CESifo
AREA CONFERENCES 2019

Energy & Climate Economics

Munich, 18–19 October 2019

Economic Growth, Population Growth and Agriculture in a Changing Climate

Simon Dietz and Bruno Lanz

20 YEARS CESifo

Economic growth, population growth and agriculture in a changing climate*

Simon Dietz[†] Bruno Lanz[‡]

This version: October 2019

Abstract

Can a growing world be fed when the climate is changing? We develop a structurally estimated model of the global economy focusing on the nexus of growth, climate change and food security. The model includes an explicit agriculture sector, endogenous fertility, directed technical change, fossil/renewable energy and multiple greenhouse gases. The model can be used to construct a counterfactual past and provides a new approach to estimating historical climate impacts. We also use the model to make future projections, with and without taxing greenhouse gas emissions. Macro-economic adjustments, including agricultural land expansion and R&D, substantially reduced climate damages in the past and would do so in the future if emissions remain unpriced. Nonetheless climate change has already limited output, food production and population. The welfare cost of not taxing emissions is large; we estimate a high optimal carbon tax today.

*We would like to thank Geir Asheim, Antoine Bommier, Henry Chen, Francis Dennig, Erwan Monnier, Samuel Okullo, Pietro Peretto, John Reilly, Hiro Sakamoto and Ingmar Schumacher, as well as seminar participants at MIT, SURED 2018 and WCERE 2018, for helpful discussions and feedback. Excellent research assistance was provided by Nathan Delacrétaz. Financial support from the Swiss National Science Foundation under grant 100018_182122 is gratefully acknowledged. The model presented here has also benefited from our previous work funded by the Mava Foundation, with contributions from Derek Eaton, Arun Jacob, Simon Neumueller, Tim Swanson and Zacharias Ziegelhofer. This work is reported in Lanz et al. (2017a, 2018, 2017b). Any errors are due to the authors of this paper.

†London School of Economics and Political Science, Grantham Research Institute on Climate Change and the Environment, ESRC Centre for Climate Change Economics and Policy, and Department of Geography and Environment, UK; Oxford University, Oxford Martin School and Smith School of Enterprise and the Environment, UK; CESifo

‡University of Neuchâtel, Department of Economics and Business, Switzerland; Massachussets Institute of Technology, Center for Energy and Environmental Policy Research and Joint Program on the Policy of Global Change, USA. Mail: A.-L. Breguet 2, CH-2000 Neuchâtel, Switzerland; Tel: +41 32 718 14 55; email: bruno.lanz@unine.ch

Keywords: agricultural productivity; climate change; directed technical change; economic growth; food security; population growth; structural estimation
JEL Classification numbers: O44, Q54

"[T]he existence of a problem in knowledge depends on the future being different from the past, while the possibility of a solution of a problem of knowledge depends on the future being like the past." (Knight, 1921)

1 Introduction

The world population is projected to grow from around 7.6 billion currently to more than 11 billion by the end of this century and possibly more than 13 billion (United Nations, 2017). Over the same time period, the consensus among forecasters of economic growth is that global GDP per capita will increase several-fold.[1] Since food consumption per capita is an increasing function of income per capita (Tilman et al., 2011), the combination of population growth and economic growth will greatly increase food demand. This is one reason why food security is a leading global concern (e.g. FAO, 2017; World Economic Forum, 2018).

Another reason for concern about food security is climate change. Agriculture is among the economic activities most exposed to climate change (Schelling, 1992; IPCC, 2014b; Carleton and Hsiang, 2016). Weather is a direct input to agricultural production, affecting fundamental biophysical factors such as plant development, photosynthesis/respiration, water availability, and the prevalence of diseases and pests (Hertel and Lobell, 2014; IPCC, 2014b).[2]

This paper asks: can a growing world population be fed under changing climatic conditions? The pessimistic, Neo-Malthusian perspective says no. It emphasizes limits to the availability of natural resources that are essential inputs to agriculture, especially under climate change. The optimistic view says yes. It foresees rapid 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 any structured assessment of the question

[1] According to the expert survey by Christensen et al. (2018), for example, 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] Agronomic models suggest that crop yields 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 CO_2 (also see Challinor et al., 2014).

must consider the joint evolution of the world economy and the climate, and integrate the key drivers of food supply and demand, such as factor allocation, fertility choices and technological progress. It must also consider the role of policies to internalize the climate-change externality.

Accordingly, we structurally estimate a dynamic, general-equilibrium model of the world economy, which co-evolves with a model of the climate system. The model builds on a number of seminal contributions to the economic growth literature. First, households have inter-temporal preferences over consumption of non-agricultural goods and fertility, in the tradition of Barro and Becker (1989). This means population growth is endogenous. Importantly, the evolution of population is constrained by the availability of food produced by an explicit agriculture sector (Strulik and Weisdorf, 2008; Vollrath, 2011; Sharp et al., 2012). Agricultural productivity, which is affected by both climate change and agricultural R&D, is therefore a determinant of the cost of children. A second important determinant of the cost of children is economy-wide technological progress and the increasing requirements it places on education/skills, as emphasized in the recent economic literature on demographic transitions (Galor and Weil, 2000; Galor, 2005).

The manufacturing sector, which produces the consumption good, uses fossil energy and emits greenhouse gases (GHGs), but it can substitute this with carbon-free energy. Agricultural production also emits GHGs, not just from the use of fossil energy, but also directly from production and land-use change. GHG emissions accumulate in the atmosphere, which causes climate damages to both agriculture and manufacturing. Damages differ between agriculture and manufacturing, and have different welfare consequences, due to the role of food in sustaining population via the food constraint.

Another important element of the model is endogenous technical progress in all four final and intermediate goods sectors. In each, productivity growth is driven by R&D in the Schumpeterian tradition (Aghion and Howitt, 1992), and R&D requires labor. This has several implications. First, CO_2 emissions abatement is subject to directed technical change (Acemoglu et al., 2012). Second, technical progress in manufacturing and agriculture can compensate for climate damages (Fried, 2018). Third, technical progress increases the cost of educating children and hence contributes to a population growth slowdown (Galor and Weil, 2000). Finally, because agricultural production requires land and land is in finite supply, endogenous growth allows the economy to escape an otherwise inevitable Malthusian trap (Lanz et al., 2017a).

The model is structurally estimated on data from 1960 to 2015. It is able to closely replicate observed trajectories for world population, GDP, agricultural land use and TFP, fossil and clean energy use. The estimation is based on a simulated method-of-moments procedure developed in Acemoglu et al. (2016) and Lanz et al. (2017a). The model also reproduces stylized facts relating to a number of untargeted moments, including agricultural yields, agriculture's share of GDP, per-capita consumption growth, sectoral and aggregate GHG emissions, and the atmospheric GHG concentration.

