Growth and adaptation to climate change in the long run∗

Simon Dietz† Bruno Lanz‡

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Abstract

As the climate changes, economies are adapting through structural change, innovation and demographic change. However, adaptation is costly, so reducing future greenhouse gas emissions could improve welfare substantially. To document this, we structurally estimate a Schumpeterian growth model that includes an explicit agriculture sector, endogenous fertility, directed technical change in fossil/renewable energy and a coupled climate, using 1960-2015 data. We provide novel evidence on the costs of long-run climate change and isolate the role of different adaptation mechanisms. We then analyze how the economy may adapt to climate change and to optimal carbon taxes over the 21st century.

Keywords: economic growth; adaptation; climate change; directed technical change; structural change; population growth; agricultural productivity; energy; structural estimation

JEL Classification numbers: C51, O13, O44, Q54

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†London School of Economics and Political Science, UK; CESifo, Germany. Email: s.dietz@lse.ac.uk

‡University of Neuchâtel and ETH Zürich, Switzerland; Massachusetts Institute of Technology, USA. Email: bruno.lanz@unine.ch
1 Introduction

World population has grown from just over 3 billion in 1960 to 7.8 billion currently and is projected to grow by several billion more this century (United Nations, 2019). Similarly, world GDP per capita has grown roughly three-fold since 1960 (World Bank, 2020), and the consensus among economic growth forecasters is that it will also increase several-fold by 2100.¹ To meet the food demand of a growing and increasingly affluent world population, global food production more than tripled in value between 1961 and 2011 (Alston and Pardey, 2014). In fact, agricultural productivity improved so much in the 20th century that many relative food prices declined (Alston and Pardey, 2014), as did undernourishment (World Bank, 2020). However, productivity growth is showing signs of slowing down, raising concerns about the capacity of the sector to keep up in the future (Alston et al., 2009; Godfray et al., 2010).

One of the reasons for that concern is climate change. To accompany the great expansion of the world economy and population, energy use has increased by a factor of around five since 1960 (BP, 2017; EIA, 2017). The vast majority of that energy has been derived from burning fossil fuels, causing greenhouse gas (GHG) emissions to roughly triple since 1960 (Meinshausen et al., 2011; World Bank, 2020). Climate science unequivocally attributes the observed increase in global temperatures to anthropogenic GHG emissions (IPCC, 2013). Agriculture finds itself at the nexus of economic growth, population growth and climate change: (i) it is a non-trivial source of emissions through farming practices and deforestation, and (ii) it is among the economic activities most exposed to climate change (Schelling, 1992; IPCC, 2014b; Carleton and Hsiang, 2016), because weather is a direct input to agricultural production.²

In this paper, we provide novel evidence on how the economy adapts to and is impacted by climate change, putting agriculture at the heart of the problem. To do so, we formulate a Schumpeterian growth model of the world economy, in which the key drivers of food supply and demand are endogenous (i.e. fertility, technical change and land use). The economy co-evolves with the climate system through GHG emissions from energy use and agriculture. We discipline the model’s empirical trajectories by taking the model to the data, using a simulated method-of-

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¹ According to the expert survey by Christensen et al. (2018), the median growth rate of global GDP per capita will be 2% between 2010 and 2100, which implies that global GDP per capita in 2100 will be around six times higher than in 2010. Christensen et al. also made statistical forecasts based on time-series data from the 20th century, using the Müller-Watson method (Müller and Watson, 2016). This yielded very similar estimates. The uncertainty around these estimates is obviously very large.

² Climate affects fundamental biophysical factors such as plant development, photosynthesis/respiration, water availability, and the prevalence of diseases and pests (Hertel and Lobell, 2014; IPCC, 2014b). Agronomic models suggest that crop yields, defined as the ratio of crop production to harvested land area, are highly responsive to temperature, with a representative response of -5% per °C (local) warming (Challinor et al., 2014). Crop yields also respond positively to rainfall, except at very high levels (e.g. Schlenker and Roberts, 2009), and heightened atmospheric CO₂ (also see Challinor et al., 2014).
moments procedure to fit observed trajectories over the period 1960 to 2015.\textsuperscript{3} We show that the structurally estimated model closely replicates targeted trajectories for world population, GDP, agricultural productivity, cropland, and fossil/renewable energy use. It also reproduces stylized facts about a number of quantities that we do not target in the estimation. Once estimated, we employ the model as an empirical framework to make future projections, as is common in economic models of climate change (e.g., Nordhaus, 1991; Golosov et al., 2014; Cai and Lontzek, 2019). However, a key advantage of structurally estimating the model using past data is that we can also construct a counterfactual past without climate change, thereby estimating what effect climate change has already had.

We show that climate change has already left its imprint on the world economy. Calibrating crop yields on leading agronomic models (Nelson et al., 2014), we estimate that climate change would have reduced agricultural output by close to 9% by 2020, relative to a counterfactual world without climate change (with an upper-bound estimate of 17%). Calibrating climate impacts in the rest of the economy on leading empirical work (Dell et al., 2012), climate change would have reduced productivity there too, but only by around 0.5% in 2020. However, the eventual reduction in agricultural output has been lower. We estimate that it was only around 2% in 2020. The reason why is that the economy has adapted. Resources have been shifted from the rest of the economy to agriculture, including capital, labor and R&D labor. To make up for lost yields, agricultural land has expanded and agricultural innovation has accelerated. Fertility has also been curtailed, because climate change has made population expansion more costly, implicitly through higher relative food prices (compared to a world without climate change). Therefore, while the global economy underwent structural change away from agriculture towards manufacturing and services over this period, our results imply that climate change has actually slowed down this process, drawing resources into agriculture.

We then use the model to make projections over the 21st century, with and without climate change, and with and without a Pigouvian tax on GHG emissions to internalize the climate change externality. Without a carbon tax, the model is able to sustain an increasing path of GDP and population that is not too far from the no-climate-change counterfactual. However, doing so comes at the cost of intensified adaptation, including further agricultural R&D, cropland expansion and population contraction. Welfare is around 23% lower than in a counterfactual world without climate change. The optimal carbon tax leads to significant reductions in GHG emissions, so that optimal global warming is well below 2°C in 2100. This shows that while macro-economic adaptation is effective in reducing climate impacts, it is costly, and some of the

\textsuperscript{3}In the micro-economic literature, this is referred to as structural estimation. In the macro-economic literature, this can be interpreted as model calibration without closed-form solutions. Our procedure extends Lanz et al. (2017). Also see Acemoglu et al. (2016) and Fried (2018) for related approaches.
welfare loss of climate change can be clawed back by reducing emissions (welfare is around 7% higher on a path with a carbon tax).

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 almost eliminates the welfare gains of GHG abatement. Second, agricultural R&D is a particularly important mechanism in adapting to climate change. Third, our welfare estimates are noticeably robust to changing model specification. This result derives from our empirical strategy, whereby the parameters of the model are re-estimated for every specification considered. Thus we show that, by fitting the model to trajectories observed in the past, policy simulations under alternative assumptions deliver a consistent message about the welfare gains of immediate climate policy at the global level.

1.1 Related literature

The structure of our growth model builds on a number of seminal contributions to the literature. We extend the model of Barro and Becker (1989), which endogenizes population growth through households' inter-temporal preferences over consumption and fertility. 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 (Aghion and Howitt, 1998; Dinopoulos and Thompson, 1998; Peretto, 1998; Young, 1998; Laincz and Peretto, 2006; Chu et al., 2013). 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, in our case with a particular focus on the role of agriculture. This literature includes Integrated Assessment Models (IAMs), pioneered by William Nordhaus (e.g. Nordhaus, 1991; Nordhaus and Boyer, 2000; Nordhaus, 2017). Recent contributions include Golosov et al. (2014),

\[4\] 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.
Cai and Lontzek (2019) and Barrage (2020). Like these studies, our empirical framework can be used to estimate the optimal GHG tax. Unlike previous IAM studies, our model is structurally estimated on more than 50 years of data, extending recent developments using simulation methods to condition models on historical data (Acemoglu et al., 2016; Fried, 2018; Lanz et al., 2017). This enables us to inform key parameters with limited evidential bases (Millner and McDermott, 2016, discuss the problems of not doing so), and conduct counterfactual analyses of the recent past. Unlike existing IAMs, our model also contains a mechanism whereby climate change constrains population expansion, which contributes to a nascent literature on the topic (e.g. Casey et al. 2019; Scovronick et al. 2017; theoretical models of resource use with endogenous fertility include Bretschger 2020; Peretto and Valente 2015).

An alternative approach is offered by reduced-form econometric studies, which use exogenous variation in past climate and weather as a natural experiment. Dell et al. (2014) and Carleton and Hsiang (2016) provide reviews. Our model does not substitute for this work, since we still require exogenous estimates of climate damages, pre-adaptation. Econometric studies that use short-run variation in climate can provide these, as adaptation responses are unlikely to be significant on short timescales (Hsiang, 2016). Rather, our approach is complementary to this, as it explicitly identifies long-run adaptation mechanisms, including how production factors are reallocated across the final goods, energy and R&D sectors. In doing so, it has an affinity with other recent work on climate change using structural models, such as Costinot et al. (2016), and Desmet and Rossi-Hansberg (2015). While these papers major on the geographical dimension, including the location of economic activities and trade patterns, we instead emphasize sectoral change, R&D, land-use change and fertility.

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 1970-2020 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 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, estimating the

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5 There is a similar strand of literature in agricultural economics concerned with building quantitative economic models of global agriculture (von Lampe et al., 2014; Cai et al., 2014). A feature of these models is that they are exceptionally detailed (e.g. spatially), but they are fundamentally partial-equilibrium and rely on exogenous income and productivity projections.
model on a shorter period, and calibration of exogenous parameters.

2 Empirical strategy

This section starts by motivating our empirical approach. We then outline the structure of the model, equation by equation. Finally, we discuss how we take the model to the data.

2.1 Motivation

At the heart of this paper is the question of how food supply and demand respond to changing climatic conditions, on top of the fundamental drivers of economic growth and population growth. The pessimistic, Neo-Malthusian view emphasizes limits to the availability of natural resources that are essential inputs to agriculture, especially under climate change. The optimistic, Cornucopian view focuses on technological progress in agriculture and substitution away from finite natural resources, enabling farmers and the agricultural system to adapt. It follows from these contrasting perspectives that a structured assessment of the question must consider the joint evolution of the world economy and the climate, and integrate the key drivers of food supply and demand, such as fertility choices, land as a primary factor and technological progress. It must also consider the potential role of policies to internalize the climate-change externality, especially when projecting forward.

