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

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ABSTRACT

As the climate is changing, the global economy is adapting. This paper describes a novel method of estimating climate adaptation globally. We quantify how much the global economy has adapted to climate change historically, how much it has cost, and how much it has reduced the direct impacts of climate change. The method is based on a structurally estimated model of long-run growth, which identifies how changes in consumption, fertility, innovation, and land use allow the economy to adapt to climate change. Agriculture plays a key role, because it is vulnerable to climate change and food cannot be perfectly substituted. We estimate that adaptation has been highly effective in reducing negative climate impacts on agricultural production. However, the cost of adaptation has been a reallocation of resources out of the rest of the economy, which has in effect slowed down the process of structural change out of agriculture into manufacturing and services. We also use the model to estimate optimal future carbon taxation. Because adaptation is effective but costly, reducing future greenhouse gas emissions would improve welfare substantially.

## 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 shows how mostly short-run fluctuations in climate affect a wide range of economic and social outcomes (Dell et al., 2014; Carleton and Hsiang, 2016). However, how climate change has shaped the *long-run* development of the world

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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 novel 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, general-equilibrium 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 analyzing 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 not just from dirty energy use but also from deforestation due to agricultural land expansion, and from agricultural production. Emissions of carbon dioxide are modeled separately to those of methane and nitrous oxide. Warming impacts productivity in the final goods sectors.

By coupling an aggregate model of long-run growth to 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 yearly data from 1960 to 2015, using a simulated method of moments (SMM) approach. We show that our model can closely approximate trajectories for key economic and climate variables over the last half century, capturing a transition of declining growth in population and agricultural land. We then "turn off" climate change and use the 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. According to the underlying literatures, 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, reallocating resources out of the rest of the economy to do so constitutes an opportunity cost, in particular of lower consumption of other goods. We estimate that the welfare cost of climate change between 1960 and 2020, which includes adaptation costs and residual climate damages, is equivalent to reducing stationary-equivalent consumption over the same period by about 6%.

We then use the estimated model to make future projections, a more conventional use of an IAM. Without a GHG 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 opportunity cost. Hence, it is optimal to tax global GHG emissions at a high rate, so that global 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, including a scenario designed to mimic the effects of agricultural trade liberalization leading to spatial reallocation, something our globally aggregated model cannot explicitly account for. This leads to four main results. First, introducing constraints on 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, implicitly allowing for spatial reallocation of agriculture reduces the cost of climate change and the burden on other adaptation channels, but to a relatively limited extent based on our calibration on results from spatial models. Fourth, 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. In particular, varying the pre-adaptation effect of climate change on the rest of the economy has minimal impact on optimal GHG taxes, but varying the corresponding effect on agriculture across the range of estimates in the agronomic literature has a large impact.

### 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. 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.

Our nearest neighbors in the literature are twofold. The first is the subset of the empirical literature aiming to identify the impacts of medium-/long-run changes in climate, i.e., Ricardian/cross-sectional studies (Mendelsohn et al., 1994; Nordhaus, 2006), and panel studies using long differences (Dell et al., 2012; Burke and Emerick, 2016). The second comprises structural models of how climate change affects the economy, e.g., multi-sectoral CGE models (Bosello et al., 2006, 2007) and spatial models (Costinot et al., 2016; Desmet and Rossi-Hansberg, 2015; Nath, 2023). Relative to the reduced-form empirical literature, our structural approach is able to simultaneously identify multiple mechanisms that enable the global economy to adapt to climate change, and we can directly estimate adaptation costs. Relative to multi-sectoral and spatial models, the latter of which build on the heterogeneity of climatic conditions to explore how climate change will affect the location of economic activities, we place our emphasis on long-run dynamics at the global level, including capital accumulation, demographic change, innovation, land-use change, and sectoral reallocation. To the best of our knowledge, this paper is the first to propose a long-run historical counterfactual of the world economy using a structural model. We provide more discussion of the pros and cons of these different approaches and compare their results in Section 8.

The remainder of the paper is set out as follows. Section 2 presents the model structure and estimation. Section 3 evaluates how well the model fits the historical evolution of the economy, population, agriculture, energy and GHG emissions. In Section 4, we construct counterfactual estimates of climate impacts over the 1960–2020 period, 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 internalized. In Section 6, we assess what role adjustment constraints might play in our analysis, including on decarbonization and on climate adaptation. Section 7 reports on our sensitivity analysis, including the implications of spatial reallocation of agriculture. Section 8 provides a discussion and concludes. We provide several appendices that explore issues such as calibration of exogenous parameters and identification of structural 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:

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

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 $\theta_i$, $i \in \{K, E\}$ 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 $\sigma_X$ is below unity, reflecting long-run empirical evidence (Wilde, 2013).

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 (Golosov et al., 2014). It is made possible by the fact that temperature responds almost instantaneously to GHG emissions (Ricke and Caldeira, 2014), so the intermediate temperature step can be omitted by suitable calibration and without getting the dynamics wrong.[1] GHG emissions from energy, agricultural production and land use increase $S_t$ and this in turn affects TFP in agriculture. The scale of climate damages in agriculture is measured by the parameter $\Omega_{ag}$. This is an estimate of the biophysical impact of climate change on global crop yields. We calibrate it using results from the literature on crop modeling (see Appendix A).

*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 to 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 $\Sigma_i \vartheta_i < 1$.[2] Similar to agriculture, climate change affects aggregate productivity through the parameter $\Omega_{mn}$. We use estimates of the short-run impact of climate change on aggregate productivity, *excluding* agriculture, to calibrate this (see Appendix A). The use of short-run responses for calibration should ensure that $\Omega_{mn}$ is not biased by implicitly including the adaptation mechanisms we later model explicitly.

*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,

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

where $\sigma_E$ is the elasticity of substitution, which 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:

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

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.