As such, our structural model provides a flexible empirical framework to study counterfactual experiments on both the past and future. First, we construct a counterfactual past *sans* climate change. From this we can estimate what effect climate change has already had. We find that it has *inter alia* reduced agricultural and manufacturing output, and world population, while resulting in an increase in arable/crop land and agricultural innovation. Macro-economic adjustments like crop land expansion and increased R&D have reduced climate damages substantially, but not wholly. Second, we use the model to make projections for the 21st century, with and without Pigouvian carbon taxes. Without carbon taxation, the model is able to sustain an increasing path of GDP and population. In that sense there is no climate catastrophe. However, it is only able to do so through large-scale macro-economic adjustment, exemplified by further agricultural expansion and more agricultural R&D. Moreover this comes at a high welfare cost; the Pigouvian carbon tax is high and significantly reduces GHG emissions, so that optimal global warming is held well below 2°C in 2100.

We conduct a number of sensitivity analyses. We compare optimal climate policies, depending on how climate change affects welfare. In our main specification, climate change affects agricultural productivity, and this constrains the supply of food and population expansion, which in turn directly impacts welfare. We compare this set-up to the more standard approach in climate economics of inflicting climate damages on economy-wide output, an approach that implicitly treats food and other consumption goods as perfect substitutes. We find that modeling food as a constraint on population expansion and welfare results in a much higher optimal carbon tax, c. four times higher in 2019. We also compare optimal climate policies under endogenous and exogenous population. Imputing a lower, exogenous population projection results in much higher consumption per capita, as households compensate for fertility preferences unmet. This delivers a carbon tax path that starts lower, but increases much more steeply than in our main specification, indicating modeling of fertility/population likely matters in this regard. Further sensitivity analysis indicates that optimal carbon taxation is relatively robust to variations in key parameters, except the intensity of damages.

1.1 Related literature

Our model of economic growth stands on three pillars. The first is growth models with endogenous fertility/population, especially Barro and Becker (1989). The second is growth models with endogenous technical change, in particular Schumpeterian models (Aghion and Howitt, 1992) and, within this class, Schumpeterian 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). 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. With two final goods and two energy intermediates, our model also relates to previous work on directed technical change and the environment, for instance Acemoglu et al. (2012, 2016). The third pillar is unified growth theory, from which we take the idea that falling birth rates in the latter stages of the demographic transition are fundamentally driven by technological progress, because technological progress increases human capital requirements and the cost of educating children (Galor and Weil, 1999, 2000).

By combining a model of the world economy with a model of the climate, our paper is also related to the literature in economics on integrated assessment models of climate change (so-called IAMs) that has been pioneered by William Nordhaus (Nordhaus, 1991; Nordhaus and Boyer, 2000; Nordhaus, 2017). Like most of this literature, we take a quantitative approach. Unlike other IAMs, ours is structurally estimated on more than half a century of data, enabling us to constrain key parameters with limited evidential bases, and conduct counterfactual analyses. Our climate model is based on the benchmark simple climate models employed in the last report of the Intergovernmental Panel on Climate Change (Geoffroy et al., 2013; Joos et al., 2013) and thereby avoids the physically inconsistent climate dynamics recently identified in the leading

IAMs (Calel and Stainforth, 2017; Rose et al., 2017). In view of our focus on agriculture, we separately model emissions of CO_2 and the two GHGs principally emitted in agricultural production, methane and nitrous oxide.

Focusing on agriculture, we contend the existing literature takes a narrow view of the welfare cost of climate change. Existing estimates of agricultural impacts are calibrated on studies imposing climate change as a supply-side shock and tracing through how this affects the market exchange of agricultural commodities (Kane et al., 1992; Darwin et al., 1995; Rosenzweig and Parry, 1994). The resulting estimates of the change in surplus are then typically combined with other climate impacts in a model with a single consumption good, implying perfect substitutability of food and other goods in individual utility. However, agriculture plays a basic role in sustaining the population: we have to eat to survive. The impacts of climate change on agriculture are therefore a potential constraint on the expansion of the human population. Previous models miss this link, because they lack a mechanism whereby agricultural production affects the size of the population (Millner, 2013). The size of the population is inherently valued in growth models with endogenous population. This also links our work with the literature in social choice on population ethics (Blackorby et al., 2005; Asheim and Zuber, 2014). Our model can be interpreted as an application of these ideas.

Our model is also related to a strand of literature in agricultural economics, which is 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 partial equilibrium models in which food demand is taken as given, whereas in our model it is endogenous. Our model also relates to a strand of literature in macro-economics concerned with stylized natural resource constraints on long-run economic and population growth (e.g. Bretschger, 2013; Peretto and Valente, 2015). In comparison, we take a quantitative approach and study climate change and agricultural land availability as specific natural resource constraints.

The remainder of the paper is set out as follows. In Sections 2 and 3, we lay out the model and describe our structural estimation procedure respectively. In Section 4, we evaluate the model's goodness of fit and use it to produce counterfactual estimates of the historical impact of climate change. In Section 5, we make projections for the 21st century, both under a laissez faire scenario and when GHG emissions are optimally controlled. Section 6 provides sensitivity analysis, including a focus on the role of our novel food-population damage pathway. Section 7 provides a discussion. Details of the model implementation and a range of further results are contained in the appendices.

2 A structural economic model of global climate change

This section presents a canonical framework to study global climate change, including production, energy and land use, sectoral technical change, fertility decisions and welfare, emissions and climate dynamics. In the next section, we explain how we take the model to the data.

The model is cast as a discrete-time planning problem. This is natural given our focus on optimal climate policies. It is also computationally efficient: our simulated method-of-moments procedure requires running the model very many times and doing so as a decentralized equilibrium is computationally infeasible.[3] Nonetheless it is important to appreciate that, although we solve a planning problem, the fact that our model is conditioned to fit the last half century of data on a number of aggregates means the baseline trajectory, which does not internalize climate-change damages, is a projection of the previously observed laissez-faire equilibrium.

2.1 Production in manufacturing

Aggregate manufacturing output at time t, denoted $Y_{t,mn}$, is described by a constant-returns-to-scale, Cobb-Douglas production function that combines capital $K_{t,mn}$, labor $L_{t,mn}$, and energy $E_{t,mn}$:

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

[3] With a planning approach, we can make a number of simplifications, including reducing the number of variables that need to be computed and using efficient solvers for non-linear programs. We use a primal formulation, so that we only compute quantities. Prices are implicitly given by Lagrange multipliers and can be retrieved at the solution point.

where $A_{t,mn}$ is an endogenous, Hicks-neutral technology index and $\vartheta_i \in (0,1)$, $i \in \{K, E\}$, are technology parameters satisfying $\Sigma_i \vartheta_i < 1$.[4]

Manufacturing output is also a function of the climate state variable S_t, the atmospheric GHG concentration (Golosov et al., 2014). As we describe below, GHG emissions from energy, agricultural production and land use increase S_t and this in turn reduces TFP in manufacturing. The scale of climate damages in manufacturing is measured by the parameter $\Omega_{mn} > 0$.