Accordingly, we formulate a dynamic, general-equilibrium model that allows us to endogenously determine the joint evolution of the world economy, including agriculture, and the climate system. The model structure builds on previous work analyzing population growth under land constraints (Lanz et al., 2017, 2018a,b), adding energy and climate. The model is estimated using a simulated method-of-moments procedure, which does not require solving the model in closed form, something that is impossible given the variety of drivers at play. In essence, estimation requires solving the model a large number of times, and selecting the parameters so as to minimize a measure of the distance between simulated trajectories and those observed over the period 1960 to 2015.

We formulate the model as a discrete-time planning problem – our solution concept maximizes the preferences of a representative household subject to feasibility/technology constraints. This is a natural way to study climate change as an externality, but it is also a computational requirement to implement the structural estimation procedure, which requires solving a model
with a large number of stock variables for many vectors of candidate estimates.\textsuperscript{6} We study paths along which the planner internalizes the climate-change externality, as well as paths along which the planner does not, including the historical, estimation period 1960-2015.\textsuperscript{7} In addition, the economy is affected by other externalities that the planner does not explicitly internalize, including those related to fertility and technological progress. Therefore, our empirical strategy implies that we cannot interpret our structural parameter estimates as those of a representative household or firm. Rather, these estimates rationalize distortions present in the empirical data. As such, when making future projections with and without internalizing the climate-change externality, we assume that society’s (in)ability to internalize fertility and innovation externalities is unchanged.

2.2 Structural model of long-run growth and climate change

This section presents our model, including production, energy and land use, sectoral technical change, fertility decisions and welfare, emissions and climate dynamics.

Agricultural production

Agricultural output $Y_{t,ag}$ is described by a constant-returns-to-scale and constant-elasticity-of-substitution (CES) production function that combines land $X_t$ with a Cobb-Douglas composite of non-land inputs (e.g. Ashraf et al., 2008):

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

where non-land inputs include capital $K_{t,ag}$, labor $L_{t,ag}$ and energy $E_{t,ag}$. $A_{t,ag}$ 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 $\Sigma \theta_i < 1$. 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).\textsuperscript{8}

\textsuperscript{6} As we show below, a social planner formulation affords a number of simplifications, including reducing the number of state variables that need to be computed. 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.

\textsuperscript{7} Towards the end of the estimation 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-2015.

\textsuperscript{8} 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.
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). As we describe below, GHG emissions from energy, agricultural production and land use increase $S_t$ and this in turn reduces 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 crop yields.

**Production in the rest of the economy**

Output in the rest of the economy at time $t$, denoted $Y_{t,mn}$ ($mn$ stands for manufacturing, but services are also included here) is described by a constant-returns-to-scale, Cobb-Douglas production function that combines capital $K_{t,mn}$, labor $L_{t,mn}$, and energy $E_{t,mn}$:

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

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 $\Sigma_i \vartheta_i < 1$.

Similar to agriculture, climate change affects aggregate productivity through the parameter $\Omega_{mn}$. This should be an estimate of the short-run impact of climate change on productivity, i.e. prior to adaptation through the mechanisms we identify.

**Clean and dirty energy**

Final energy $E_t$ is used in both final goods sectors. The energy sector produces $E_t$ by combining dirty ($dt$) and clean ($cl$) energy intermediates. Dirty/fossil energy comprises coal, natural gas and oil. Clean energy comprises e.g. biofuels, hydroelectric power, nuclear, solar, wind, and fossil energy when combined with carbon capture and storage. The functional relationship is CES (Acemoglu et al., 2016),

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

---

7 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 constant-elasticity-of-substitution function, in which the elasticity of substitution between energy and other inputs is less than unity (Fried, 2018; Hassler et al., 2016b). Baqae 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 $\sigma_E$ is the elasticity of substitution between clean and fossil energy. In our main specification, we assume that $\sigma_E$ is 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 (Barrage, 2020; Acemoglu et al., 2019):

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

(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

$$\bar{R} \geq \sum_{0}^{T} R_t,$$

(5)

where $\bar{R}$ 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 $X$ and slowly reverts back to its natural state if left unmanaged. As in Lanz et al. (2017), the evolution of land available for agricultural production is given by

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

(6)

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

$$\psi_t = \psi \cdot L_{t,X}^{\varepsilon},$$

(7)

where $\psi$ and $\varepsilon \in (0, 1)$ are productivity parameters.

Note that 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.
In (1992, 1998), in which the use of labor determines the arrival rate of new innovations. In each sector \( j \in \{ag, mn, cl, dt\} \), we denote productivity improvements of each innovation by \( s_j \), and, without loss of generality, we assume there is a maximum of \( \iota_j > 0 \) innovations in each time period. This implies the sectoral TFP growth rate in each period is bounded above by \( \lambda_j = (1 + s_j)^{\iota_j} - 1 \). It follows that the evolution of sectoral TFP can be written as

\[
A_{t+1,j} = A_{t,j} \cdot (1 + \lambda_j \cdot \rho_{t,j}),
\]

where \( \rho_{t,j} \) is the endogenous arrival rate of innovations in the sector and represents the fraction of maximum growth \( \lambda_j \) 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, \( L_{t,A_j} \),

\[
\rho_{t,j} = \left( \frac{L_{t,A_j}}{N_t} \right)^{\mu_j},
\]

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. 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**

Population plays a central role in our model and is endogenous. The evolution of population is given by

\[
N_{t+1} = N_t(1 + n_t - \delta_N), \quad N_0 \text{ given},
\]

\[10\]

In Aghion and Howitt (1992), \( s_j \) represents the size of an innovation required to obtain a patent, and the firm that holds the most productive technology has a monopoly until a new innovation arrives. In continuous time, the arrival of innovations is modeled as a Poisson process, and our discrete-time representation uses the law of large numbers to integrate out the random nature of short-term growth over discrete time intervals. Thus \( \lambda_j \) can be interpreted as the maximum growth rate of sectoral TFP in each period.
where \( n_t \) is the endogenous fertility rate, determined by household preferences (see below), and \( \delta_N \) is the exogenous mortality rate.\(^{11}\) Raising children requires labor, the aggregate cost of which is given by

\[
\begin{align*}
    n_t N_t &= \bar{\chi}_t \cdot L_{t,N} .
\end{align*}
\]

Labor productivity in fertility is determined by the coefficient \( \bar{\chi}_t \), which in turn is given by

\[
\begin{align*}
    \bar{\chi}_t &= \chi L_{t,N}^{\zeta-1} ,
\end{align*}
\]

where \( \chi \) and \( \zeta \in (0, 1) \) are labor productivity parameters. In this way, \( 1/\bar{\chi}_t \) is 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).

Aside from the opportunity cost of time, the need to feed the population creates an additional effective cost of fertility. Formally, clearing of the food market requires that agricultural output matches contemporaneous aggregate food consumption:

\[
\begin{align*}
    Y_{t,ag} &= N_t \cdot \xi_t
\end{align*}
\]

where \( \xi_t \) is per-capita food demand, determined by household preferences (see below). Since climate change affects agricultural productivity, this creates a link between climate change, fertility and demographic change.

**Capital dynamics**

Output of the non-agricultural part of the economy can be consumed or invested:\(^{12}\)

\[
\begin{align*}
    Y_{t,mn} &= C_t + I_t .
\end{align*}
\]

This investment allows for accumulation of capital,

\[
\begin{align*}
    K_{t+1} &= K_t (1 - \delta_K) + I_t , \quad K_0 \text{ given} ,
\end{align*}
\]

\(^{13}\) 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.

\(^{12}\) See Ngai and Pissarides (2007) for a similar treatment of savings and capital accumulation in a multi-sector model.
where \( \delta_K \) is the depreciation rate.

**Intertemporal preferences**

The representative household has preferences over (i) own consumption of food and the composite non-agricultural good, (ii) the number of children it produces and (iii) the total future utility of these children.

Preferences over own consumption are described by an isoelastic utility function:

\[
 u(c_t) = \frac{c_t^{1-\gamma} - u}{1 - \gamma} 
\]

where \( \gamma \) is the inverse of the intertemporal elasticity of substitution and \( u > 0 \) represents the consumption level at which per-period utility becomes positive. The consumption flow per capita \( c_t \) is further written as:

\[
 c_t = \min \left( \xi^{-1/\kappa} y_{t,ag}^{1/\kappa}, y_{t,mn} \right) - i_t, \tag{17} \]

where \( \xi \) is a scale parameter, \( \kappa \) is the income elasticity of food consumption, \( y_{t,ag} \) and \( y_{t,mn} \) are food and goods production per capita, and \( i_t \) is investment/savings per capita. This preference structure implies that food and the composite good are partial complements, capturing the role food plays in meeting subsistence needs, but also recognizing that food expenditure continues to rise once subsistence needs have been met. Per capita demand for food, \( \xi_t = \xi \cdot y_{t,mn}^\kappa \), increases as a function of income per capita, and we assume \( \kappa < 1 \) so that the increase is less than proportional (Subramanian and Deaton, 1996; Thomas and Strauss, 1997; Tilman et al., 2011).

Next, we follow Barro and Becker (1989) and assume that fertility preferences are also isoelastic:

\[
 b(n_t) = n^{-\eta} \tag{18} \]

where \( \eta \in (0, 1) \) determines how fast marginal utility declines as \( n \) increases. All children \( k \) are assumed identical, so that the future utility of a household’s children \( \sum_k U_{k,t+1} = n_t U_{t+1} \). 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. This enables parents’ own future utility and the future utility of their children to be combined so that the number of agents entering utility at \( t + 1 \) is \( \tilde{n} = (1 - \delta_N) + n_t \) (see Jones and Schoonbroodt, 2010). Using the recursive formulation of Barro and Becker (1989), the utility function in period \( t \) is then

\[
 U_t = u(c_t) + \beta b(\tilde{n_t})[\tilde{n_t}]U_{t+1}, \tag{19} \]
where \( \beta \in (0, 1) \) is the discount factor.

Under these assumptions, we can exploit the recursive nature of Barro-Becker preferences to derive the intertemporal welfare function of a dynastic household head:13

\[
W = \sum_{t=0}^{\infty} \beta^t N_t^{1-\eta} \frac{c_t^{1-\gamma} - u}{1-\gamma}.
\]

Because population is endogenous in our model and one of our core aims is to evaluate the Pigouvian GHG tax that optimally internalizes the climate-change externality, Equation (20) can be interpreted as a social welfare function (SWF) and therefore implies a position on population ethics. Specifically, Equation (20) belongs to the class of (discounted) number-dampened critical-level utilitarian SWFs (Asheim and Zuber, 2014). The critical level \( u \) captures the level of consumption that makes the life of an additional person worth living. Appendix A provides further discussion of the ethical properties of this SWF.