[1] Golosov et al. (2014) show that the composition of the functions mapping (i) the atmospheric $CO_2$ concentration into temperature and (ii) temperature into damages is well approximated by an exponential function. Function (i) is concave and approximated by the natural logarithm of the atmospheric $CO_2$ concentration. Function (ii) is typically assumed to be convex (usually quadratic). The composition of these functions is close to linear and given (i) derives from basic physical properties, it will hold true more generally provided (ii) is convex but not very convex. An exponential function can approximate the close-to-linear relationship well while being mathematically convenient.

[2] This is a plausible representation of long-run substitution (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., 2016a). Baqaee and Farhi (2019) show that short-run complementarity between energy and non-energy inputs can be used to explain the disproportionate macroeconomic impact of the 1970s oil shock.

*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 $\psi_t$ 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 $L_{t,X}$:

$$\psi_t = \psi \cdot L^{\varepsilon}_{t,X}, \tag{7}$$

where $\psi$ and $\varepsilon \in (0,1)$ 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 $\varepsilon$, 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

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

where $\rho_{t,j}$ is the endogenous arrival rate of innovations in the sector and represents the fraction of maximum growth $\lambda$ 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 (Jones, 1995). 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 $\delta_N$ is the exogenous mortality rate. Climate change also affects mortality (Carleton et al., 2022), thus setting an exogenous mortality rate is a simplification to make the model more tractable.

Raising children requires labor, the aggregate cost of which 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

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

where $\chi$ 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 (similar to Ngai and Pissarides, 2007):

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

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 $\delta_K$ 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.

(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.[3] Consumption preferences are characterized by a utility function that is implicitly defined by the constraint

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

which simply says that the sum of expenditure shares on food and other goods equals one. The parameter $\sigma_c$ is the elasticity of substitution between food and other goods, the utility elasticities $\epsilon_i$, $i \in \{ag, mn\}$ control the degree of non-homotheticity, and the parameters $\kappa_i$ 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

$$\frac{\partial \log c_i}{\partial \log E} = \sigma_c + \left(1-\sigma_c\right)\frac{\epsilon_i}{\bar{\epsilon}}, \tag{17}$$

where $E$ denotes total expenditure and $\bar{\epsilon}$ 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 $\gamma$ is the intertemporal elasticity of substitution.

(ii) Preferences over fertility/additions to the family are represented by

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

where $\tilde{n}_t = (1-\delta_N) + n_t$ is the net increase in family size, and $\eta \in (0,1)$ determines how fast marginal utility declines as family size increases. For the special case of $\delta_N = 1$, where individuals survive for just one period, these preferences are identical to Barro and Becker (1989). Thus, like Jones and Schoonbroodt (2010), we generalize 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 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:[4]

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

*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,

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

[3] 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.

[4] This is obtained through 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 Eq. (10) can be rewritten as $N_{t+1} = N_t \tilde{n}_t$, we have $\Pi_{\tau=0}^{t} \tilde{n}_\tau^{1-\eta} = (N_t/N_0)^{(1-\eta)}$.

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.

*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., $CH_4/N_2O$), $\pi_X$ is $CO_2$ emissions per unit of agricultural land expansion, and $\pi_{ag}$ is $CH_4/N_2O$ emissions per unit input of the capital-labor-energy composite in agriculture.[5] $\pi_{E,NCO2}$ and $\pi_{ag}$ 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:

$$S_t = \sum_{i=0}^{3} S_{t,i} \tag{26}$$

$$S_{t,0} = a_0 \left[\pi_{E,CO2} E_{t,dt} + \pi_X \left(X_t - X_{t-1}\right)\right] + (1-\delta_{S,0}) S_{t-1,0} \tag{27}$$

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

where $\sum_{i=0}^{3} a_i = 1$. The decay rate of the first reservoir $S_0$ is almost zero and this represents 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.[6]

*Solution concept*

Structural estimation via SMM requires solving the model for a large number of candidate parameters in order to fit targeted trajectories. On the one hand, this implies that the solution method needs to be fast and efficient, even though we track seven economic state variables (population, land, capital, and four TFP indices) and four atmospheric GHG stocks. On the other hand, we need to allow for declining growth rates, including because of accumulating GHG emissions and associated productivity damages, and therefore we cannot rely on standard balanced growth properties.

To accommodate the high dimensionality of the state space and declining growth rates, we employ a discrete-time primal formulation. Formally, 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 technological constraints described above. This implies that we only compute quantities; prices are implicitly given by Lagrange multipliers and can be retrieved at the solution point. This

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

[6] 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.

formulation allows us to exploit efficient solvers for non-linear mathematical programs. Appendix B contains a formal statement of the primal optimization problem and discusses some further computational considerations.

While our primal formulation is computationally efficient and makes the structural estimation problem tractable, it has implications for the interpretation of estimates. In particular, our structural parameter estimates come to embody market imperfections present in the observations, as these are the free parameters that permit the model to reproduce the past on multiple dimensions. It follows that the parameter estimates we obtain should not be interpreted as those of a representative household or firm operating in an economy with complete and perfect markets. In addition, market imperfections embodied in the parameter estimates are assumed scenario-invariant, with the exception of $CO_2$ emissions.[7] 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. This assumption is dictated by the use of a common model for baseline and counterfactual worlds and is a feature of structural work (see Keane, 2010, for a discussion). While we cannot directly provide evidence to support this assumption, below we show that the policy results and associated welfare estimates are qualitatively consistent across simulations for a large range of structural assumptions and changes in the period used for the estimation. Appendix E also reports structural parameter estimates across different exogenous parameter variations.

### 2.2. Estimation

Our approach to model estimation proceeds in two steps.