2.2 Production in agriculture

In our model, the agricultural sector produces food, the sole purpose of which is to sustain contemporaneous population, as in e.g. Strulik and Weisdorf (2008). 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):

$$Y_{t,ag} = A_{t,ag} \left[(1-\theta_X) \left(K_{t,ag}^{\theta_K} E_{t,ag}^{\theta_E} L_{t,ag}^{1-\theta_K-\theta_E} \right)^{\frac{\sigma_X - 1}{\sigma_X}} + \theta_X X_t^{\frac{\sigma_X - 1}{\sigma_X}} \right]^{\frac{\sigma_X}{\sigma_X - 1}} \cdot \exp(-\Omega_{ag} \left[S_t - \overline{S} \right]), \quad (2)$$

where non-land inputs include capital $K_{t,ag}$, labor $L_{t,ag}$ and energy $E_{t,ag}$. $A_{t,ag}$ is endogenous agricultural TFP and θ_i, $i \in \{K, E\}$ are technology parameters again satisfying $\theta_i \in (0,1)$ and $\Sigma_i \theta_i < 1$. In our main specification, we assume the elasticity of substitution between land and the capital-energy-labor composite σ_X is below unity, reflecting long-run empirical evidence (Wilde, 2013).[5] As in manufacturing, climate change affects aggregate productivity through the parameter Ω_{ag}.

4 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., 2016). Baqaee and Farhi (2018) show that complementarity between energy and non-energy inputs in the short run can be used to explain the disproportionate macroeconomic impact of the 1970s oil shock.

5 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.

2.3 Clean and dirty energy intermediates

Final energy E_t is used as an input in both manufacturing and agriculture. We characterize an energy sector that produces E_t by combining clean and dirty/fossil energy intermediates (denoted respectively by $E_{t,cl}$ and $E_{t,dt}$) in a CES function (Acemoglu et al., 2016):

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

where $\vartheta_D \in (0,1)$ represents the relative efficiency of clean and dirty energy sources in final energy production, and σ_E is the elasticity of substitution between clean and dirty energy intermediates. In our main specification, we assume that σ_E is greater than unity.

The production of clean and dirty intermediates is a function of labor (respectively $L_{t,cl}$ and $L_{t,dt}$):

$$E_{t,cl} = A_{t,cl}L_{t,cl} \qquad \text{and} \quad E_{t,dt} = A_{t,dt}L_{t,dt} \tag{4}$$

where $A_{t,cl}$ and $A_{t,dt}$ are endogenous technology indices. We assume that dirty energy is in finite supply, and denote global reserves by $\overline{R} > 0$. This yields the following fossil resource constraint:

$$\overline{R} \geq \sum_{0}^{T} E_{t,dt} \tag{5}$$

where $T > 0$ is the time at which reserves are exhausted.

2.4 Land input

Land used in agriculture has to be converted from a finite reserve stock of natural land $\overline{X}$ and slowly reverts back to its natural state if left unmanaged. As in Lanz et al. (2017a), the evolution of land available for agricultural production is given by

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

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

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

where $\psi > 0$ 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 ε, implies that the marginal cost of land conversion increases with the total agricultural land area, in the spirit of Ricardo.

2.5 Innovations

Innovations drive the evolution of sectoral TFP. We formulate a simple discrete-time version of the model of Aghion and Howitt (1992, 1998), in which the use of labor determines the arrival rate of new innovations. In each sector $j \in \{mn, ag, cl, dt\}$, we denote productivity improvements of each innovation by $s_j > 0$, and, without loss of generality, we assume there is a maximum of $I_j > 0$ innovations in each time period. This implies the sectoral TFP growth rate in each period is bounded above by $\lambda_j = (1 + s_j)^{I_j} - 1$.[6] It follows that the evolution of sectoral TFP can be written as:

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

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

Further, the arrival rate of innovations is assumed to be an increasing function of labor

[6] In the model by 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 λ_j can be interpreted as the maximum growth rate of sectoral TFP in each period.

employed in sectoral R&D, L_{t,A_j}:

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

where $\mu_j \in (0,1)$ is a labor productivity parameter that captures the duplication of ideas among researchers (Jones and Williams, 2000). One important feature of this representation is that we dispose of the population scale effect by dividing the labor force in R&D by total population N_t. In particular, along a balanced growth path in 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.[7]

2.6 Population dynamics

Population, described by stock variable N_t, is endogenous in the model. We make the usual assumption that population equals the total labor force,[8] and consider three drivers of the cost of incremental labor units. First, child rearing and education are time-intensive and compete with other labor-market activities, so the opportunity cost of time affects fertility (Becker, 1960). Second, there is a trade-off between child quantity and quality, because the cost of educating children increases with technological progress in the economy (Galor, 2005). Third, the population needs food produced by the agricultural sector. We introduce a constraint to the population trajectory by requiring that the market for food clears each period (Strulik and Weisdorf, 2008; Vollrath, 2011; Sharp et al., 2012). We now discuss each of these in turn.

[7] Dinopoulos and Thompson (1999) show that a model in which *aggregate* TFP growth increases with the share of labor allocated to R&D is equivalent to Schumpeterian growth models in which R&D firms hire workers and entry of new firms is allowed. See also Chu et al. (2013).

[8] See Mierau and Turnovsky (2014) for a growth model with age-structured population, albeit with exogenous population dynamics.

The evolution of population over time is given by

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

where n_t is the endogenous fertility rate (see below for its determination and $\delta_N > 0$ is the mortality rate, so that $1/\delta_N$ can be interpreted as the expected working lifetime. Therefore, since we do not explicitly model human capital, $n_t N_t$ captures net increments of *effective* labor units, which are an increasing function of $L_{t,N}$, the time spent rearing and educating workers:

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

where $1/\overline{\chi}_t$ measures the time-cost of workforce increments (as per Becker, 1960).

The second driver of population dynamics in our model is technology. In particular, complementarity between skills and technology (Goldin and Katz, 1998) implies that the cost of incremental workers increases with the level of technology in the economy (proxied by the TFP index in manufacturing, $A_{t,mn}$):

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

where $\chi > 0$ and $\zeta \in (0, 1)$ are labor productivity parameters. With this representation, technological progress increases the cost of children through the parameter $\omega > 0$. This is intended as a reduced-form representation of the model of Galor and Weil (2000), in which technological progress induces an increase in the demand for human capital and education. Our model can therefore generate a gradual decline in fertility reflective of the trade-off between child quantity and quality, without the need to explicitly model human capital.[9]

The final component of population dynamics is the food constraint, which requires that agricultural output is used to meet the demand for food by contemporaneous population. This constitutes a constraint on the development of population over time, making food production

[9] Note also that, combining (11) and (12), the parameter ζ captures possible scarce factors in child-rearing and education, so that the cost of incremental labor units is convex (see Barro and Sala-i Martin, 2004, p.412, Moav, 2005, and Bretschger, 2013).