**Allocation of capital, labor and energy**

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

\[
K_t = K_{t,ag} + K_{t,mn} + K_{t,cl} + K_{t,dt}. 
\]

Energy is allocated between the two final goods sectors,

\[
E_t = E_{t,ag} + E_{t,mn}. 
\]

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

\[
N_t = L_{t,ag} + L_{t,mn} + L_{t,cl} + L_{t,dt} + \sum_j L_{t,A_j} + L_{t,X} + L_{t,N}. 
\]

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 that these inputs 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.

---

13 This is obtained through sequential substitution in \( U_0 = u(c_0) + \beta b(\bar{n}_0)\bar{n}_0U_1 \), yielding \( U_0 = \sum_{t=0}^{\infty} \beta^t u(c_t)\Pi_{t=0} b(\bar{n}_t)\bar{n}_t \). Further, noting that Equation (10) can be rewritten as \( N_{t+1} = N_t\bar{n}_t \), we have \( \Pi_{t=0} b(\bar{n}_t)\bar{n}_t = (N_t/N_0)^{(1-\eta)} \).
GHG emissions and climate

We include three GHGs – CO₂, methane and nitrous oxide – which have four sources: (i) CO₂ emissions from burning fossil fuels, (ii) methane and nitrous oxide emissions associated with burning fossil fuels (primarily methane emissions as a waste product of fossil-fuel extraction and distribution), (iii) CO₂ emissions from expanding agricultural land (e.g. deforestation), and (iv) methane and nitrous oxide emissions from agricultural production. Total GHG emissions at time $t$ are given by

$$GHG_t = (\pi_{E,CO_2} E_t, dt + \pi_X (X_t - X_{t-1}) + \pi_{ag} \left(K_{t,ag} E_t, K_{t,ag} + L_{t,ag}^{1-\theta_K - \theta_E}\right), \qquad (23)$$

where $\pi_{E,CO_2}$ is CO₂ emissions per unit of dirty energy, $\pi_{E,NCO_2}$ is non-CO₂ emissions per unit of dirty energy (i.e. methane and nitrous oxide), $\pi_X$ is CO₂ emissions per unit of agricultural land expansion, and $\pi_{ag}$ is methane and nitrous oxide emissions per unit input of the capital-labor-energy composite in agriculture.\footnote{We assume net radiative forcing from other GHGs and aerosols is zero, which has been approximately true in recent years (IPCC, 2013).}$\pi_{E,NCO_2}$ and $\pi_{ag}$ are expressed in units of CO₂-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 in the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC). This model was built to replicate the behavior of more complex carbon-cycle models and it conforms better with them than the carbon cycles used in some key economic models (Dietz et al., forthcoming). In the model, atmospheric CO₂ is divided into four reservoirs, indexed by $r$, with $S_t = \Sigma_r S_{t,r}$, each of which decays at a different rate:

$$S_t = \sum_{i=0}^{3} S_{t,i} \qquad (24)$$

$$S_{t,0} = a_0 \left[\pi_{E,CO_2} E_t, dt + \pi_X (X_t - X_{t-1})\right] + \left(1 - \delta_{S,0}\right)S_{t-1,0} \qquad (25)$$

$$S_{t,i} = a_i \left[\pi_{E,CO_2} E_t, dt + \pi_X (X_t - X_{t-1})\right] + \sum_{i=1}^{3} \frac{a_i}{a_i} \left[\pi_{E,NCO_2} E_t, dt + \pi_{ag} \left(K_{t,ag} E_t, K_{t,ag} + L_{t,ag}^{1-\theta_K - \theta_E}\right)\right] + \left(1 - \delta_{S,i}\right)S_{t-1,i}, \quad i = 1, 2, 3, \quad (26)$$

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 CO₂. 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 methane and nitrous oxide
emissions are converted into CO₂-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.\textsuperscript{15}

**Optimization and solution concept**

The model is solved as a constrained non-linear optimization problem. The intertemporal welfare function (20) is maximized by selecting aggregate consumption, as well as the allocation of capital, energy and labor across activities, subject to technological constraints. Given the parameter restrictions, the ensuing mathematical programming problem is convex, which ensures a global optimum.

We formulate the numerical problem with the algebraic modeling language GAMS, and solve it with the KNITRO package (Byrd et al., 2006). This combination 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.\textsuperscript{16} Appendix B contains a formal statement of the primal optimization problem and discusses some further computational considerations.

### 2.3 Estimation

Our approach to model estimation builds on Acemoglu et al. (2016) and Lanz et al. (2017) and proceeds in two steps. The first step is to impose a subset of exogenous model parameters (Table 1). These are parameters whose values are fairly standard in the literature and/or well pinned down by external sources. Appendix D provides further details. It also discusses how we calibrate initial values of the eleven state variables, and reports the parametrization of the emissions/climate module. At the second step, given imposed parameter values and initial conditions, we use a simulated method-of-moments procedure developed in Lanz et al. (2017) to identify the vector comprising the remaining parameters: \( \Theta = \{ \eta, \chi, \zeta, \psi, \varepsilon, \mu_{mn}, \mu_{ag}, \mu_{cl}, \mu_{dt} \} \).

In broad terms, we select values for the elements of the vector that jointly minimize the distance between targeted, observed variables over the estimation period and their counterparts as

\textsuperscript{15} A more complete model would have fully independent climate dynamics for methane and nitrous oxide, but this would add excessive complexity.

\textsuperscript{16} Note that, for the numerical solution, the domain of per-capita consumption is constrained to be strictly greater than \( u/(1 - \gamma) \) so that per-period utility is positive (see Jones and Schoonbroodt, 2010, for a discussion). This restriction does not affect the actual solution of the problem, since per-capita consumption is initialized above \( u/(1 - \gamma) \) and grows thereafter. Therefore, this additional constraint only serves the purpose of avoiding bad function calls by the solver, which could compromise the optimization algorithm.
simulated by the model.

Table 1: Parameters imposed for estimation

<table>
<thead>
<tr>
<th>Parameter value</th>
<th>Definition</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Preferences and population</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta = [0.99, 0.97]$</td>
<td>Discount factor</td>
<td>Giglio et al. (2015)</td>
</tr>
<tr>
<td>$\gamma = 2$</td>
<td>Intertemporal elasticity of substitution</td>
<td>Guvenen (2006)</td>
</tr>
<tr>
<td>$\nu = 1$</td>
<td>Critical level of utility</td>
<td>Calibrated</td>
</tr>
<tr>
<td>$\kappa = [0.5, 0.2]$</td>
<td>Food income elasticity</td>
<td>Thomas and Strauss (1997)</td>
</tr>
<tr>
<td>$\xi = [0.11, 0.17]$</td>
<td>Unit food demand</td>
<td>Echevarria (1997)</td>
</tr>
<tr>
<td>$\delta_N = [0.022, 0.0166]$</td>
<td>Mortality rate</td>
<td>Calibrated</td>
</tr>
<tr>
<td><strong>Manufacturing and capital accumulation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\vartheta_K = 0.3$</td>
<td>Capital share</td>
<td>Various</td>
</tr>
<tr>
<td>$\vartheta_E = 0.04$</td>
<td>Energy share</td>
<td>Golosov et al. (2014)</td>
</tr>
<tr>
<td>$\delta_K = 0.1$</td>
<td>Capital depreciation</td>
<td>Various</td>
</tr>
<tr>
<td>$\Omega_{mn} = {1.2312E-05, 9.1134E-07, 2.382E-05}$</td>
<td>Manufacturing damage intensity</td>
<td>Dell et al. (2012)</td>
</tr>
<tr>
<td><strong>Agricultural sector</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_X = [0.6, 0.2]$</td>
<td>Substitutability of land in agriculture</td>
<td>Wilde (2013)</td>
</tr>
<tr>
<td>$\theta_K = 0.25$</td>
<td>Capital share</td>
<td>Various</td>
</tr>
<tr>
<td>$\theta_X = 0.3$</td>
<td>Land share</td>
<td>Lanz et al. (2017)</td>
</tr>
<tr>
<td>$\theta_E = 0.04$</td>
<td>Energy share</td>
<td>Golosov et al. (2014)</td>
</tr>
<tr>
<td>$\delta_X = 0.02$</td>
<td>Land depreciation</td>
<td>Calibrated</td>
</tr>
<tr>
<td>$\bar{X} = 3$</td>
<td>Land reserves (billion ha)</td>
<td>Alexandratos and Bruinsma (2012)</td>
</tr>
<tr>
<td>$\Omega_{ag} = {2.07E-04, 1.5E-04, 4.15E-04}$</td>
<td>Agricultural damage intensity</td>
<td>Nelson et al. (2014)</td>
</tr>
<tr>
<td><strong>Energy sector and R&amp;D activities</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_E = {1.5, 0.95}$</td>
<td>Substitutability of energy intermediates</td>
<td>Stern (2012)</td>
</tr>
<tr>
<td>$\alpha = 0.6$</td>
<td>Capital share</td>
<td>Barrage (2020)</td>
</tr>
<tr>
<td>$\bar{T} = {5000, \infty}$</td>
<td>Dirty energy (Gt oil eq)</td>
<td>Rogner (1997)</td>
</tr>
<tr>
<td>$\lambda_j = 0.05$</td>
<td>Innovation size in R&amp;D</td>
<td>Fuglie (2012)</td>
</tr>
</tbody>
</table>

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 D for a discussion of parameter selection.

Formally, for a given candidate vector of parameter estimates $\Theta_v$, we solve the model to obtain simulated trajectories for $k$ targeted quantities $Z_{\tau,k}^{model}; \Theta_v$, where $\tau$ 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 $\Theta_v$ as the relative squared deviation summed over the estimation period:

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

(27)

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

$$\min_{\Theta} \sum_k \omega_k e_k^{\Theta},$$

(28)
Table 2: Parameters estimated with simulated method of moments

<table>
<thead>
<tr>
<th>Parameter estimates</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\chi = 0.120$</td>
<td>Labor productivity in fertility and education</td>
</tr>
<tr>
<td>$\zeta = 0.458$</td>
<td>Elasticity of labor productivity in fertility and education</td>
</tr>
<tr>
<td>$\eta = 0.151$</td>
<td>Elasticity of intergenerational altruism</td>
</tr>
<tr>
<td>$\psi = 0.060$</td>
<td>Labor productivity in agricultural land conversion</td>
</tr>
<tr>
<td>$\varepsilon = 0.155$</td>
<td>Elasticity of labor productivity in agricultural land conversion</td>
</tr>
<tr>
<td>$\mu_{mn} = 0.523$</td>
<td>Elasticity of labor productivity in manufacturing R&amp;D</td>
</tr>
<tr>
<td>$\mu_{ag} = 0.524$</td>
<td>Elasticity of labor productivity in agricultural R&amp;D</td>
</tr>
<tr>
<td>$\mu_{cl} = 0.193$</td>
<td>Elasticity of labor productivity in clean energy R&amp;D</td>
</tr>
<tr>
<td>$\mu_{dt} = 0.372$</td>
<td>Elasticity of labor productivity in dirty energy R&amp;D</td>
</tr>
</tbody>
</table>

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

with weights $\omega_k$ inversely proportional to the volatility of the observations of $k$.\textsuperscript{17} In order to find a solution to Equation (28), 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 $\Theta_2$, solving the model again for 10,000 draws. This procedure leads us to gradually update the distribution of parameters considered until we converge to the set of estimates reported in Table 2.