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

Given imposed parameter values and initial conditions, the second step is to use an SMM procedure to find an estimate for the vector of remaining parameters,

$$\Theta = \{\mu_{mn}, \mu_{ag}, \mu_{cl}, \mu_{dt}, \psi, \varepsilon, \eta, \chi, \zeta, \sigma_c, \kappa_{ag}\}. \tag{29}$$

This method selects values for the elements of the vector so that the distance between observed target variables and their simulated counterparts is jointly minimized over the estimation period. Specifically, for a given candidate vector of parameter estimates $\Theta_v$, we solve the model to obtain simulated trajectories for $k$ targeted quantities $Z^{model;\Theta_v}_{\tau,k}$, where $\tau$ indexes years over which the estimation is performed. Denoting the observations of each targeted quantity by $Z^{data}_{\tau,k}$, we then measure the error $e^{\Theta_v}_k$ associated with $\Theta_v$ as the relative squared deviation summed over the estimation period:

$$e^{\Theta_v}_k = \sum_\tau \left[\log(Z^{model;\Theta_v}_{\tau,k}) - \log(Z^{data}_{\tau,k})\right]^2. \tag{30}$$

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

$$\min_{\hat{\Theta}} \sum_k \omega_k \, e^{\Theta}_k , \tag{31}$$

with weights $\omega_k$ inversely proportional to the volatility of the observations of $k$.[8] In order to find a solution to Eq. (31), we use an iterative procedure. We start with a vector $\Theta_1$ of parameters that coarsely approximates the observed trajectories, and solve the model for 10,000 vectors randomly drawn from a uniform distribution around $\Theta_1$. 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 $\Theta_2$, leading us to gradually update the distribution of parameters considered. The resulting vector associated with the baseline assumption for imposed parameters is reported in Appendix A. The following yearly time-series of 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 Eq. (31) cannot be formally proved, a well-known issue with the estimation of non-linear models (see Gourieroux and Monfort, 1996). We note, however, that the set of estimated parameters is jointly identified from a large set of moments that includes yearly observations from 1960 to 2015 for the eight variables we target, which makes the criterion highly demanding. Moreover, using a primal formulation allows us to solve the model for a very large number of parameter combinations and carry out an extensive search for alternative combinations of parameters in the neighborhood of our initial guess. Appendix C provides further evidence on the sensitivity of total model error and the error for each target variable with respect to changes in each structural parameter, and further discusses identification of each parameter in relation to the set of targeted variables.

[7] In laissez faire simulations, the planner does not control $CO_2$ emissions either. While prototypical climate policies such as the Kyoto Protocol and the European Union Emissions Trading System were introduced toward the end of the estimation period, these attempts had a trivial effect on total global GHG emissions pre-2020. See Appendix B for more details.

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

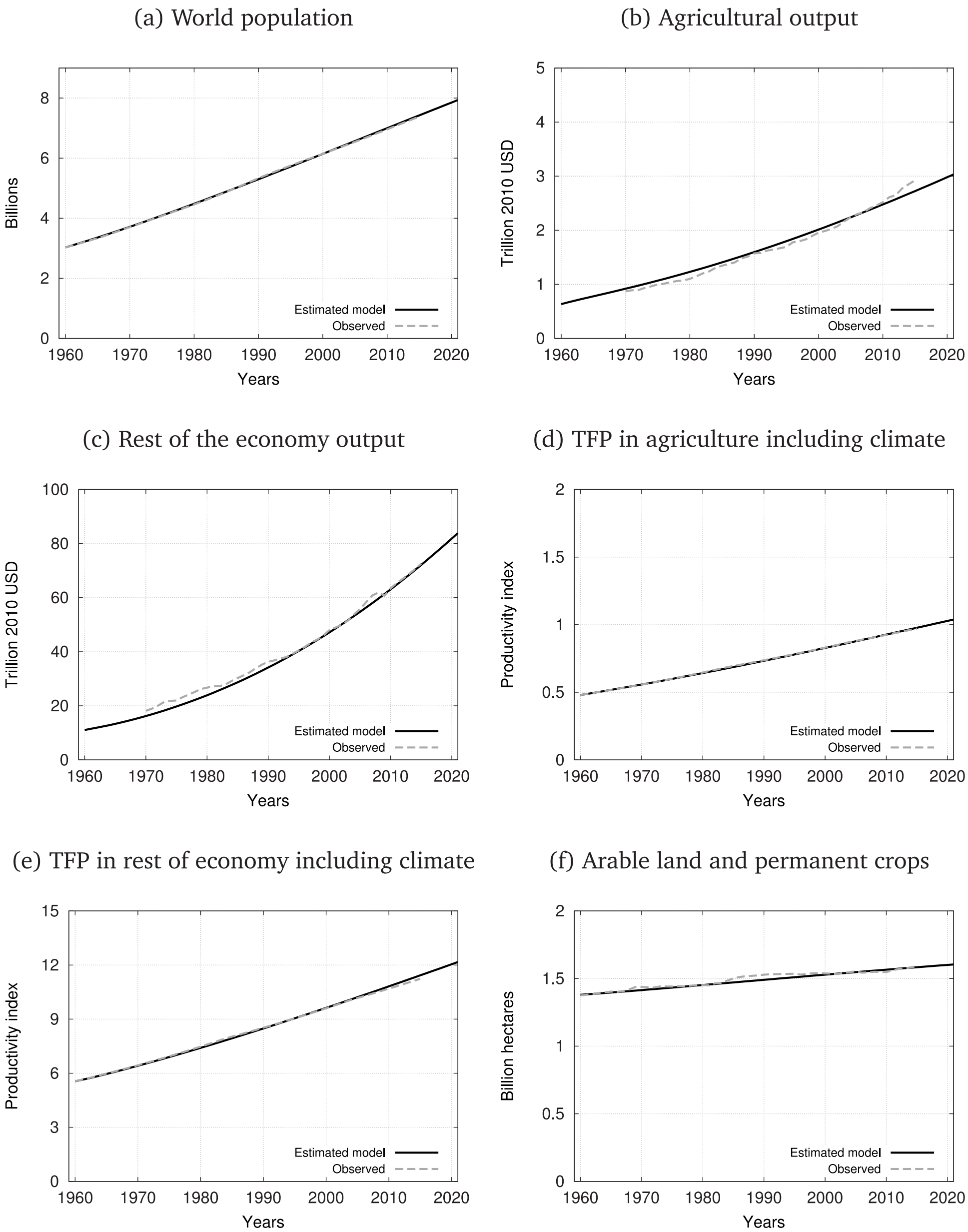


**Fig. 1.** Estimation results for population, output, productivity and land.

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

This section documents how well the baseline 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.