– and the impact of climate change on food production – a key driver of the cost of fertility. Formally, clearing of the food market links agricultural output to aggregate food consumption:

$$Y_{t,ag} = N_t \cdot \xi_t \tag{13}$$

where ξ_t is per-capita food demand. This formulation is in line with Strulik and Weisdorf (2008), Vollrath (2011) and Sharp et al. (2012). However, while these models assume constant per-capita food demand, we account for empirical evidence suggesting that diets evolve with affluence, such that the demand for calories is increasing and concave in per-capita income (e.g. Subramanian and Deaton, 1996; Thomas and Strauss, 1997):

$$\xi_t = \xi \left(\frac{Y_{t,mn}}{N_t}\right)^{\kappa}, \tag{14}$$

where $\xi > 0$ is a scale parameter and $\kappa \in (0, 1)$ is the income elasticity of food consumption. Note that for simplicity per-capita income is measured by manufacturing output, which implies food and the manufactured good are complementary and a declining food expenditure share as consumption per capita grows.

2.7 Intertemporal preferences

The representative household/agent has preferences over own consumption of the manufactured good c_t, the number of children it produces n_t, indexed by k, and the total future utility of their children $\sum_k U_{k,t+1}$. All children are assumed identical, so that $\sum_k U_{k,t+1} = n_t U_{t+1}$, and parents care equally about their own future utility (conditional on survival probability $1 - \delta_N$) and the future utility of their children (see Jones and Schoonbroodt, 2010), so the number of agents entering utility at $t + 1$ is $\tilde{n} = (1 - \delta_N) + n_t$. Using the recursive formulation of Barro and Becker (1989), the utility function in period t is then

$$U_t = u(c_t) + \beta b(\tilde{n}_t)[\tilde{n}_t]U_{t+1}, \tag{15}$$

where $\beta \in (0, 1)$ is the discount factor. Per-period utility from consumption is assumed to be isoelastic $u(c_t) = \frac{c_t^{1-\gamma} - u}{1-\gamma}$, where γ is the inverse of the intertemporal elasticity of substitution and

$u > 0$ represents the consumption level at which per-period utility becomes positive. Similarly, we follow Barro and Becker (1989) and assume fertility preferences are isoelastic $b(\tilde{n}_t) = \tilde{n}^{-\eta}$, where $\eta \in (0, 1)$ determines how fast marginal utility declines as $\tilde{n}$ increases.

Under these assumptions, we can exploit the recursive nature of Barro-Becker preferences to derive the intertemporal welfare function of a dynastic household head:[10]

$$W = \sum_{t=0}^{\infty} \beta^t \, N_t^{1-\eta} \, \frac{(C_t/N_t)^{1-\gamma} - u}{1-\gamma} \, . \tag{16}$$

Because population is endogenous in our model and one of our core aims is to evaluate the Pigouvian carbon tax that optimally internalizes the climate-change externality, (16) can be interpreted as a social welfare function (SWF) and therefore implies a position on population ethics. Specifically, equation (16) belongs to the class of (discounted) number-dampened critical-level utilitarian SWFs (Asheim and Zuber, 2014). The critical level u is the level of consumption that makes the life of an additional person worth living. Number-dampened critical-level utilitarian SWFs multiply average utility, minus the critical level, by a positive valued function of population size. In the limit as $\eta \to 1$, the special case of discounted average utilitarianism is obtained, whereby social welfare depends only on average utility in the population. Conversely in the limit as $\eta \to 0$ the special case of discounted classical/total utilitarianism is obtained, whereby social welfare is the sum of the utilities of each member of the population and is increasing in population size. Appendix B provides further discussion of the ethical properties of number-dampened critical-level utilitarian SWFs.

Aggregate consumption $C_t = c_t N_t$ in equation (16) is produced by the manufacturing sector. Manufacturing output (only) can be either consumed C_t or invested I_t into a stock of capital:[11]

$$Y_{t,mn} \ = \ C_t + I_t \, . \tag{17}$$

[10] This is obtained though sequential substitution in $U_0 = u(c_0) + \beta b(\tilde{n}_0)\tilde{n}_0 U_1$, yielding $U_0 = \sum_{t=0}^{\infty} \beta^t u(c_t) \Pi_{\tau=0}^{t} b(\tilde{n}_\tau)\tilde{n}_\tau$. Further, noting that equation (10) can be rewritten as $N_{t+1} = N_t \tilde{n}_t$, we have $\Pi_{\tau=0}^{t} b(\tilde{n}_\tau)\tilde{n}_\tau = (N_t/N_0)^(1-\eta)$.

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

In turn,

$$K_{t+1} \;=\; K_t(1-\delta_K) + I_t\,, \quad K_0 \text{ given}\,, \tag{18}$$

where $\delta_K > 0$ the capital depreciation rate. In this setting, aggregate consumption C_t (or equivalently the savings rate $I_t/Y_{t,mn}$) is one of the key decision variables, along with the allocation of capital, labor and energy across sectors, which is discussed next.

2.8 Sectoral allocation of capital, labor and energy

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. Capital is used in either manufacturing or agriculture, $K_t = K_{t,mn} + K_{t,ag}$, as is final energy, $E_t = E_{t,mn} + E_{t,ag}$. The allocation constraint for labor is extended to include R&D activities, land clearing and fertility, as well as the clean and dirty energy sectors:

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

2.9 Emissions and climate

We include three GHGs – CO_2, methane and nitrous oxide – which have four sources: (i) CO_2 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) CO_2 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

$$GHG_t = \left(\pi_{E,CO2} + \pi_{E,NCO2}\right) E_{t,dt} + \pi_X \left(X_t - X_{t-1}\right) + \pi_{ag} \left(K_{t,ag}^{\theta_K} E_{t,ag}^{\theta_E} L_{t,ag}^{1-\theta_K-\theta_E}\right)\,, \tag{19}$$

where $\pi_{E,CO2}$ is CO_2 emissions per unit of dirty energy, $\pi_{E,NCO2}$ is non-CO_2 emissions per unit of dirty energy (i.e. methane and nitrous oxide), π_X is CO_2 emissions per unit of agricultural land expansion, and π_{ag} is methane and nitrous oxide emissions per unit input of the capital-labor-energy composite in agriculture.[12] $\pi_{E,NCO2}$ and π_{ag} are expressed in units of CO_2-equivalent.

The state variable S_t represents the atmospheric GHG concentration. The evolution of S_t is based on the carbon-cycle model of Joos et al. (2013) used extensively 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 and Venmans, 2019; Mattauch et al., 2018). In the model, atmospheric CO_2 is divided into four reservoirs, indexed by r, with $S_t = \Sigma_r S_{t,r}$, each of which decays at a different rate:

$$
\begin{aligned}
S_t &= \sum_{i=0}^{3} S_{t,i} && (20)\\
S_{t,0} &= a_0 \left[\pi_{E,CO2} E_{t,dt} + \pi_X \left(X_t - X_{t-1}\right)\right] + (1-\delta_{S,0}) S_{t-1,0} && (21)\\
S_{t,i} &= a_i \left[\pi_{E,CO2} E_{t,dt} + \pi_X \left(X_t - X_{t-1}\right)\right] \\
&\quad + \frac{a_i}{\sum_{i=1}^{3} a_i} \left[\pi_{E,NCO2} E_{t,dt} + \pi_{ag}\left(K_{t,ag}^{\theta_K} E_{t,ag}^{\theta_E} L_{t,ag}^{1-\theta_K- \ +eta_E}\right)\right] \\
&\quad + (1-\delta_{S,i}) S_{t-1,i}, \ i = 1,2,3. && (22)
\end{aligned}
$$

Since methane and nitrous oxide emissions are converted into CO_2-equivalent using their 100-year Global Warming Potential, we exclude them from the first reservoir. Doing so ensures these two gases are approximately completely removed from the atmosphere 100 years after their emission.[13]

2.10 Optimization

The model is solved as a constrained non-linear optimization problem. The intertemporal welfare function (16) is maximized by selecting aggregate consumption, as well as the allocation of capital, energy and labor across sectors, subject to the various technological constraints. Appendix A contains a formal statement of the primal optimization problem.