We use the joint evolution of world population (United Nations, 2019) and GDP (World Bank, 2020) to help identify the fertility preference parameter $\eta$, the parameters $\chi$ and $\zeta$ that determine labor productivity in fertility, as well as $\mu_{mn}$, the productivity of R&D labor in the rest of the economy (this last parameter plays a key role in determining fertility via its effect on wages/opportunity costs). We use data on agricultural TFP growth (Martin and Mitra, 2001; Fuglie, 2012) to help identify the productivity of R&D labor in agriculture, $\mu_{ag}$. Data on cropland area from FAO (2018) are used to help identify the parameters determining labor productivity in land clearing for agriculture ($\psi$ and $\varepsilon$). Lastly, data on global fossil and non-fossil energy use (BP, 2017) are used to help identify labor productivity in clean and dirty energy R&D ($\mu_{cl}$ and $\mu_{dt}$ respectively).

The uniqueness of the solution to Equation (28) 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

\textsuperscript{17} 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.
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 C shows how total model error increases as we introduce deviations from each best parameter estimate, providing suggestive evidence of the existence of a global minimum of Equation (28),\[^{18}\] as well as evidence that each of our structural parameters is generally well identified by the data.

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 (see Table 1).\[^{19}\]

### 3 Estimation results: targeted and untargeted moments

In this section, we document how well the model is able to track the evolution of observed outcomes since 1960. We also discuss robustness of model fit to the use of a shorter estimation period (1960-2000).

Figure 1 plots model trajectories of the variables we target in our structural estimation and compares them with observed trajectories, thus demonstrating goodness of fit. Six variables are included: population (panel a); GDP (b); cropland area (c); agricultural TFP (net of climate damages, i.e. $A_{t,ag} \cdot \exp(-\Omega_{ag}[S_t - \bar{S}])$, panel d); and fossil and non-fossil energy use (e and f respectively). The comparison shows that the model closely replicates the observed trajectories, particularly the more stable time series for population, GDP, cropland and agricultural TFP. The figure also illustrates some of the key trends described in the introduction – the huge expansion of population and GDP, with the latter growing exponentially and the former growing roughly arithmetically, slow but continued expansion of agricultural land, slowing agricultural TFP growth that also gives rise to an arithmetic/linear trend, and growing energy use, especially from non-fossil sources.

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\[^{18}\] Assuming there are no significant interaction effects between the structural parameters, this can be interpreted as demonstrating the existence of a global minimum of total model error.

\[^{19}\] 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 targeted variables

(a) World population

(b) World GDP

(c) Arable land and permanent crops

(d) TFP in agriculture net of climate damages

(e) Global non-fossil energy use

(f) Global fossil energy use
Figure 2 plots model estimates of four quantities that are not directly targeted by our structural estimation and compares them with observations: agricultural yield growth (panel a); agriculture’s share of GDP (b); per-capita consumption growth (c); and investment (d). In general, the model fits the untargeted moments reasonably well, without of course capturing the short-run volatility inherent in empirical data. Specifically, it captures the slowdown in agricultural yield growth, agriculture’s declining share of global GDP and slowing growth in consumption per capita. Historical growth in aggregate investment is somewhat overestimated. Given that the model fits GDP very closely, this implies the returns to capital accumulation implied by the parameters of the model are somewhat too low.

Figure 3 similarly compares model estimates of four key emissions/climate variables with observations: total GHG emissions (a); agricultural GHG emissions (b); the share of GHG emissions from fossil fuel burning (c); and the atmospheric GHG stock (d). These variables are also untargeted. The model closely tracks the observations. Aggregate 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 F, we provide evidence on the robustness of our estimation procedure by restricting the interval over which the model is estimated to 1960-2000. We then compare the resulting projections for 2020 with those obtained from our baseline estimation covering the whole period 1960-2015. We can already be confident from the analysis above that the latter projections will be very close to the observations, and the model estimated on 1960-2000 is itself very close to the projections from the model estimated on 1960-2015. The largest deviation is observed for non-fossil energy use in 2020, which is around eight percent higher in the restricted model, whereas fossil energy use is around three percent lower. Interestingly this implies the transition from dirty to clean energy slowed down after 2000. Overall, these results suggest that the trajectories derived from our model are not unduly affected by the most recent

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20 Aside from the effect of the Covid-19 pandemic on 2020 data; that is why we rely on the projections of the model estimated on 1960-2015, rather than the observations.
years of data, but rather build on long-term trends observed over the past decades.

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

By the end of our estimation period in 2015, anthropogenic GHG emissions had already caused roughly 1°C global warming (IPCC, 2018). Simulation models of climate impacts, as well as empirical studies looking mainly at short-run climate variability, imply this observed warming has already affected agriculture and the rest of the economy (see Dell et al., 2014; Carleton and Hsiang, 2016). We now use our structural model to provide novel evidence on how much, and quantify the role of adaptation channels such as structural change, innovation and fertility in reducing climate damages. To do so, we employ the estimated model 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 4, we start by quantifying overall climate damages and how much they have been reduced by adaptation. The top two panels plot climate damages to agriculture and the rest of the economy respectively, pre-adaptation, as measured by direct productivity losses. These are obtained simply by taking the atmospheric GHG stock estimated by the model and plugging it into the sectoral damage multipliers, i.e. $\exp(-\Omega_{ag} [S_t - \bar{S}])$ and $\exp(-\Omega_{mn} [S_t - \bar{S}])$ respectively. We estimate that, absent any adaptation, climate damages would have reduced agricultural output by 3.1% in 1970, relative to a counterfactual world without climate change. This is within a sensitivity range of 2.3% to 6.1%, estimated by running the model with the damage coefficient $\Omega_{ag}$ set to its lower/upper bounds (see Appendix D for further details). By 2020, rising temperatures would have caused agricultural damages to rise to 8.5%, within a range of 6.3-16.6%. 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% to 0.4% (also obtained by setting $\Omega_{mn}$ to its lower/upper bounds). By 2020, damages in the rest of the economy would have risen to 0.5% (range 0-1%).

In comparison, the bottom two panels of Figure 4 plot lost output in agriculture and the rest of the economy after macro-economic 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.

21 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 4: Estimated climate change impacts since 1970, before and after adaptation

(a) Agriculture (pre-adaptation)

(b) Rest of the economy (pre-adaptation)

(c) Agricultural output (post-adaptation)

(d) Rest of economy output (post-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 1.1% lower than the counterfactual world without climate change (range 0.7-2.3%), rising to 2.0% lower in 2020 (range 1.4-4.4%). 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 1.7% lower than the counterfactual in 1970 (range 1.1-3.5%), rising to 2.8% lower in 2020 (range 1.9-5.9%). 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 3, we document several important adaptation mechanisms that the economy has used to reduce the damaging effects of climate change. We focus on cropland area, agricultural innovation, population change, and reallocation of capital and labor. For each quantity, we report the difference between the baseline model with climate impacts and the counterfactual
Table 3: Historical adaptation to climate change

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Cropland (million ha.)</td>
<td>+1.36</td>
<td>+2.29</td>
<td>+3.09</td>
<td>+3.98</td>
<td>+5.14</td>
<td>+6.68</td>
</tr>
<tr>
<td>Ag. innovation rate (%)</td>
<td>+0.07</td>
<td>+0.08</td>
<td>+0.09</td>
<td>+0.10</td>
<td>+0.11</td>
<td>+0.12</td>
</tr>
<tr>
<td>Population (millions)</td>
<td>-17.83</td>
<td>-35.56</td>
<td>-52.92</td>
<td>-69.90</td>
<td>-86.47</td>
<td>-102.60</td>
</tr>
<tr>
<td>Shares of capital (ppts.)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture</td>
<td>+0.61</td>
<td>+0.51</td>
<td>+0.46</td>
<td>+0.44</td>
<td>+0.47</td>
<td>+0.55</td>
</tr>
<tr>
<td>Rest of economy</td>
<td>-0.60</td>
<td>-0.51</td>
<td>-0.45</td>
<td>-0.44</td>
<td>-0.47</td>
<td>-0.55</td>
</tr>
<tr>
<td>Shares of labor (ppts.)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture</td>
<td>+0.23</td>
<td>+0.18</td>
<td>+0.15</td>
<td>+0.14</td>
<td>+0.15</td>
<td>+0.16</td>
</tr>
<tr>
<td>Rest of economy</td>
<td>-0.07</td>
<td>-0.05</td>
<td>-0.03</td>
<td>-0.02</td>
<td>-0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>Agriculture R&amp;D</td>
<td>+1.20</td>
<td>+1.18</td>
<td>+1.16</td>
<td>+1.16</td>
<td>+1.15</td>
<td>+1.15</td>
</tr>
<tr>
<td>Rest of economy R&amp;D</td>
<td>-0.15</td>
<td>-0.10</td>
<td>-0.07</td>
<td>-0.05</td>
<td>-0.04</td>
<td>-0.03</td>
</tr>
<tr>
<td>Land clearing</td>
<td>+0.02</td>
<td>+0.02</td>
<td>+0.02</td>
<td>+0.02</td>
<td>+0.03</td>
<td>+0.03</td>
</tr>
<tr>
<td>Fertility</td>
<td>-1.22</td>
<td>-1.22</td>
<td>-1.23</td>
<td>-1.25</td>
<td>-1.28</td>
<td>-1.31</td>
</tr>
</tbody>
</table>

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

Our results suggest that cropland area has increased to compensate for the negative productivity impacts of climate change. We estimate that by 2020 an additional 6.7 million hectares of cropland had been brought into use, cumulatively, just to cope with climate change, which is 0.4% above the counterfactual level. Climate change has also induced an increase in agricultural innovation, as measured by the growth rate of the gross technology index $A_{t,ag}$. By 2020, agricultural TFP growth was 0.12 percent higher than in the absence of climate change. As a result of consistently higher innovation, the level of agricultural technology was 6.5% higher than the counterfactual in 2020. Further adjustments can be seen 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 production and especially to agricultural R&D.\textsuperscript{22} Thus climate change has been a countervailing force to the wider macro-economic forces driving structural change out of agriculture. World population is lower as a result of climate change. We estimate that by 2020 world population was 103 million (1.3%) smaller than in the counterfactual without climate change. Recall that in our model the main mechanism bringing this about is an increase in the cost of feeding children, which affects fertility choices. Accordingly we estimate less labor was allocated to fertility.