Fig. 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) 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.

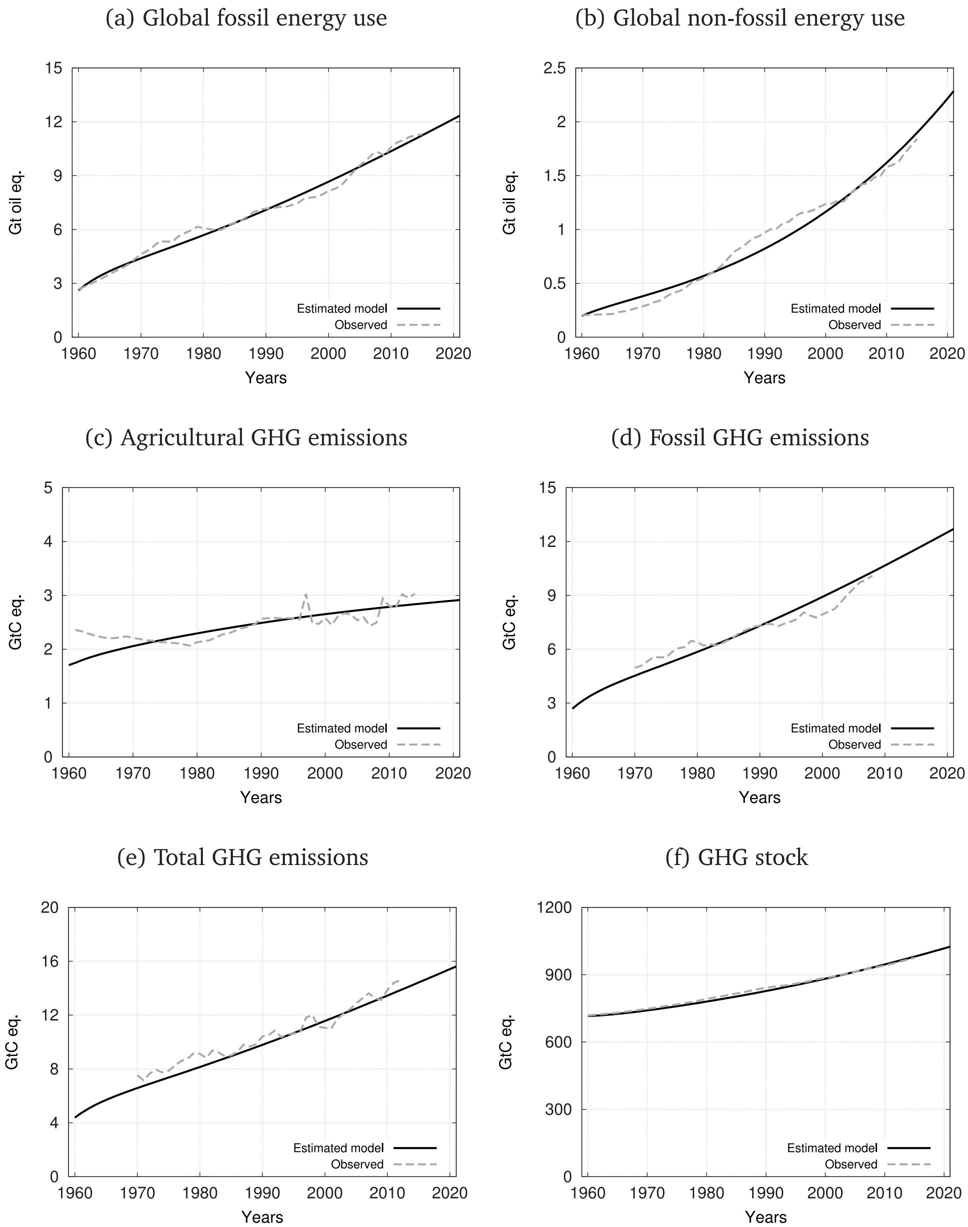


**Fig. 2.** Estimation results for energy, emissions and climate variables.

Fig. 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 source of evidence about goodness of fit. The remaining emissions/climate variables are not directly targeted by the estimation procedure, however. Therefore, this provides some evidence of the model's ability to match empirical patterns beyond the specific moments it was calibrated to, within the estimation period. 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 D, we report corresponding results derived from targeting a subset of the observed data. 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.