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

[13] A more complete model would have fully independent climate dynamics for methane and nitrous oxide, but this would add excessive complexity.

3 Implementation and empirical strategy

Our approach to disciplining the trajectories simulated by the model builds on Acemoglu et al. (2016) and Lanz et al. (2017a) and proceeds in three steps. First, a set of parameter values is imposed, based on values used in other studies and in some cases on our own judgment. A second set of parameters can be calibrated on empirical data, including initial values of the stock variables; the model is initialized on observed data for 1960. For the last set of parameters (μ_j, ω, χ, ζ, ψ, and ε), there exist no direct observations or estimates in the literature. We use the flexibility offered by these parameters to fit the model to observed data from 1960 to 2015. We report a selection of the most important parameter choices in Table 1. These choices are motivated in Appendix A, which also reports values of the full set of parameters.

Table 1: Selected parameter values (values used in sensitivity analysis reported in parenthesis)

Parameter/values	Definition	Source
$\beta = 0.99$ (0.97)	Discount factor	Drupp et al. (2018) Giglio et al. (2015)
$\gamma = 2$ (≈ 1)	Elasticity of marginal utility of consumption	Guvenen (2006)
$\eta = 0.001$ (0.5)	Elasticity of utility w.r.t. population increments	Assumed
$u = 1$	Critical level of utility	Assumed
$\Omega_{ag} = 0.000207$ (0.00015, 0.000415)	Agricultural damage intensity	Nelson et al. (2014)
$\Omega_{mn} = 1.66\text{E}^{-5}$ (-0.8E^{-5}, 3.73E^{-5})	Manufacturing damage intensity	Nordhaus and Moffat (2017)
$\sigma_X = 0.6$ (0.2)	Elasticity of substitution between land and capital-labor-energy in agriculture	Wilde (2013)
$\sigma_E = 1.5$ (0.95)	Elasticity of substitution between clean and dirty energy	Stern (2012)
$\kappa = 0.25$	Income elasticity of food consumption	Thomas and Strauss (1997) Beatty and LaFrance (2005)

The structural estimation procedure targets the following quantities over the period 1960 to 2015, all defined at the global level.[14] First, we use population from the United Nations (2017) to identify the parameters determining the cost of incremental labor units, χ and ζ. Second, we use aggregate GDP data from the World Bank (2018) to pin down both μ_{mn} and ω, the latter being identified from co-variations in both technology and population (i.e. the drivers of the

[14] The choice of estimation period is mainly driven by the availability of consistent data. Below we check the model approximates a number of non-targeted quantities, which are observed only during the more recent past.

demographic transition). Third, the parameters determining labor productivity in land clearing for agriculture (ψ and ε) are based on data on crop land from FAO (2018). Fourth, empirical evidence on agricultural productivity growth reported in Martin and Mitra (2001), Fuglie (2012) and Alston and Pardey (2014) are used to estimate the parameter μ_{ag}.[15] Finally, we estimate parameters determining the speed of technological progress in the production of dirty and clean energy intermediates using data from BP (2017) on global fossil versus non-fossil energy use, converted into units of oil equivalent.

The simulated method-of-moments procedure involves minimizing a measure of the distance between trajectories simulated with the model and those observed in the data (see Appendix A). This approach implies that the estimands 'rationalize' observed trajectories with the model.[16] One implication is that the trajectories derived from the estimated model account for pre-existing market imperfections in the economy, such as tax distortions. It also follows that carrying out sensitivity analysis on some of the imposed parameters (see Section 6) requires the model to be re-estimated in order to provide a good fit of the 1960-2015 trajectories that we target.

The observed trajectories targeted by our estimation procedure are the outcomes of a laissez faire equilibrium, specifically in which climate damages have not been internalized.[17] This implies climate damages over the estimation period were exogenous to the planner's decision problem in our model. This creates a challenge, which we solve through an iterative procedure (Böhringer et al., 2007). The first step is to solve the model assuming the stock of GHGs entering the damage function is exogenous.[18] This implies the planner cannot reallocate resources to

[15] More specifically, we assume that global agricultural TFP has growth at 1.5 percent per annum over the first twenty years of the estimation period (1960 to 1980), 1.2 percent in the subsequent twenty years (1981 to 2000), and at 1 percent in the recent past (2001 to 2015). For further discussion see (see Lanz et al., 2017a).

[16] Given the planning approach and the presence of externalities, the estimated parameters cannot be interpreted as the technology of a representative firm. In a related setting, Lanz et al. (2017a) provide evidence that the value of parameters estimated via a planning approach should not be very different from those obtained via a decentralized equilibrium. In any case, we are not interested in the interpretation of the value of the estimands, or in statistical inference. Instead, these parameters are used for their their ability to fit observed trajectories on a number of important dimensions.

[17] 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 have had a trivial effect on total global GHG emissions.

[18] Note that to solve the model we require a first guess as to the trajectory of emissions over the entire model horizon. To obtain this, we first estimate the model without climate damages, which gives a good approximation of the trajectory of GHG emissions. In turn, the climate module delivers the entire path for GHG concentrations.

reduce climate damages. However, doing so creates a discrepancy between the emissions that solve the planner's problem and those consistent with the exogenous atmospheric GHG stock entering the damage functions. Therefore, the second step is to update the exogenous stock entering the damage functions with the GHG stock from step one, and re-estimate the model to ensure consistency between the GHG stock implied by emissions along the solution path and that entering the sectoral damage functions.

4 Estimation results and counterfactual analysis

This section focuses on the period from 1960 to the present. First, we document how well the model is able to track the evolution of observed outcomes. Second, we use the model to provide evidence on the impact of climate change over the estimation period.

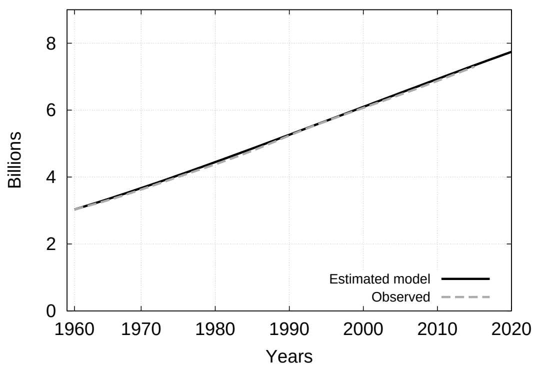
4.1 Estimated model: goodness of fit

Figure 1 reports model estimates of the variables targeted in our structural estimation: population; GDP; crop land; agricultural TFP (net of climate damages, i.e. $A_{t,ag} \cdot \exp(-\Omega_{ag}\left[S_t - \overline{S}\right]))$; and global fossil and non-fossil energy use. We also include observed trajectories of these variables in the figure. The comparison shows the model is able to replicate observed trajectories quite closely.