\textsuperscript{22} 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.
What has the welfare cost of climate change been? We compute the change in ‘stationary
equivalent’ consumption, i.e. the consumption level which, if held constant, yields the same
welfare value as the actual consumption stream (Weitzman, 1976). The welfare cost of climate
change between 1960 and 2020 is equivalent to a loss of stationary consumption of 4% in 1960,
relative to the counterfactual world without climate change. This is within a sensitivity range
of 2.6% (low damages in both sectors) to 9% (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, has produced a non-trivial deadweight
loss globally.

5 Future projections and policy simulations

We now use the model to generate projections for the rest of the 21st century. Our first set
of projections is an extension of the comparison made in the previous section between the
world in a changing climate and a counterfactual world absent climate change. This is under a
continued, laissez-faire emissions scenario, which we generate by solving the model from 2015
on without allowing the planner to correct the climate-change externality (sometimes called
‘business as usual’). Our second set of projections is of the optimal policy that internalizes
climate damages through a global Pigouvian carbon price/tax.

5.1 Laissez-faire equilibrium

Figure 5 reports our estimates of laissez-faire output and population in a changing climate. Pan-
els (a), (c) and (e) plot the level of each. Despite climate change, aggregate GDP (i.e. agriculture
plus the rest of the economy) increases nearly four-fold over the course of the century. Agricul-
tural output also increases, but only by a factor of 2.6. Population growth slows throughout the
century, but population still increases by a further 80%.

Panels (b), (d) and (f) report differences in output and population relative to the counterfac-
tual without climate change and also include low and high damage specifications. We estimate
that climate change will reduce GDP by 6.3% in 2100 relative to the counterfactual, with a range
of 4.1% to 13.5%. It will reduce agricultural output by 3.9% in 2100 relative to the counterfac-
tual, with a range of 2.6% to 8.5%. The reduction in population due to climate change is 1.5%

---

23 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
level that, if held constant, gives the same welfare value as the actual consumption/population path being
evaluated.

24 The counterfactual simulation also solves the model from 2015 onward, but switches off climate damages as
before.
Table 4: Future adaptation to climate change in laissez-faire equilibrium

<table>
<thead>
<tr>
<th></th>
<th>2025</th>
<th>2050</th>
<th>2075</th>
<th>2100</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cropland (million ha.)</td>
<td>+7.47</td>
<td>+13.89</td>
<td>+23.54</td>
<td>+35.79</td>
</tr>
<tr>
<td>Ag. innovation rate (%)</td>
<td>+0.13</td>
<td>+0.17</td>
<td>+0.22</td>
<td>+0.26</td>
</tr>
<tr>
<td>Shares of capital (ppts.)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture</td>
<td>+0.76</td>
<td>+1.27</td>
<td>+2.02</td>
<td>+2.92</td>
</tr>
<tr>
<td>Rest of economy</td>
<td>-0.76</td>
<td>-1.27</td>
<td>-2.04</td>
<td>-2.96</td>
</tr>
<tr>
<td>Shares of labor (ppts.)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture</td>
<td>+0.21</td>
<td>+0.29</td>
<td>+0.40</td>
<td>+0.51</td>
</tr>
<tr>
<td>Rest of economy</td>
<td>0.00</td>
<td>+0.01</td>
<td>+0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>Agriculture R&amp;D</td>
<td>+1.17</td>
<td>+1.13</td>
<td>+1.05</td>
<td>+0.93</td>
</tr>
<tr>
<td>Rest of economy R&amp;D</td>
<td>-0.02</td>
<td>-0.01</td>
<td>-0.01</td>
<td>-0.01</td>
</tr>
<tr>
<td>Land clearing</td>
<td>+0.04</td>
<td>+0.05</td>
<td>+0.07</td>
<td>+0.08</td>
</tr>
<tr>
<td>Fertility</td>
<td>-1.41</td>
<td>-1.48</td>
<td>-1.52</td>
<td>-1.51</td>
</tr>
</tbody>
</table>

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

in 2100 (range 1.0-3.5%).

Table 4 shows how the economy is projected to adapt to climate change in the laissez-faire equilibrium relative to a counterfactual without climate change. Cropland is projected to further expand relative to the counterfactual, reaching 36 million ha. greater (+2.0%) in 2100. Agricultural innovation is projected to be faster, and the difference in the innovation rate with and without climate change grows over the course of the century. Capital is shifted from other production sectors to agriculture, as is labor. Therefore, the baseline projection is of a continuation of the past trends we identified above, albeit with rising climate impacts.

However, estimated over the next 200 years, the welfare cost of laissez-faire climate change is equivalent to a loss of stationary consumption of 23.2% today, relative to the counterfactual, within bounds of 15-69%. This shows that adaptation to ever-increasing temperatures would come at a substantial welfare cost.
Figure 5: Estimated climate impacts on output and population over the 21st century

(a) GDP baseline
(b) GDP difference from counterfactual

(c) Agricultural output baseline
(d) Ag. output difference from counterfactual

(e) Population baseline
(f) Population difference from counterfactual
Figure 6: Baseline and optimal paths over the 21st century

(a) GHG tax

(b) Total energy use

(c) Fossil GHG emissions

(d) Agricultural GHG emissions

(e) Atmospheric GHG stock

(f) Temperature relative to pre-industrial
5.2 Optimal policy

Figure 6 projects the Pigouvian GHG tax (panel a) and the resulting optimal paths of total energy use (b), fossil GHG emissions (c), agricultural GHG emissions (d), the atmospheric GHG stock (e), and temperature (f). The Pigouvian GHG tax is $88/tCO\textsubscript{2}eq in 2020 (in 2010 US dollars). This increases in real terms to $167 in 2050 and $350 in 2100. The GHG tax significantly reduces total energy use. In 2050, the energy demand of the laissez-faire economy is equivalent to 24 gigatonnes of oil equivalent, while on the optimal path it is only around 10Gt. Optimal GHG emissions are significantly lower than in the laissez-faire equilibrium, particularly fossil GHG emissions, which are 78% lower in 2050. Agricultural GHG emissions are 12% lower in 2050, illustrating that emissions in agriculture are more costly to abate given food supply needs. The large reduction in GHG emissions slows growth in the atmospheric stock of GHGs and, in turn, in global mean temperature. The optimal policy reduces the atmospheric stock of GHGs by 20% 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. The optimal policy reduces warming from 3.3°C in 2100 to 1.8°C.

Table 5 compares cropland, agricultural TFP, agricultural output and population on the optimal path and on the laissez-faire path. Substantially less cropland is used on the optimal path. The difference is 73 million ha. in 2100 (-4.0%). This reflects two factors. First, climate damages are lower on the optimal path, necessitating less expansion in order to compensate for yield losses. Second, land conversion results in CO\textsubscript{2} emissions – limiting agricultural land expansion thus avoids CO\textsubscript{2} emissions and the GHG tax. Agricultural innovation is also lower on the optimal path, by up to 7.4% in 2100. Like cropland, GHG abatement means that there is less of an inducement to innovate new agricultural technologies to compensate for climate damages to yields. Agricultural output is initially lower on the optimal path than on the laissez-faire path, but later in the century the situation is reversed and by 2100 agricultural output on the optimal path is $48 billion higher. In effect, there is an optimal investment in long-term agricultural production, with an up-front cost. The optimal path sustains a larger world population than the baseline path. The world population is 36 million higher in 2050 and 93 million higher in 2100.

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25 This tax is implicitly levied not only on CO\textsubscript{2}, but also on methane and nitrous oxide in proportion to their CO\textsubscript{2}-equivalence. Formally, it is derived as the marginal rate of substitution between GHG emissions and consumption (Nordhaus, 1991).

26 As we feed not only CO\textsubscript{2} emissions into the model of Geoffroy et al. (2013), but also methane and nitrous oxide (in tCO\textsubscript{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\textsubscript{2}, methane and nitrous oxide through our carbon cycle and the temperature model of Geoffroy et al. (2013), starting in 1765.
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 itself. We estimate that the welfare gain from optimal emissions abatement is equivalent to an increase of stationary consumption today of around 6.8%, relative to the laissez faire path.

6 Adjustment constraints

This section provides 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. Results are reported in Table 6, focusing on welfare, GHG tax levels, and differences in cropland, agricultural R&D and population between the optimal path and the laissez-faire equilibrium.

The first four rows of the table focus on different frictions in the low-carbon transition, i.e. in the shift from a fossil-based 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, resulting in a much lower welfare gain from GHG taxation, a higher tax path, and higher climate damages, as demonstrated by greater cropland expansion and smaller population relative to the unconstrained optimum (smaller and larger differences from laissez faire respectively). The results for agricultural R&D are particularly striking – agricultural R&D is not only higher than the optimum, it is even higher than the laissez-faire equilibrium. However, fixed fossil energy capital is quite an 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.
Table 6: Optimal paths with adjustment constraints