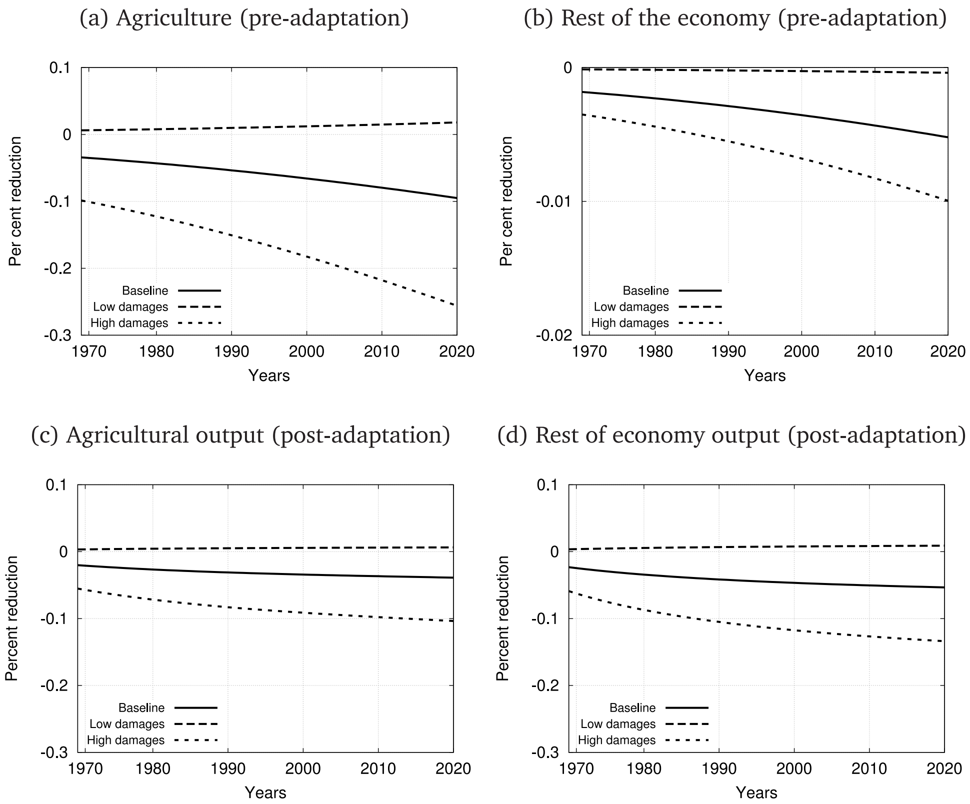


**Fig. 3.** Estimated climate change impacts since 1970, before and after adaptation.

## 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 Fig. 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.[9] This is within a sensitivity range from a 0.6% increase in agricultural output to a 10.3% decrease, which reflects pre-adaptation damages in models estimated with damage coefficient $\Omega_{ag}$ set to its lower/upper bounds. By 2020, rising temperatures would have caused agricultural damages to rise to 9.6% of output, within a range from a 1.8% increase to a 26.6% 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 evaluating damages in a model estimated with $\Omega_{mn}$ set 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%).

9 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.

**Table 1**
Historical adaptation to climate change, as measured by the difference in key inputs and variables with and counterfactually without climate damages.

| | 1970 | 1980 | 1990 | 2000 | 2010 | 2020 |
|---|---|---|---|---|---|---|
| Ag. innovation rate (% diff) | +7.6 | +8.4 | +9.6 | +11.0 | +12.8 | +14.9 |
| Population (% diff) | −0.9 | −1.4 | −1.7 | −1.9 | −2.1 | −2.2 |
| Cropland (% diff) | 0.0 | 0.0 | 0.0 | −0.1 | −0.1 | −0.1 |
| *Shares of capital (ppts.)* | | | | | | |
| Agriculture | +0.53 | +0.42 | +0.35 | +0.30 | +0.29 | +0.30 |
| Rest of economy | −0.53 | −0.42 | −0.35 | −0.30 | −0.29 | −0.31 |
| *Shares of labor (ppts.)* | | | | | | |
| Agriculture | +0.20 | +0.13 | +0.09 | +0.08 | +0.09 | +0.10 |
| Rest of economy | −0.21 | −0.19 | −0.16 | −0.13 | −0.11 | −0.08 |
| Agriculture R&D | +1.94 | +1.99 | +2.06 | +2.17 | +2.29 | +2.41 |
| Rest of economy R&D | −0.77 | −0.55 | −0.41 | −0.31 | −0.24 | −0.18 |
| Fertility | −1.17 | −1.38 | −1.59 | −1.82 | −2.04 | −2.26 |

*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 comparison, the bottom two panels of Fig. 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. 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 2.1% lower than the counterfactual world without climate change, within a range from 0.3% higher to 5.7% lower. In 2020, we estimate post-adaptation agricultural output was 3.9% lower, within a range from 0.6% higher to 10.4% 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 2.4% lower than the counterfactual in 1970, within a range from 0.4% higher to 6.2% lower. In 2020, we estimate that post-adaptation output in the rest of the economy was 5.3% lower than the counterfactual, within a range from 0.9% higher to 13.4% 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.

In Table 1, 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 15 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. Climate change increases the relative price of food, given differential impacts on agricultural and non-agricultural productivity, and imperfect substitutability of food and other goods. This creates an incentive for agricultural innovation. We further estimate that world population is slightly lower as a result of climate change. By 2020, world population was 2.2% 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 labor has been allocated to fertility.[10] We estimate that in 2020 the share of the world labor force in agricultural R&D was 2.4 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?[11] 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 5.5% over the same period, relative to the

[10] 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.

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

counterfactual world without climate change. This is within a sensitivity range of −0.9% (low damages in both sectors) to 15.3% (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[12] in 2016, the year following the United Nations Paris Agreement on Climate Change.

Fig. 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 \$166/t$CO_2$eq in 2025 (in 2010 US dollars). This increases in real terms to \$273/t in 2050 and \$513/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 20% in 2050 and 40% 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.[13] 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 2, 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 25% 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 5% 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 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% (i.e., the change in stationary consumption), relative to the laissez faire path.[14]

## 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'

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. This welfare measure has the advantage of working for non-marginal changes.

12 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.

13 As we feed not only $CO_2$ emissions into the model of Geoffroy et al. (2013), but also $CH_4$ and $N_2O$ (in t$CO_2$eq), 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.

14 Appendix D analyzes the effects of using different estimation periods for our policy scenarios (1960–1990; 1990–2015; 1960–2015), showing that estimated welfare gains and trajectories of key variables such as GHG taxes are similar.

