parameters.

Table D1: Elasticity of total model error and of fit to each target variable with respect to each structural parameter

Parameter	Total model error	Population	Agri. output	Rest of econ. output	Agri. TFP	Rest of econ. TFP	Crop-land	Dirty energy	Clean energy
μ_{mn}	11.94	39.98	4.66	8.46	11.14	28.28	0.99	0.61	0.64
μ_{ag}	5.50	41.76	4.87	6.20	6.41	12.05	0.01	0.54	0.29
μ_{cl}	0.03	0.81	0.11	0.16	0.48	0.43	0.03	0.23	1.47
μ_{dt}	0.17	0.49	0.08	0.08	0.15	0.45	0.01	1.03	0.08
ψ	2.76	10.30	1.72	2.13	12.92	4.72	10.84	0.36	0.16
ϵ	1.46	3.84	0.66	0.86	7.22	2.06	12.04	0.13	0.06
η	0.70	5.17	0.42	1.07	1.47	1.78	0.17	0.06	0.13
χ	4.12	17.81	10.55	5.80	70.17	0.64	1.99	2.06	1.22
ζ	2.22	3.82	4.37	8.81	18.74	8.43	1.94	0.36	0.37
σ_c	5.70	6.66	3.35	4.15	9.43	9.33	0.57	0.44	0.25
κ_{ag}	26.69	84.31	12.15	13.66	189.87	32.84	1.91	1.07	1.25

Notes: This table reports the percentage change in total model error, as well as the percentage change in estimation error associated with individual target variables, for a 1% deviation in each parameter value.

Our estimation strategy is based on joint identification of the parameters, so total model error, as well as the error in predicting each target variable, responds significantly to several structural parameters. Nonetheless, the patterns in Table D1 are intuitive. They imply labor productivity in rest-of-economy R&D (μ_{mn}) and agricultural R&D (μ_{ag}) are most strongly identified by variation in population, sectoral output, and sectoral TFP. By contrast, labor productivity in clean energy R&D (μ_{cl}) and fossil energy R&D (μ_{dt}) are most strongly identified by clean and fossil energy use, respectively. Labor productivity in agricultural land conversion – the pair of parameters ψ and ϵ – is most strongly identified by agricultural TFP and cropland. The elasticity of intergenerational altruism (η) is most strongly identified by population, while labor productivity in fertility/education (χ) is most strongly identified by agricultural output, TFP and population. The same is true of the food consumption parameters σ_c and κ_{ag}.

Appendix E Structural parameter estimates accompanying sensitivity analysis

In Table E1, we report structural parameter estimates to accompany our sensitivity analysis of exogenous parameters discussed in Section 7, as well as the estimation of the model on different time periods presented in Appendix B. Reading each column from top to bottom, it is apparent that the estimated parameters are highly consistent across the different specifications in each row. A much higher discount rate ($\beta = 0.97$) can only be reconciled with the data if the labor productivity of R&D in the rest of the economy is lower, and with altered fertility cost parameters.

Table E1: Structural parameter estimates for different scenarios corresponding to variations in exogenous parameters and different estimation periods

	μ_{mn}	μ_{ag}	μ_{cl}	μ_{dt}	ψ	ϵ	η	χ	ζ	σ_c	κ_{ag}
Main spec.	0.91	0.76	0.20	0.45	0.05	0.14	0.16	0.19	0.30	0.13	0.23
Low damages	0.92	0.77	0.20	0.44	0.05	0.14	0.14	0.18	0.30	0.11	0.22
High damages	0.90	0.72	0.20	0.46	0.05	0.14	0.16	0.19	0.31	0.14	0.23
Low damages ag	0.92	0.77	0.20	0.44	0.05	0.14	0.14	0.18	0.30	0.11	0.22
High damages ag	0.89	0.72	0.20	0.46	0.05	0.14	0.16	0.19	0.31	0.14	0.23
Low damages mn	0.91	0.76	0.20	0.45	0.05	0.14	0.16	0.19	0.30	0.13	0.23
High damages mn	0.91	0.76	0.20	0.45	0.05	0.14	0.16	0.19	0.30	0.13	0.23
Slow CO_2 removal	0.91	0.76	0.20	0.45	0.05	0.14	0.16	0.19	0.30	0.13	0.23
Fast CO_2 removal	0.91	0.76	0.20	0.45	0.05	0.14	0.16	0.19	0.30	0.13	0.23
$\beta = 0.97$	0.52	0.71	0.19	0.45	0.05	0.15	0.16	0.23	0.20	0.12	0.24
$sigma_X = 0.2$	0.94	0.71	0.18	0.37	0.05	0.13	0.16	0.18	0.28	0.13	0.21
$\overline{R} = \infty$	0.91	0.76	0.20	0.47	0.05	0.14	0.16	0.19	0.30	0.13	0.23
1960-1990	0.94	0.64	0.11	0.45	0.06	0.15	0.16	0.18	0.30	0.13	0.21
1990-2015	0.89	0.79	0.28	0.45	0.05	0.14	0.16	0.19	0.30	0.13	0.23

Notes: This table reports parameters estimated for the main specification of the model and for the instances of the model considered in the sensitivity analysis and in Appendix B.