<table>
<thead>
<tr>
<th>Frictions in the low-carbon transition</th>
<th>2025</th>
<th>2050</th>
<th>2075</th>
<th>2100</th>
<th>2025</th>
<th>2050</th>
<th>2075</th>
<th>2100</th>
<th>2025</th>
<th>2050</th>
<th>2075</th>
<th>2100</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Unconstrained optimum</strong></td>
<td>+6.78</td>
<td>98.84</td>
<td>166.76</td>
<td>251.95</td>
<td>349.57</td>
<td>-13.14</td>
<td>-37.82</td>
<td>-56.65</td>
<td>-73.23</td>
<td>-0.59</td>
<td>-2.44</td>
<td>-4.71</td>
</tr>
<tr>
<td><strong>Frictions in the low-carbon transition</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed fossil capital</td>
<td>+1.05</td>
<td>109.13</td>
<td>189.43</td>
<td>292.48</td>
<td>411.16</td>
<td>-10.78</td>
<td>-28.90</td>
<td>-39.77</td>
<td>-47.22</td>
<td>+0.10</td>
<td>+0.25</td>
<td>+0.24</td>
</tr>
<tr>
<td>No fossil to clean capital</td>
<td>+5.36</td>
<td>101.26</td>
<td>157.02</td>
<td>228.06</td>
<td>314.72</td>
<td>-12.75</td>
<td>-37.56</td>
<td>-57.93</td>
<td>-76.37</td>
<td>-0.58</td>
<td>-2.47</td>
<td>-4.92</td>
</tr>
<tr>
<td>Fixed clean energy R&amp;D</td>
<td>+6.78</td>
<td>98.88</td>
<td>166.86</td>
<td>252.12</td>
<td>349.84</td>
<td>-13.13</td>
<td>-37.80</td>
<td>-56.62</td>
<td>-73.18</td>
<td>-0.58</td>
<td>-2.41</td>
<td>-4.66</td>
</tr>
<tr>
<td>Fixed fossil energy R&amp;D</td>
<td>+6.69</td>
<td>98.85</td>
<td>166.86</td>
<td>252.10</td>
<td>349.74</td>
<td>-13.15</td>
<td>-37.84</td>
<td>-56.65</td>
<td>-73.20</td>
<td>-0.59</td>
<td>-2.44</td>
<td>-4.70</td>
</tr>
<tr>
<td><strong>Frictions in adaptation to climate change</strong></td>
<td></td>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed cropland</td>
<td>+6.70</td>
<td>98.72</td>
<td>166.42</td>
<td>251.43</td>
<td>348.96</td>
<td>-0.70</td>
<td>-2.84</td>
<td>-5.38</td>
<td>-8.16</td>
<td>+12.00</td>
<td>+35.85</td>
<td>+62.83</td>
</tr>
<tr>
<td>Fixed agricultural R&amp;D</td>
<td>+5.42</td>
<td>92.17</td>
<td>152.56</td>
<td>226.85</td>
<td>310.84</td>
<td>-16.37</td>
<td>-50.64</td>
<td>-81.04</td>
<td>-110.65</td>
<td>-4.18</td>
<td>+9.62</td>
<td>+22.87</td>
</tr>
<tr>
<td>Fixed population</td>
<td>+6.82</td>
<td>99.17</td>
<td>167.76</td>
<td>255.73</td>
<td>360.25</td>
<td>-11.54</td>
<td>-33.32</td>
<td>-49.63</td>
<td>-76.37</td>
<td>-6.65</td>
<td>-2.58</td>
<td>-4.77</td>
</tr>
<tr>
<td>Fixed ag. prod. capital</td>
<td>+6.74</td>
<td>98.84</td>
<td>166.76</td>
<td>251.95</td>
<td>349.57</td>
<td>-13.10</td>
<td>-37.66</td>
<td>-56.24</td>
<td>-72.55</td>
<td>-0.64</td>
<td>-2.58</td>
<td>-4.92</td>
</tr>
</tbody>
</table>

Notes: This table reports estimates of welfare impacts and optimal trajectories for GHG taxes, cropland, agricultural innovation and population relative to the laissez-faire equilibrium (base damage specification). Aside from the unconstrained optimum discussed in Section 5.2, we report optimal policy results for models in which alternative variables are constrained to follow their laissez-faire trajectory.
capital is allowed. With this constraint, the welfare gain from GHG taxation is smaller than the unconstrained optimum, although the difference is only around 1.4 percentage points. 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. Changes in cropland, agricultural R&D and population are similar to the unconstrained optimum. Lastly we consider scenarios where clean and fossil energy R&D respectively are fixed to their laissez-faire trajectories. Neither of these constraints has a significant impact on model outcomes.

In the bottom four rows, we consider frictions in adapting to climate change, fixing cropland, agricultural R&D, population and then 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. Constraining agricultural innovation implies that the welfare gains of optimal policy are noticeably lower than in the unconstrained optimum, as too little cropland is used and too many resources are put in agricultural R&D. This reduces agricultural output and consequently the food cost of population is inefficiently high, resulting in a smaller population than the unconstrained optimum.

7 Sensitivity analysis

In this section, we document the robustness/sensitivity of our optimal policy results to a number of exogenous parameters. The analysis covers the following dimensions (see Appendix D for a discussion): (i) the joint intensity of agricultural and manufacturing damages, $\Omega_{ag}$ and $\Omega_{mn}$; (ii) the carbon cycle, specifically the speed of removal of CO$_2$ from the atmosphere, $\alpha_i$ and $\delta_{S,i}$; (iii) the elasticity of substitution between clean and dirty energy, $\sigma_E$; (iv) the elasticity of substitution between land and the capital-labor-energy composite in agriculture, $\sigma_X$; (v) the discount factor, $\beta$; (vi) the income elasticity of food consumption, $\kappa$; (vii) the mortality rate, $\delta_N$; and (viii) the fossil fuel constraint, $\overline{R}$. As explained above, given that the model is structurally estimated, changing exogenous parameters is not a trivial step, as it may imply the model no longer fits observed data over the estimation period. This means the model must be re-estimated.

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27 The welfare change estimated in the fixed population case is difficult to interpret, as our approach to estimating stationary equivalent consumption constrains population on both paths being evaluated to the baseline trajectory. The fact that welfare appears higher than the unconstrained optimum despite imposing a constraint is an artefact of this.
whenever a parameter is varied, so that the distance between the model estimates and our targeted variables is kept to a minimum. In Appendix E, we report the structural parameter estimates accompanying the sensitivity analysis.\textsuperscript{28}

Table 7 summarizes the results, reporting the sensitivity of five key variables: the welfare gain from the laissez-faire equilibrium, the GHG tax, total GHG emissions, and the differences in cropland and population from the laissez-faire equilibrium. Overall, results are highly sensitive to the intensity of damages. Higher damages imply a larger welfare gain from controlling the climate-change externality, much higher GHG taxes, much lower GHG emissions, bigger differences in cropland and population relative to the laissez-faire equilibrium, and vice versa for lower damages. Results are also moderately sensitive to the efficacy of the carbon cycle in removing CO\textsubscript{2} from the atmosphere. Slower CO\textsubscript{2} removal results in greater accumulation of CO\textsubscript{2} in the atmosphere for given emissions, so in this run of the model we also see a larger welfare gain from emissions taxation, higher GHG taxes, lower emissions, and bigger differences in cropland and population. The opposite is true of faster CO\textsubscript{2} removal.

Results are generally less sensitive to variations in the other parameters. The only other parameters that generate somewhat different GHG taxation and optimal emissions are the discount factor and the income elasticity of food consumption. With less weight placed on future utility, a higher utility discount rate ($\beta = 0.97$) yields a smaller welfare gain from GHG taxation, lower optimal GHG taxes, higher optimal GHG emissions, and some differences in cropland and population. With a lower income elasticity of food consumption $\kappa = 0.2$, the food cost of children becomes relatively less important with time, so the welfare gain from GHG taxation is lower, optimal GHG taxes are lower and optimal emissions are higher.

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), the demographic transition (Galor and Weil, 2000) 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

\textsuperscript{28} 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. For the sensitivity analysis of the income elasticity of food consumption, we also re-calibrate the scale parameter $\xi$ in order to continue matching the initial share of agricultural production.
### Table 7: Sensitivity of optimal paths to variations in exogenous parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Δ welfare (%)</th>
<th>GHG tax ($/tCO₂eq)</th>
<th>Total GHG emissions (GtCeq)</th>
<th>Δ cropland from laissez faire (mn. ha.)</th>
<th>Δ population from laissez faire (mn.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>2020</td>
<td>2050</td>
<td>2100</td>
<td>2020</td>
</tr>
<tr>
<td>Main specification</td>
<td>+6.78</td>
<td>88.03</td>
<td>166.76</td>
<td>349.57</td>
<td>6.94</td>
</tr>
<tr>
<td>Low damages</td>
<td>+3.42</td>
<td>59.93</td>
<td>113.70</td>
<td>238.23</td>
<td>8.61</td>
</tr>
<tr>
<td>High damages</td>
<td>+22.14</td>
<td>171.09</td>
<td>326.15</td>
<td>686.45</td>
<td>4.27</td>
</tr>
<tr>
<td>Slow CO₂ removal</td>
<td>+8.95</td>
<td>104.39</td>
<td>197.29</td>
<td>412.45</td>
<td>6.21</td>
</tr>
<tr>
<td>Fast CO₂ removal</td>
<td>+5.92</td>
<td>80.81</td>
<td>153.41</td>
<td>323.25</td>
<td>7.33</td>
</tr>
<tr>
<td>σₖ = 0.95</td>
<td>+5.82</td>
<td>87.96</td>
<td>170.95</td>
<td>370.87</td>
<td>6.11</td>
</tr>
<tr>
<td>σₓ = 0.2</td>
<td>+6.57</td>
<td>85.99</td>
<td>160.02</td>
<td>325.10</td>
<td>6.92</td>
</tr>
<tr>
<td>β = 0.97</td>
<td>+3.67</td>
<td>58.08</td>
<td>116.61</td>
<td>276.15</td>
<td>9.59</td>
</tr>
<tr>
<td>κ = 0.2</td>
<td>+4.33</td>
<td>84.33</td>
<td>148.31</td>
<td>254.15</td>
<td>7.95</td>
</tr>
<tr>
<td>δₓ = 0.0166</td>
<td>+5.81</td>
<td>85.60</td>
<td>162.30</td>
<td>341.36</td>
<td>7.21</td>
</tr>
<tr>
<td>R = ∞</td>
<td>+9.68</td>
<td>88.02</td>
<td>166.79</td>
<td>349.84</td>
<td>6.91</td>
</tr>
</tbody>
</table>

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).
estimating damages from long-run 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 climate change. 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 therefore complements recent empirical studies on climate impacts (Dell et al., 2012; Carleton and Hsiang, 2016). More specifically, it is complementary to studies of the short-run productivity effects of climate change, because the intensity of damages in our model is captured by exogenous parameters that we calibrate to the empirical 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. Agro-nomic evidence suggests that climate change has already depressed agricultural yields and would do so much more in a laissez-faire future. However, we estimate that this does not lead to equivalently large reductions in agricultural output due to general-equilibrium adjustments, such as agricultural land expansion and R&D. 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, emphasizing the importance of further empirical work in that area.

We can compare some of our model projections with others in the literature. Our population projections are higher than those of 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 child-rearing. 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 (Lanz et al., 2018a). We project average GDP per capita growth between 2015 and 2100 of around 1.7%. This is well within the 50% confidence interval of expert forecasts reported in Christensen et al. (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 carbon tax in 2020 is close to the mean of the literature on the social cost/marginal damage cost of carbon for a comparable 1% utility discount rate, which Tol (2018) estimates is $98/tCO₂. As an alternative point of comparison, it is within the range of estimates of marginal abatement costs necessary to limit global warming to below 2°C, as meta-analyzed by Dietz et al. (2018).

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 numbered-dampened critical-level utilitarian SWF (20) 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.