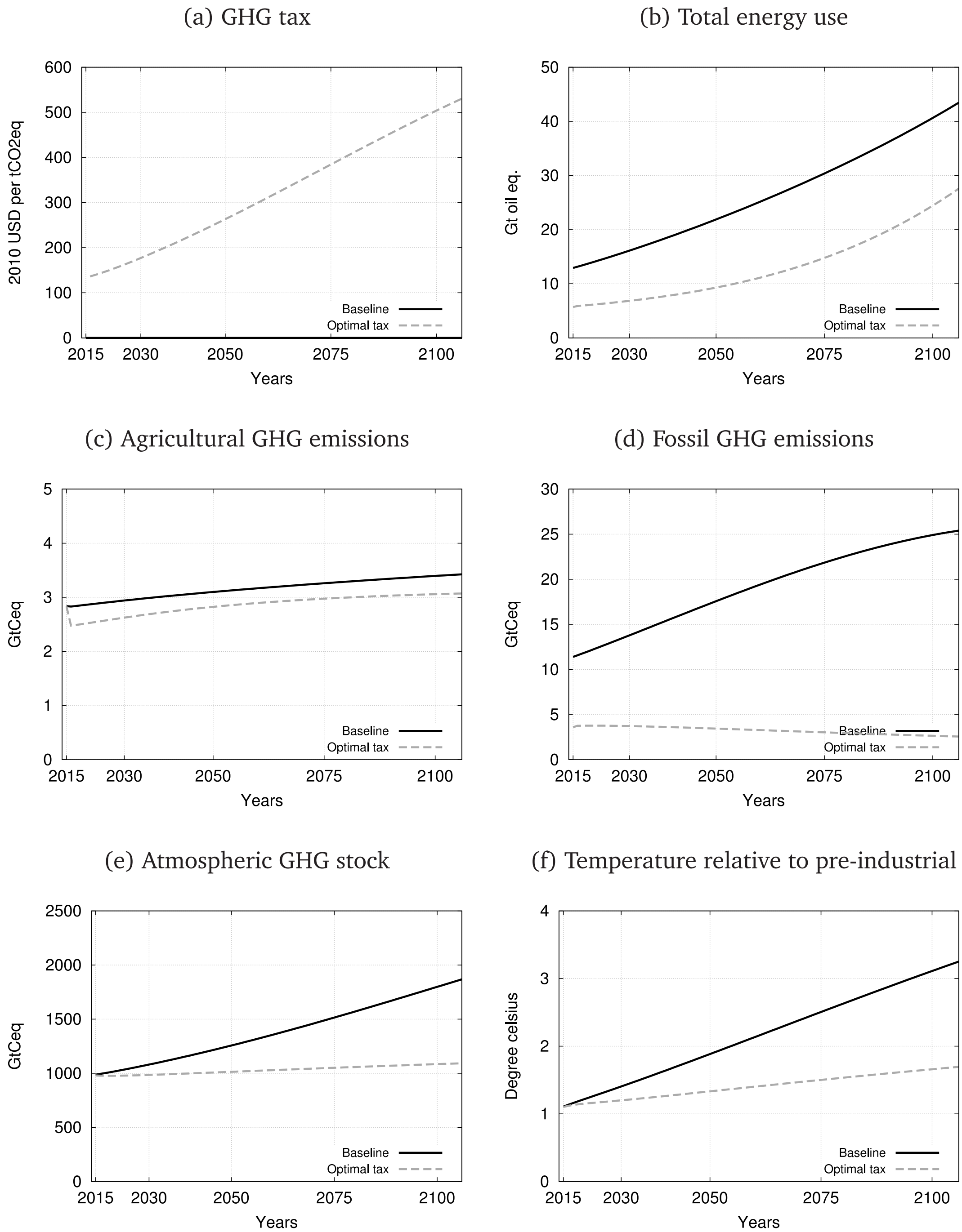


**Fig. 4.** laissez faire (baseline) and optimal GHG taxation, energy, emissions and climate outcomes over the 21st century.

our findings from above. Note that this analysis requires a slightly stronger version of the 'scenario-invariance' assumption discussed in Section 2.1 – we must assume that the constraints we are explicitly modeling did not significantly affect any of the structural parameters in the estimation period. Results are reported in Table 3, 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

**Table 2**
Laissez faire and optimal climate damages and adaptation.

| | 2025 | 2050 | 2075 | 2100 |
|---|---|---|---|---|
| *Pre-adaptation climate damages to agriculture (% change in output/productivity)* | | | | |
| Baseline | −10.40 | −14.89 | −19.96 | −25.14 |
| Optimal | −8.79 | −9.55 | −10.33 | −11.03 |
| *Post-adaptation agricultural output (% diff. with counterfactual)* | | | | |
| Baseline | −4.02 | −4.46 | −4.90 | −5.30 |
| Optimal | −4.20 | −3.99 | −3.58 | −3.10 |
| *Post-adaptation output in the rest of the economy (% diff. with counterfactual)* | | | | |
| Baseline | −5.47 | −5.95 | −6.22 | −6.34 |
| Optimal | −8.37 | −7.92 | −7.08 | −6.00 |
| *Agricultural innovation (gross TFP index in agriculture)* | | | | |
| Baseline | 1.16 | 1.52 | 1.92 | 2.34 |
| Optimal | 1.16 | 1.48 | 1.80 | 2.12 |
| *Population (billions)* | | | | |
| Baseline | 8.18 | 10.17 | 11.97 | 13.52 |
| Optimal | 8.15 | 10.23 | 12.07 | 13.67 |
| *Cropland (billion hectares)* | | | | |
| Baseline | 1.61 | 1.69 | 1.75 | 1.79 |
| Optimal | 1.60 | 1.66 | 1.71 | 1.74 |

*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.