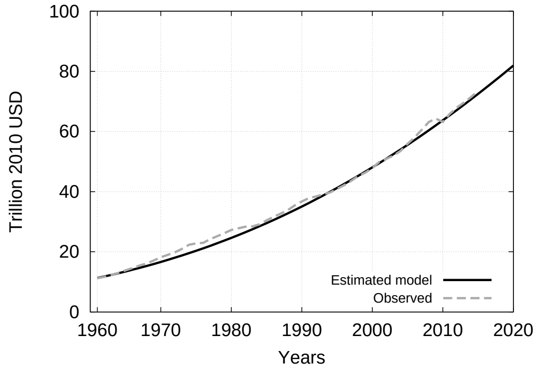
World population has grown arithmetically over the last half century; the population growth rate has halved. GDP has grown more than arithmetically, but the GDP growth rate has also decreased. Global crop land has expanded only marginally (and this expansion has been concentrated in certain parts of the world, e.g. tropical developing countries), while agricultural TFP has roughly doubled. Energy use has grown several-fold, both fossil and non-fossil.

Figure 1: Estimation results for targeted variables

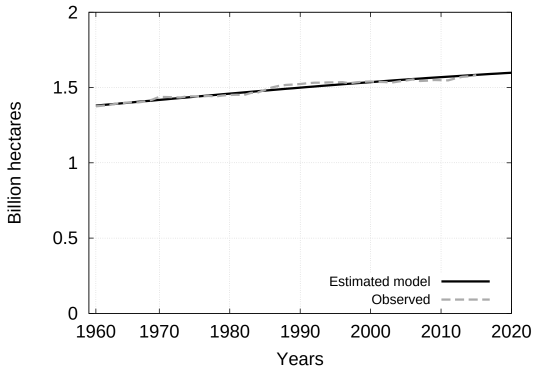
(a) World population



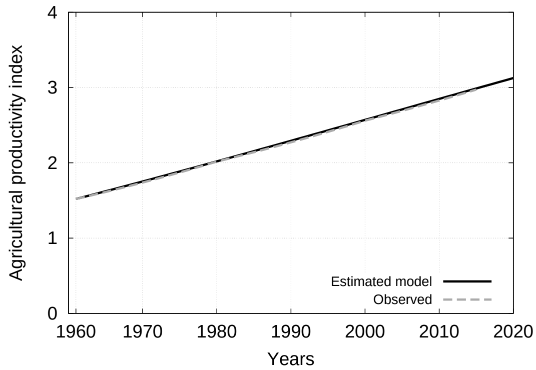
(b) World GDP



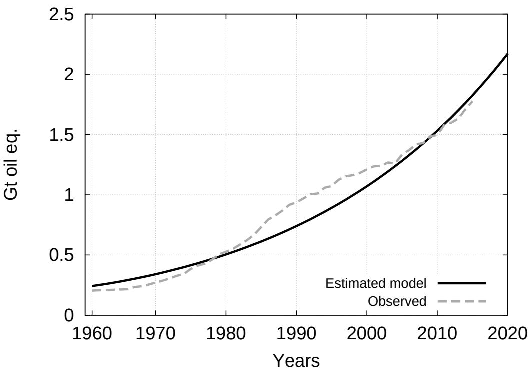
(c) Arable land and permanent crops



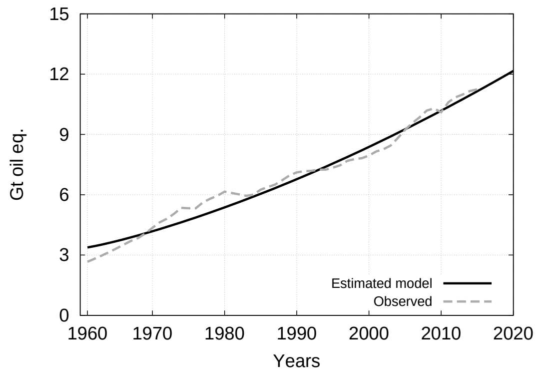
(d) TFP in agriculture net of climate damages



(e) Global non-fossil energy use



(f) Global fossil energy use

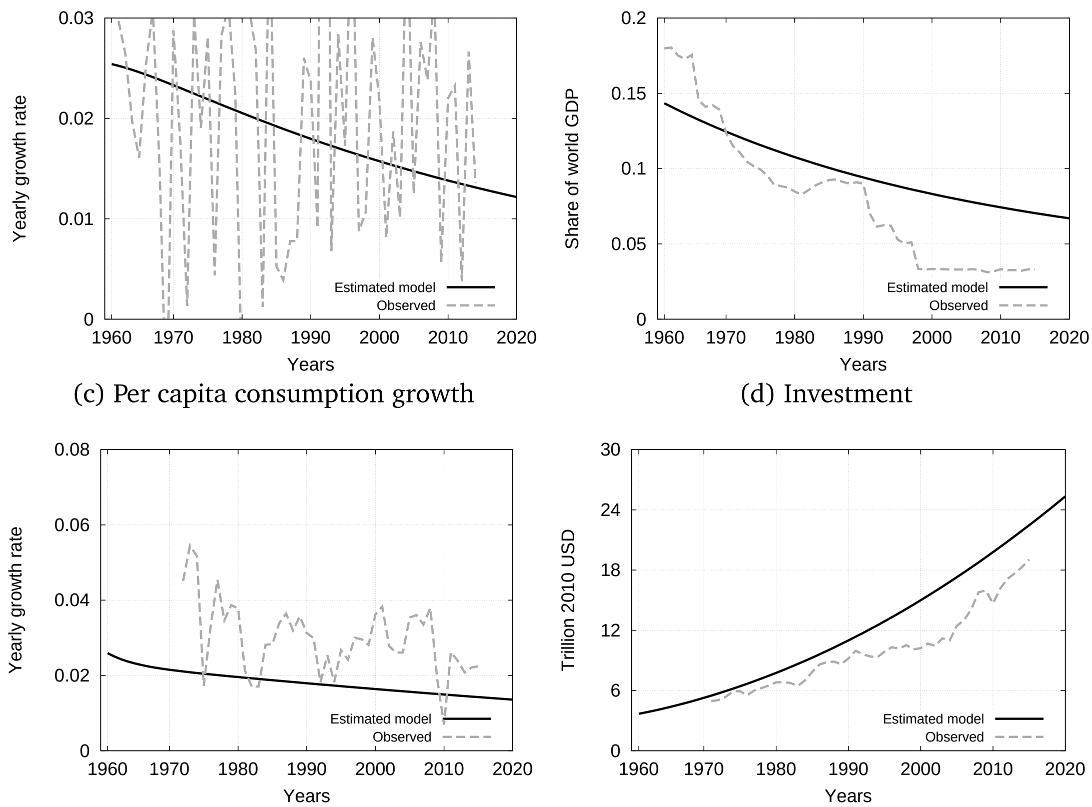


A better test of the model's goodness of fit is provided by comparing its estimates with untargeted quantities. Figure 2 panel (a) reports historical estimates from the model of the growth rate of agricultural yields, defined as the ratio of agricultural output to land area, together with observed data from FAO (2018). Using data from the World Bank (2018), panel (b) compares the share of agriculture in total GDP estimated by the model with observations, panel (c) makes the same comparison for per-capita consumption growth, and panel (d) does so for investment (gross fixed capital formation).[19]