Another extension is further study of the optimal carbon price trajectory. Our optimal carbon price grows at roughly the same rate as the economy: 2.1% between 2025 and 2050; 1.7% between 2050 and 2075; and 1.3% between 2075 and 2100. This echoes the well-known findings of Golosov et al. (2014), and inspecting the GHG tax data in Table 7 implies that it is robust to exogenous parameter variation. Yet it is in contrast to other more recent work suggesting the optimal carbon price should grow faster than GDP (Rezai and van der Ploeg, 2016; Dietz and Venmans, 2019). Further analysis of what factors drive this difference would be useful. The valuation of population is likely to matter.

The structure of the model could be extended to take in a number of additional issues, particularly on the environmental/climate side. 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 CO₂ 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’.

Lastly 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 (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  A sketch of the ethical properties of number-dampened critical-level utilitarianism

Our SWF is given by

\[ W = \sum_{t=0}^{\infty} \beta^t N_t^{1-\eta} \left( \frac{C_t}{N_t} \right)^{1-\gamma} - u \left( \frac{1}{1-\gamma} \right), \]

where \( \eta \in (0, 1) \). As such it is a so-called (discounted) number-dampened critical-level utilitarian social welfare ordering (NDCLU). An NDCLU SWF multiplies average utility, minus the critical level, by a positive-valued function of population size. A number of well-known SWFs are sub-classes of NDCLU. These include critical-level utilitarianism if \( \eta = 0 \), classical or total utilitarianism if \( \eta = u = 0 \), and average utilitarianism if \( \eta = 1 \) and \( u = 0 \).

Here we sketch the ethical properties of NDCLU for \( 0 < \eta < 1 \), following closely the expositional approach and terminology of Blackorby et al. (2005, chapter 5, part A). A formal treatment has been provided by Asheim and Zuber (2014). First, since average utility is multiplied by a positive-valued function of population size and this function is increasing and strictly concave, NDCLU does not satisfy existence independence. Existence independence requires that the ranking of any two social alternatives does not depend on the existence of individuals who ever live and have the same utility in both alternatives.

Second, NDCLU does not satisfy priority for lives worth living, which requires that all alternatives in which each person has a utility above zero (neutrality; a life worth living) are preferred to all those in which each person has negative utility. It is the existence of a positive critical level that causes this. This is illustrated in Figure 1, which plots iso-value curves corresponding with an average utility of 60, 30, 0 and -30 in a population of one individual. The NDCLU function is based on \( \beta = 1, \eta = 0.5 \) and \( u = 30 \). The alternative in which one person is alive with a utility of -30 is preferred to the alternative in which ten people are alive and all have a utility of ten.

Third, adding a positive critical level means that NDCLU satisfies both negative expansion and avoids the repugnant conclusion. Negative expansion requires that when an individual with utility below zero is added to the population, welfare is reduced. This is guaranteed by the positive critical level. The repugnant conclusion is that any alternative, in which each member of the population has positive utility, is ranked as worse than some alternative in which a larger population has an average utility above zero, but arbitrarily close to it. CU falls into this trap, since the iso-value curve approaches an average utility of zero as population increases. Either a positive critical level or strict concavity of the multiplying function avoid this (in the latter case, because utility no longer increases without bound as population increases). NDCLU has both features.

It is an impossibility theorem in population ethics that no SWF satisfies all four of these axioms. See Blackorby et al. (2005) for a full discussion. Classical/total utilitarianism satisfies existence independence, negative expansion and priority for lives worth living, but does not avoid Parfit’s (1984) repugnant conclusion. Average Utilitarianism avoids the repugnant
Figure A1: Critical-level number-dampened utilitarianism

conclusion and satisfies priority for lives worth living, but neither existence independence nor negative expansion. Critical-level utilitarianism avoids the repugnant conclusion and satisfies existence independence as well as negative expansion, but now priority for lives worth living is not satisfied.
Appendix B Optimization problem

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

$$\max_{C_t, K_t, \ldots, L_t} \ W = \sum_{t=0}^{\infty} \beta^t \ N_t^{1-\eta} \ c_t^{1-\gamma-u}$$

s.t.  
$$Y_{t,mn} = C_t + I_t$$  
$$Y_{t,ag} = N_t \cdot \xi \left( \frac{Y_{t,mn}}{N_t} \right)^{\kappa}$$  
$$X_t = X_{t-1}(1 - \delta_X) + \psi L_{t-1,X}, \quad X_t \leq \bar{X}$$  
$$A_{t,j} = A_{t-1,j} \left[ 1 + \lambda_j \left( \frac{C_{t-1,A_j}}{N_{t-1}} \right) \right]^{\mu_j}, \quad j \in \{mn, ag, cl, dt\}$$  
$$N_t = N_{t-1}(1 - \delta_N) + \chi L_{t-1,N}$$  
$$K_t = K_{t-1}(1 - \delta_K) + I_{t-1}$$  
$$S_t = \sum_{i=0}^{3} S_{t,i}$$  
$$S_{t,0} = a_0 \left[ \pi_{E,CO2} E_{t,dt} + \pi_X (X_t - X_{t-1}) \right] + (1 - \delta_{S,0}) S_{t-1,0}$$  
$$S_{t,i} = a_i \left[ \pi_{E,CO2} E_{t,dt} + \pi_X (X_t - X_{t-1}) \right]$$  
$$+ \sum_{i=1}^{a_i} \left[ \pi_{E,NCO2} E_{t,dt} + \pi_{ag} \left( K_{t,ag}^{\theta_{E}} E_{t,ag}^{\theta_{K}} L_{t,ag}^{1-\theta_{K} - \theta_{E}} \right) \right]$$  
$$+ (1 - \delta_{S,i}) S_{t-1,i}, \quad i = 1, 2, 3$$  
$$E_t = E_{t,mn} + E_{t,ag}, \quad \sum_{0}^{T} E_{t,dt} \leq \bar{R}$$  
$$N_t = L_{t,mn} + L_{t,ag} + L_{t,cl} + L_{t,dt} + \sum_{j} L_{t,A_j} + L_{t,X} + L_{t,N}$$  
$$K_t = K_{t,ag} + K_{t,mn} + K_{t,cl} + K_{t,dt}$$  
$$K_0, N_0, X_0, S_{0,i}, A_{0,j} \forall i, j \text{ given}$$

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.\textsuperscript{29} 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 over the period of interest to us (i.e. up to 2100). We select $T = 300$ based on evidence that an

\textsuperscript{29} 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.
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 contradiction, 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.\footnote{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.} 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.
Appendix C  Parameter identification and total model error

In Figure C1, we report total model error as a function of parameter estimates. In the different panels, we hold all the structural parameters at their estimated value (see Table 2), and sequentially solve the model by varying each parameter over the space of values considered in the estimation. Therefore, each dot in the figures represents total model error associated with one instance of the model, whereas the vertical lines represent the parameter estimate resulting from the estimation procedure. Overall, the steep increase in total model error around the vector of estimates indicates that the parameters are fairly well identified. Moreover, the fact that a sharp minimum is reached at the estimated value provides suggestive evidence that a global optimum exists for the model error minimization problem and that the simulated method-of-moments procedure is able to locate it.

Figure C1: Total model error as a function of structural parameter estimates
(a) Estimates for $\chi$
(b) Estimates for $\zeta$
(c) Estimates for $\eta$
(d) Estimates for $\psi$
(e) Estimates for $\epsilon$
(f) Estimates for $\mu_{mn}$
(g) Estimates for $\mu_{ag}$
(h) Estimates for $\mu_{cl}$
(i) Estimates for $\mu_{dt}$
Appendix D  Selection of parameter values

This section provides a discussion of how we select the value of exogenous parameters in the model, all of which are reported in Table 1. Starting with household preferences, 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 macro-economic estimates reported in Guvenen (2006), and we calibrate $u = 1$ so that the consumption level that makes incremental population units desirable is 1,000 US dollars. This is broadly in line with the definition of a poverty level by the World Bank. The income elasticity of food consumption $\kappa = 0.5$ is in line with empirical evidence in Thomas and Strauss (1997), and the scale parameter $\xi = 0.11$ is selected to match the share of agricultural GDP in 1960 from World Bank (2020). As an alternative, in the sensitivity analysis we consider $\kappa = 0.2$, which is at the lower end of estimates reported in the empirical literature, and accordingly set $\xi = 0.17$.

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 sensitivity analysis, we consider a lower rate of 0.0166, which corresponds to an expected lifetime of 60 years.

In manufacturing, 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., 2016). 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 $X = 3$ 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). In the sensitivity analysis, we consider a case with lower substitution possibilities, using $\sigma_E = 0.95$ as an alternative estimate (following Golosov et al., 2014). The capital share $\alpha = 0.6$ is taken from Barrage (2020), and total reserves of fossil fuels are set to $R = 5,000$ 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 $\lambda_j = 0.05$, which can be interpreted as the maximum feasible rate of yearly TFP growth.

The extent of sectoral climate damages is determined by the parameters $\Omega_{ag}$ and $\Omega_{mn}$. We calibrate $\Omega_{ag}$ on the major agricultural model inter-comparison exercise (AgMIP) reported in Nelson et al. (2014). This work shows that baseline climate change (along the RCP8.5 emissions scenario by IPCC, 2014a) reduces agricultural yields by an average of 15.4 percent in 2050 (range 8.9 to 28.5 percent), relative to a reference scenario without climate change.\(^{31}\) Using IPCC (2014a), we estimate the atmospheric GHG concentration (CO\(_2\), methane and nitrous oxide) in the RCP8.5 scenario will be 1399 GtCeq in 2050, yielding $\Omega_{ag} = 0.000207$ (sensitivity range: 0.000115 to 0.000415). We calibrate $\Omega_{mn}$ on empirical estimates of the 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. Our resulting central parameter estimate is $\Omega_{mn} = 1.23E^{-5}$ and we use the 95% confidence interval reported in Dell et al. (2012) to estimate lower and upper bounds of $9.11E^{-7}$ and $2.38E^{-5}$ respectively.

In Table D1, 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, 2018; 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).