**Table 3**
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 | – | 165.89 | 272.56 | 394.27 | 512.82 | 1.60 | 1.66 | 1.71 | 1.74 | 1.16 | 1.48 | 1.80 | 2.12 | 8.19 | 10.23 | 12.07 | 13.67 |
| *Frictions in the low-carbon transition* | | | | | | | | | | | | | | | | | |
| Fixed fossil capital | −6.9 | +8.4 | +11.4 | +14.1 | +16.6 | 0.0 | +0.2 | +0.4 | +0.6 | +0.8 | +3.7 | +7.3 | +11.3 | −0.2 | −0.5 | −0.8 | −1.0 |
| No fossil to clean capital | −1.2 | +3.6 | −4.4 | −7.9 | −8.3 | 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 | +0.2 | +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 |
| 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 | +0.1 | 0.0 | 0.0 | −0.1 | Fixed at baseline | | | | −0.1 | −0.5 | −0.8 | −1.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Fixed agricultural R&D | −1.6 | −8.1 | −12.5 | −16.9 | −20.8 | −0.2 | −0.7 | −1.4 | −2.2 | Fixed at baseline | | | | −0.1 | −0.3 | −0.4 | −0.5 |
| Fixed population | −0.4 | +0.2 | −0.1 | +0.4 | +1.7 | +0.1 | +0.2 | +0.3 | +0.3 | 0.0 | 0.0 | +0.1 | +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 | −0.1 |

*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.

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 11% 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 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, including spatial reallocation of agriculture

The impacts of climate change are heterogeneous across space, so spatial reallocation of agriculture and economic activity is a possible response. In particular, growing conditions for crops are expected to worsen in already hot climates, but they may improve in currently cold climates, or at least worsen less. Our model structure aggregates over space, so when we calibrate the agricultural damage coefficient $\Omega_{ag}$ we aggregate yield effects from the literature over space to produce an average pre-adaptation effect. But research suggests that spatial reallocation could reduce negative yield effects globally by directing more resources to production in cold climates at the expense of hot climates, thus constituting a potentially important adaptation margin that our model does not pick up. How important it is likely depends on trade costs and frictions.

The literature quantifying climate impacts on agriculture using spatial models provides ambiguous results in this regard. Costinot et al. (2016) find that liberalizing trade in their high-resolution spatial model of agriculture has virtually no effect on their results. Domestic food consumption continues to be met with domestic production, but farmers adapt by changing their inputs. In their comparison of a large number of agriculture-focused IAMs, Nelson et al. (2014) find a range of trade responses to a climate-induced shock to crop productivity, but the median change in the share of agricultural products traded across countries is approximately zero, implying minimal spatial reallocation. In a similar study, Wiebe et al. (2015) find liberalizing trade hardly affects the median impact of the climate shock on yields. By contrast, Nath (2023) finds the potential gains to spatial reallocation are relatively large, but trade barriers have prevented them from being realized so far. Across most of the world, particularly the developing world, the vast majority of food demand has historically been met with domestic production (Gollin et al., 2007). Conte et al. (2021) simulate substantial spatial reallocation in response to climate change, but this again depends sensitively on trade costs (they also show that trade and migration are substitutes as adaptation channels). Overall, these results give us some confidence that our historical estimates do not conflate the effect of spatial reallocation on productivity with the effect of innovation. If trade barriers persist, then the adaptive responses we identify are likely to remain of first-order importance. But if trade barriers are removed, the story could potentially be quite different.

To investigate how spatial reallocation of agricultural production would affect our results, within the confines of our globally aggregated model, we introduce a scenario mimicking the effect of a future liberalization of trade to exploit climate-driven changes in comparative advantage. We do this by gradually reducing the agricultural damage coefficient $\Omega_{ag}$ from its calibrated value to a new, lower value. We calibrate the overall reduction in $\Omega_{ag}$ on a key result in Nath (2023), whereby relaxing trade barriers reduces the impact of climate change on agriculture by c. 20%.[15] Since spatial reallocation of agricultural production is expected to take time, we introduce this 20% reduction in $\Omega_{ag}$ linearly over 10 years from 2030, still a relatively rapid change.

Table 4 compares five model outputs under our main specification and under this trade liberalization scenario. These are the welfare gain from the laissez faire equilibrium, the GHG tax, total GHG emissions, and two examples of adaptation to climate change that are explicitly represented by the model – the differences in cropland and population from the laissez faire equilibrium. Under trade liberalization and spatial reallocation, the global economy benefits from an additional (off-model) adaptation margin, reducing the need to adapt by, for example, expanding aggregate cropland or curbing fertility. There is also less need to reduce GHG emissions, exemplified by lower optimal GHG taxes and higher optimal emissions. However, the effects are not radical: the optimal GHG tax in 2020 (perfectly anticipating the reduction in trade barriers from 2030) is about 12% lower, for example, while the change in cropland from laissez faire is about 6% smaller than in the main specification. Of course, this relatively simple scenario does not capture all of the complex, second-order effects of spatial reallocation of agricultural production.

We further test the robustness/sensitivity of our optimal policy results to wide range of alternative values for exogenous parameters. We pay particular attention to the damage intensity parameters $\Omega_{ag}$ and $\Omega_{mn}$, 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. We therefore re-estimate the model for each variation in the exogenous parameters. The results are added to Table 4. In Appendix E, we report the structural parameter estimates accompanying the sensitivity analysis.[16]

We analyze three pairs of variations of the damage intensity parameters. First, we simultaneously vary $\Omega_{ag}$ and $\Omega_{mn}$. Second, we vary only $\Omega_{ag}$, leaving $\Omega_{mn}$ at its best estimate ('low damages ag' and 'high damages ag'). Third we do the opposite, varying only $\Omega_{mn}$ ('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

[15] Specifically all estimated bilateral trade costs are reduced to the level corresponding to the 90th percentile of trade openness. Note the 20% reduction in damages refers to welfare rather than productivity *per se*.