Figure 2: Estimation results: Untargeted variables

(a) Agricultural yield growth (b) Agriculture share of GDP

(c) Per capita consumption growth (d) Investment



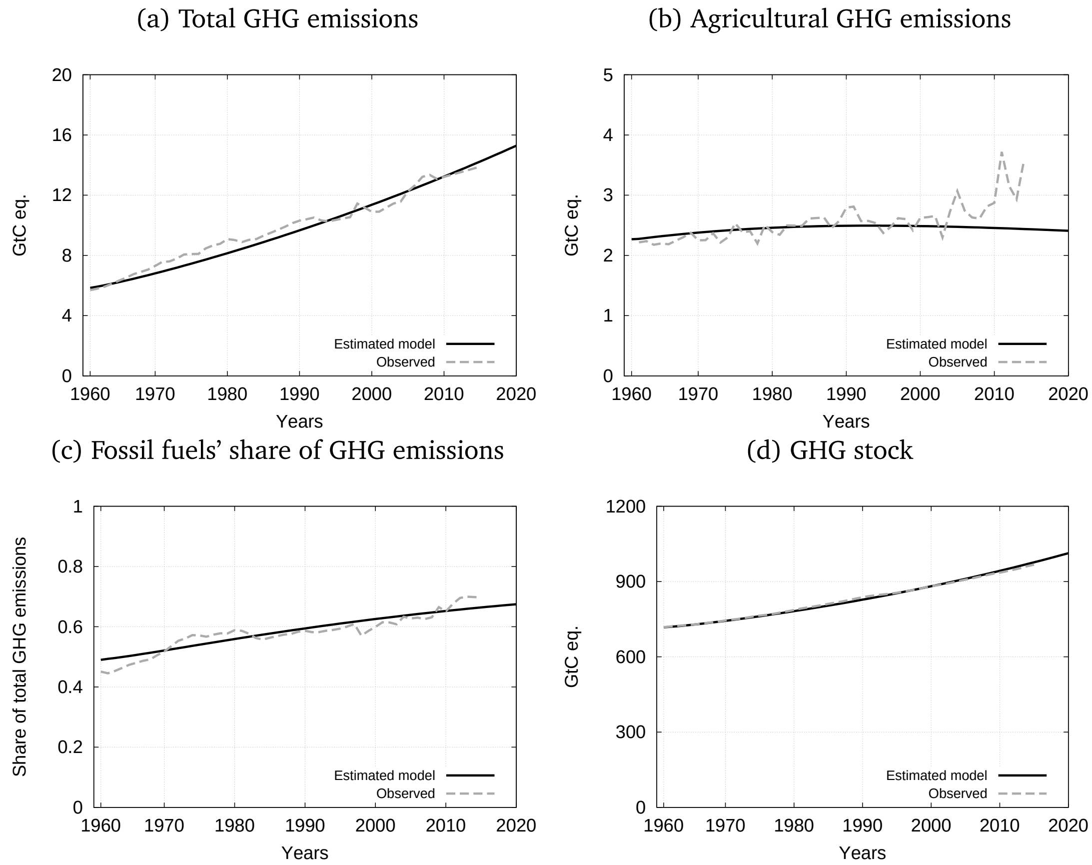
In general, the model fits the untargeted moments reasonably well, without of course capturing the short-run volatility inherent in the growth time series especially. The slowdown in agricultural yield growth, which has resulted in an approximately linear trend in absolute yields, is discussed at length in the literature (e.g. Alston and Pardey, 2014). The model also produces a declining trend. The historical decrease in agriculture's share of GDP is also qualitatively replicated by the model, although the decline is somewhat underestimated. The model exhibits the declining per-capita consumption growth found in the data, but the growth rate itself is

[19] Note that, by construction, some of these variables indirectly relate to the targeted moments. For example, given the definition of agricultural yields, declining yield growth partly results from a slowdown in agricultural land expansion (Figure 1, panel c) and from agricultural TFP growth (Figure 1, panel d). Agricultural output itself is not targeted in the estimation, however.

somewhat underestimated. This is related to the model somewhat overestimating the historical increase in investment.

We next consider the fit of the model to the emissions/climate variables, also untargeted. Figure 3 reports total GHG emissions, agricultural GHG emissions, the share of GHG emissions from fossil fuels, and the atmospheric GHG stock. Observed emissions data are taken from Boden et al. (2017), FAO (2017), Janssens-Maenhout et al. (2017) and Le Quéré et al. (2018), while estimates of the GHG stock are from Meinshausen et al. (2011). The model closely tracks observed quantities. Aggregate GHG emissions almost triple over the estimation period (panel a), an increase captured well by our representation. The model tracks agricultural GHG emissions well until after 2000, when it misses out on a jump in observed emissions from land-use change (panel b). It is uncertain whether this is a transitory phenomenon. However, because the share of emissions from burning fossil fuels increased significantly over the estimation period (panel c), this does not translate into a significant deviation in total GHG emissions. One implication is that the trajectory of the GHG stock estimated by our model closely aligns with the data (panel d).

Figure 3: Estimation results: Climate dynamics

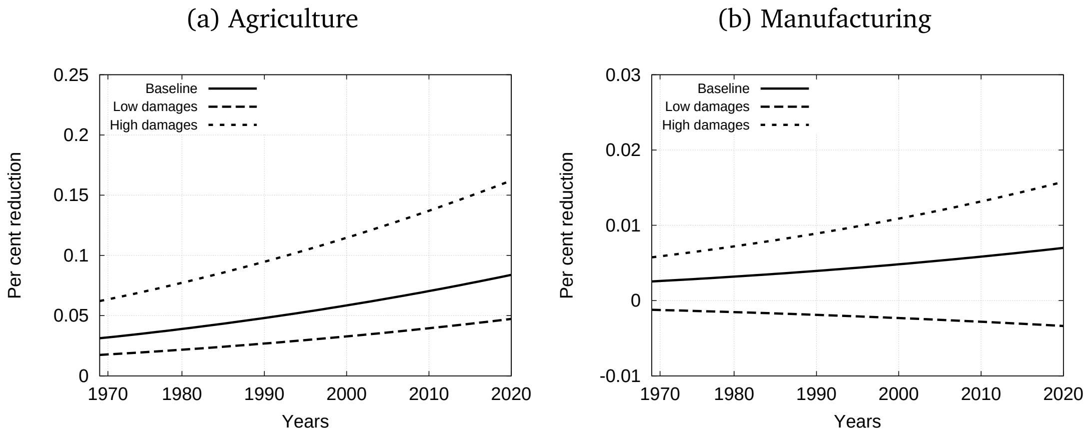


4.2 Counterfactual analysis: an evaluation of global climate impacts

Anthropogenic GHG emissions have already caused c. 1°C global warming relative to pre-industrial levels (IPCC, 2018). Simulation models of climate impacts, as well as empirical studies looking mainly at short-run climate variability (see Carleton and Hsiang, 2016; Dell et al., 2014), imply this observed warming has already affected productivity in agriculture and the rest of the economy, but by how much, and what have the consequences been for the economy and population?