\(^{31}\) This is an unweighted average across the four combinations of global circulation models and crop models, seven AgMIP models and 5 crop types.
Table D1: Initial conditions and parameters for the climate module

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Definition</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_0$</td>
<td>1.38</td>
<td>Agricultural cropland in 1960 (billion ha)</td>
<td>FAO (2018)</td>
</tr>
<tr>
<td>$A_0,\text{mm}$</td>
<td>6.74</td>
<td>Initial TFP in manufacturing</td>
<td>Calibrated on 1960 world GDP, estimated share of agricultural output in 1960 world GDP, and assumed capital depreciation</td>
</tr>
<tr>
<td>$A_0,\text{ag}$</td>
<td>0.62</td>
<td>Initial TFP in agriculture</td>
<td></td>
</tr>
<tr>
<td>$K_0$</td>
<td>22.38</td>
<td>Initial stock of capital (trillion 2010 USD)</td>
<td></td>
</tr>
<tr>
<td>$A_0,\text{cl}$</td>
<td>0.62</td>
<td>Initial TFP in clean energy</td>
<td></td>
</tr>
<tr>
<td>$K_0$</td>
<td>22.38</td>
<td>Initial stock of capital (trillion 2010 USD)</td>
<td></td>
</tr>
<tr>
<td>$A_0,\text{dt}$</td>
<td>2.64</td>
<td>Initial TFP in fossil energy</td>
<td></td>
</tr>
<tr>
<td>$S_0,0$</td>
<td>28.115</td>
<td>Stock of carbon in reservoir 0 in 1960 (GtC eq)</td>
<td>Obtained by initializing model in pre-industrial conditions and running forward to 1960 with reported parameters</td>
</tr>
<tr>
<td>$S_0,1$</td>
<td>29.570</td>
<td>Stock of carbon in reservoir 1 in 1960 (GtC eq)</td>
<td></td>
</tr>
<tr>
<td>$S_0,2$</td>
<td>16.017</td>
<td>Stock of carbon in reservoir 2 in 1960 (GtC eq)</td>
<td></td>
</tr>
<tr>
<td>$S_0,3$</td>
<td>6.257</td>
<td>Stock of carbon in reservoir 3 in 1960 (GtC eq)</td>
<td></td>
</tr>
<tr>
<td>$S$</td>
<td>590</td>
<td>Pre-industrial stock of atmospheric carbon (GtC eq)</td>
<td>IPCC (2013)</td>
</tr>
<tr>
<td>$\pi_{E,CO_2}$</td>
<td>0.858</td>
<td>Fossil energy $CO_2$ emissions factor (GtC eq. per Gt oil eq.)</td>
<td>Boden et al. (2017)</td>
</tr>
<tr>
<td>$\pi_{E,NCO_2}$</td>
<td>0.171</td>
<td>Fossil energy non-$CO_2$ emissions factor (GtC eq. per Gt oil eq.)</td>
<td>World Bank (2020)/EDGAR</td>
</tr>
<tr>
<td>$\pi_X$</td>
<td>348.859</td>
<td>Land use change emissions factor (Gt C eq. per bn ha)</td>
<td>Le Quéré et al. (2018)</td>
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<tr>
<td>$\pi_{ag}$</td>
<td>0.698</td>
<td>Agricultural emissions factor (Gt C eq. per unit of input)</td>
<td>FAO (2018)</td>
</tr>
<tr>
<td>$a_0$</td>
<td>${0.217, 0.285, 0.178}$</td>
<td>Share of $CO_2$ going to geological re-absorption</td>
<td>Joos et al. (2013)</td>
</tr>
<tr>
<td>$a_1$</td>
<td>${0.224, 0.294, 0.165}$</td>
<td>Share of $CO_2$ going to deep ocean</td>
<td></td>
</tr>
<tr>
<td>$a_2$</td>
<td>${0.282, 0.238, 0.380}$</td>
<td>Share of $CO_2$ going to biospheric uptake / ocean thermocline</td>
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</tr>
<tr>
<td>$a_3$</td>
<td>${0.276, 0.183, 0.277}$</td>
<td>Share of $CO_2$ going to rapid biospheric uptake / ocean mixed layer</td>
<td></td>
</tr>
<tr>
<td>$\delta_{S,0}$</td>
<td>$1 E^{-6}$</td>
<td>Geological re-absorption rate</td>
<td></td>
</tr>
<tr>
<td>$\delta_{S,1}$</td>
<td>${0.000254, 0.00022, 0.00026}$</td>
<td>Deep ocean invasion/equilibration rate</td>
<td></td>
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<tr>
<td>$\delta_{S,2}$</td>
<td>${0.0325, 0.04, 0.027}$</td>
<td>Biospheric uptake/ocean thermocline invasion rate</td>
<td></td>
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<tr>
<td>$\delta_{S,3}$</td>
<td>${0.232, 0.4965, 0.2686}$</td>
<td>Rapid biospheric uptake/ocean mixed layer invasion rate</td>
<td></td>
</tr>
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</table>

Notes: For parameters considered in the sensitivity analysis, we report multiple values, starting with our baseline assumption.
Appendix E  Structural parameter estimates accompanying sensitivity analysis

In Table E1, we report structural parameter estimates to accompany our sensitivity analysis of exogenous/imposed parameters discussed in Section 7. Recall that re-estimating these structural parameters allows us to continue to fit past observations, despite changing assumptions about the exogenous parameters. Reading each row from left to right, it is apparent that the estimated parameters are consistent across specifications, even for the models where we vary the intensity of damages, which we found to be an important drivers of quantitative results.

Table E1: Structurally estimated parameters for the sensitivity analysis

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Main specification</th>
<th>Low damages</th>
<th>High damages</th>
<th>Slow CO₂ removal</th>
<th>Fast CO₂ removal</th>
<th>σE = 0.95</th>
<th>σX = 0.2</th>
<th>β = 0.97</th>
<th>κ = 0.2</th>
<th>δN = 0.017</th>
<th>Π = ∞</th>
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<tbody>
<tr>
<td>χ</td>
<td>0.120</td>
<td>0.119</td>
<td>0.124</td>
<td>0.120</td>
<td>0.120</td>
<td>0.122</td>
<td>0.121</td>
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<td>0.162</td>
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<td>ζ</td>
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<td>0.462</td>
<td>0.448</td>
<td>0.458</td>
<td>0.458</td>
<td>0.458</td>
<td>0.458</td>
<td>0.452</td>
<td>0.432</td>
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<td>0.458</td>
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<td>η</td>
<td>0.151</td>
<td>0.146</td>
<td>0.157</td>
<td>0.151</td>
<td>0.151</td>
<td>0.151</td>
<td>0.151</td>
<td>0.150</td>
<td>0.151</td>
<td>0.080</td>
<td>0.150</td>
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<td>0.060</td>
<td>0.059</td>
<td>0.060</td>
<td>0.060</td>
<td>0.062</td>
<td>0.055</td>
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<td>0.058</td>
<td>0.050</td>
<td>0.060</td>
</tr>
<tr>
<td>σ</td>
<td>0.155</td>
<td>0.153</td>
<td>0.156</td>
<td>0.155</td>
<td>0.155</td>
<td>0.155</td>
<td>0.120</td>
<td>0.142</td>
<td>0.159</td>
<td>0.!154</td>
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<tr>
<td>ρ_{mn}</td>
<td>0.523</td>
<td>0.528</td>
<td>0.526</td>
<td>0.523</td>
<td>0.523</td>
<td>0.523</td>
<td>0.522</td>
<td>0.530</td>
<td>0.375</td>
<td>0.887</td>
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</tr>
<tr>
<td>ρ_{ks}</td>
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<td>0.521</td>
<td>0.539</td>
<td>0.524</td>
<td>0.524</td>
<td>0.523</td>
<td>0.498</td>
<td>0.488</td>
<td>0.561</td>
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<td>0.524</td>
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<tr>
<td>ρ_{el}</td>
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<td>0.193</td>
<td>0.196</td>
<td>0.193</td>
<td>0.193</td>
<td>0.194</td>
<td>0.187</td>
<td>0.171</td>
<td>0.219</td>
<td>0.200</td>
<td>0.191</td>
</tr>
<tr>
<td>ρ_{el}</td>
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<td>0.367</td>
<td>0.357</td>
<td>0.372</td>
<td>0.372</td>
<td>0.372</td>
<td>0.360</td>
<td>0.324</td>
<td>0.455</td>
<td>0.383</td>
<td>0.389</td>
</tr>
</tbody>
</table>

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.

Estimates of χ and ζ, which mainly determine the cost of children, are most affected by changes in the discount factor, β, the income elasticity of food demand κ and mortality δN. By contrast, the parameter η, which determines fertility preferences, is only significantly affected by the change in κ, as it adjusts to a lower food cost of fertility. The parameters determining the cost of land conversion, ψ and ε, are significantly different from the main specification when we consider σX = 0.2 and δN = 0.0166, as these two parameters directly affect the relative demand for land in the production of food. Finally, technology parameters are very similar across specifications, with the exception of μ_{mn}, which is slightly lower for β = 0.97 and significantly higher for κ = 0.2. The latter finding is due to the fact that κ affects the complementarity between food and non-food consumption, with the share of non-food products growing more rapidly.
Appendix F  Estimating the model on 1960-2000 data

This appendix provides further evidence on the ability of our model to fit the data. We do this by estimating the parameters of the model on a restricted period of time, considering only observations for the period 1960 to 2000. In other words, the estimated model rationalizes a shorter period of time, discarding information about the latest 15 years of data. We then compare the 2020 predictions of the model estimated on the restricted sample with the 2020 predictions of the model estimated on the full data set extending to 2015. The results are reported in Table F1.

Table F1: Out-of-sample comparison for targeted moments evaluated in 2020

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Population (billion)</td>
<td>7.839</td>
<td>7.862</td>
<td>-0.003</td>
</tr>
<tr>
<td>GDP (trillion 2010 USD)</td>
<td>87.08</td>
<td>86.41</td>
<td>0.008</td>
</tr>
<tr>
<td>Cropland (billion ha)</td>
<td>1.635</td>
<td>1.617</td>
<td>0.011</td>
</tr>
<tr>
<td>Ag. innovation rate (ppts.)</td>
<td>0.0097</td>
<td>0.0095</td>
<td>0.026</td>
</tr>
<tr>
<td>Non-fossil energy (Gt oil eq.)</td>
<td>2.361</td>
<td>2.190</td>
<td>0.078</td>
</tr>
<tr>
<td>Fossil energy (Gt oil eq.)</td>
<td>12.17</td>
<td>12.51</td>
<td>-0.027</td>
</tr>
</tbody>
</table>

Notes: This table provides the value of variables targeted in the estimation. We report predicted values for 2020 from models estimated from 1960 to 2000 and from 1960 to 2015, as well as percentage between the two instances of the model.

Overall, the 2020 predictions derived from the restricted and unrestricted estimation periods are relatively close. The largest deviation is observed for non-fossil energy, which is around 8% larger if we only use data up to the year 2000 to inform the estimation of the model. By contrast, fossil energy is around 3% lower. This indicates that emissions from the model would tend to be under-estimated, if the model were estimated with data up to 2000 only. Apart from energy, other aggregates targeted in the estimation are very similar. This provides confidence in the use of medium-term projections for a set of key variables considered in the analysis.