[16] 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 4**
Sensitivity of optimal paths to variations in exogenous parameters.

| | Δ welfare (%) | GHG tax ($/tCO$_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 | +8.0 | 148.39 | 272.56 | 512.82 | 6.3 | 6.3 | 5.7 | −4.7 | −25.8 | −47.8 | +7.4 | +54.0 | +149.2 |
| Trade liberalization | +5.8 | 129.89 | 223.26 | 423.43 | 6.8 | 7.1 | 6.5 | −4.4 | −21.5 | −38.5 | +5.9 | +40.4 | +110.8 |
| Low damages | +0.4 | −24.63 | −46.69 | −87.98 | 18.3 | 28.8 | 40.4 | +0.6 | +2.8 | +3.8 | −1.5 | −3.7 | +3.4 |
| High damages | +44.1 | 373.51 | 693.73 | 1286.66 | 2.9 | 3.3 | 3.3 | −20.2 | −105.6 | −185.1 | +30.1 | +227.8 | +568.4 |
| Low damages ag | +0.2 | −16.22 | −29.42 | −51.09 | 17.3 | 26.1 | 36.0 | +0.4 | +1.9 | +2.5 | −1.0 | −2.7 | +0.3 |
| High damages ag | +38.4 | 360.73 | 658.68 | 1184.77 | 2.9 | 3.3 | 3.3 | −19.9 | −104.3 | −183.2 | +26.6 | +201.4 | +503.8 |
| Low damages mn | +7.4 | 141.88 | 259.28 | 481.82 | 6.5 | 6.5 | 6.0 | −4.5 | −24.7 | −46.2 | +6.8 | +49.8 | +139.8 |
| High damages mn | +8.8 | 156.25 | 288.33 | 547.68 | 6.1 | 6.0 | 5.5 | −5.0 | −27.1 | −49.9 | +8.0 | +59.1 | +161.5 |
| Slow $CO_2$ removal | +10.4 | 174.30 | 320.62 | 605.08 | 5.7 | 5.6 | 5.1 | −5.6 | −30.3 | −56.0 | +8.5 | +65.2 | +186.3 |
| Fast $CO_2$ removal | +7.0 | 136.73 | 250.77 | 472.09 | 6.7 | 6.6 | 6.0 | −4.3 | −24.0 | −44.5 | +6.9 | +49.3 | +132.3 |
| $\beta = 0.97$ | +5.1 | 142.31 | 287.54 | 713.48 | 9.3 | 9.6 | 9.2 | −5.0 | −27.4 | −50.0 | +7.4 | +64.5 | +201.1 |
| $\sigma_X = 0.2$ | +10.7 | 166.44 | 302.95 | 591.96 | 4.9 | 4.3 | 3.3 | −2.6 | −13.4 | −23.9 | +9.6 | +68.1 | +176.4 |
| $\overline{R} = \infty$ | +10.1 | 148.39 | 272.64 | 512.99 | 6.3 | 6.3 | 5.7 | −4.5 | −24.2 | −44.2 | +8.9 | +64.6 | +179.0 |
| $\alpha = 0.8$ in clean energy | +7.4 | 149.02 | 274.81 | 522.87 | 6.3 | 6.5 | 6.3 | −4.8 | −26.4 | −48.7 | +6.5 | +49.0 | 137.6 |

*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.

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 very similar, 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.

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 (i.e., a lower discount factor $\beta = 0.97$) 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 relatively insensitive to lowering the elasticity of substitution between land and the capital-labor-energy composite in agriculture, removing the fossil-fuel resource constraint, and increasing the capital share in clean energy.

## 8. Discussion

In this paper, we built a structural model of the world economy to study the relationship between 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). 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 without rising temperatures. This allows us to study how the global economy has already been affected by long-run climate change. Second, our approach allows us to quantify adaptation to climate change through channels including factor reallocation, agricultural land expansion, and R&D investments.

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 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 to mute climate damages, 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. 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 child-rearing. We project that technological progress will itself slow down, such that fertility holds up. 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.

We can also compare our results qualitatively with the nearest neighbors in the literature, namely medium-/long-run estimates from climate econometrics and results from structural models. Our results play into an emerging debate. A striking result from the few empirical studies to have investigated long differences is that long-run responses to climate change are not statistically different from short-run responses (Dell et al., 2012; Burke and Emerick, 2016). By contrast, structural models tend to simulate large-scale adaptation to climate change in equilibrium, which is highly effective at reducing climate impacts (Costinot et al., 2016; Cruz and Rossi-Hansberg, 2024; Nath, 2023). Thus, these two results are apparently in direct contradiction. Our results belong in the latter camp, despite making some assumptions that may underestimate future adaptation (e.g., a fixed crop mix and no spatial reallocation).

At this stage, one cannot be definitive on who is right, but it is possible to highlight where to look for answers. One simple point is that studies tend to vary in scope; sectoral, spatial and temporal. A long difference in Dell et al. (2012) is 15 years, while in Burke and Emerick (2016) the central case is 20 years but it can be as long as 30 years. Still, this is considerably shorter than the timescale considered in this paper, or in many other structural models that either analyze comparative statics or simulate centuries into the future. Similarly, Burke and Emerick (2016) analyze corn and soy crops in the US, while our study looks at aggregate global food production. Methodological comparisons are less straightforward. In principle, identification in reduced-form empirical studies of climate variation can be robust, so the consistency of short-run and long-run responses in these studies should be taken seriously. However, long differences require a stronger form of the unit homogeneity assumption than the standard approach which uses annual variations (Hsiang, 2016). It becomes harder to control for omitted variables and the credibility of identification is decreasing in the timescale. In structural models, the possibilities to adapt – the adaptation margins – are baked into the structure of the model. However, the extent to which these margins are used depends on identification of the elasticities of climate impacts with respect to adaptation, broadly speaking. If these are low and the model is well identified, there should be little adaptation. Another issue that may be important is uncertainty. For reasons of computational tractability, structural models like ours are deterministic and therefore run under conditions of perfect foresight. Agents know the pay-offs to adaptation. But in the real world agents' pay-offs from adaptation are uncertain and this could be an important barrier to adaptation. Insofar as this effect is present, it would be implicit in the estimates from reduced-form studies (Hsiang, 2016). Therefore, resolution of the debate would be aided by, first, being able to compare studies with the same scope, second, understanding how well identified different types of model are, and, thirdly, developing structural models under uncertainty.

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. 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. 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. 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, including linking climate change with mortality, and modeling the effects of land expansion on carbon sequestration and lost biodiversity. 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 (2023).

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.euroecorev.2025.104982.

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