Our structural estimation approach enables us to provide an answer to these questions by creating a counterfactual global economy in the absence of climate change. We construct the counterfactual by first structurally estimating the model including climate damages to agriculture and manufacturing. The model run we just evaluated on goodness of fit was estimated in this way. We then re-run the model – without re-estimating it – with climate damages 'turned

Figure 4: Climate damages since 1970; reduction in TFP relative to counterfactual



off', that is when $\Omega_{ag} = \Omega_{mn} = 0$.

Figure 4 plots historical climate damages, that is, historical estimates of Ω_{ag} and Ω_{mn}. It is important to remember these estimates constitute the 'gross' productivity loss from climate change, before adaptation through factor re-allocation and (dis)investment. Therefore they can be compared, as we do below, with 'net' productivity, which means we can also provide estimates of the effects of adaptation. With that caveat in mind, we estimate climate damages equal to a 3.2% reduction in agricultural TFP in 1970,[20] relative to a counterfactual world without climate change. This is within a range of 1.8% to 6.4%, estimated by running the model with Ω_{ag} set to its lower and upper bounds respectively (see Appendix A for further details of the parameter values). By 2018, rising temperatures caused damages to rise to 8.2%, with a range of 4.6-16.0%. In the rest of the economy, climate damages amounted to a 0.3% reduction in TFP in 1970, with a range of a 0.1% increase to a 0.6% reduction, obtained by setting Ω_{mn} to its lower and upper bounds respectively. By 2018, damages in the rest of the economy rose to 0.7% of TFP (range -0.3-1.5%).

In Figure 5, we compare various aspects of the world in a changing climate with the counterfactual world absent climate change, taking adaptation into account. The top row examines differences in two key inputs: land and agricultural innovation/technology. We see that the world agricultural system has responded to reduced yields as a result of climate change by em-

[20] 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.

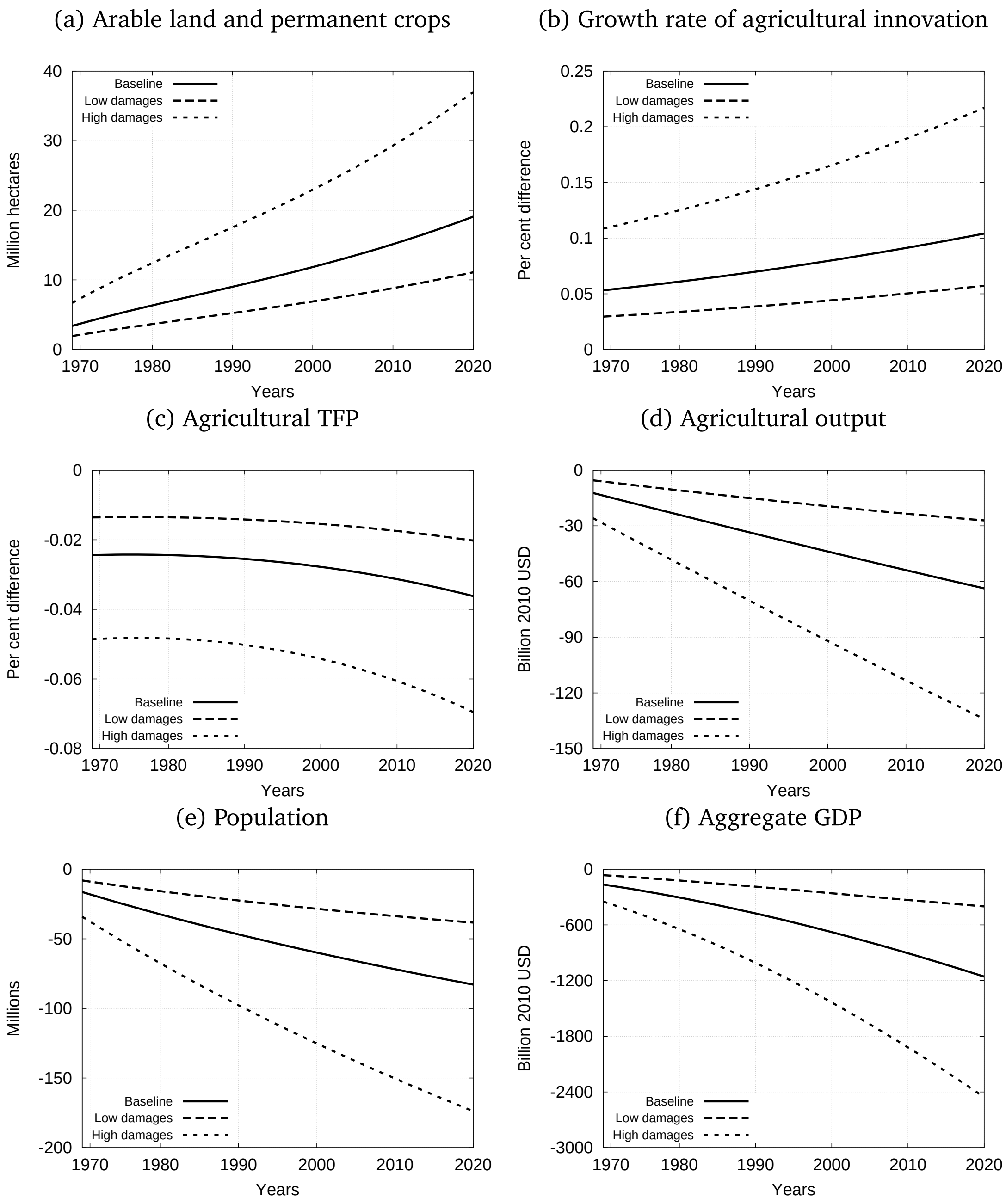
ploying more agricultural land. We estimate that by 2018 an additional 19 million hectares of arable/crop land had been brought into use just to cope with climate change (with a range of 11 to 36 million ha), which is 1.2% above the counterfactual level, or in the ballpark of the amount of arable land currently in use in France.[21] Climate change has also stimulated an increase in agricultural innovation, as measured by the growth rate of the gross technology index $A_{t,ag}$. We estimate that in 1970 the innovation rate for global agriculture was 5.4% higher than in the absence of climate change (range 3.0-11.0%). To put this in context, the counterfactual innovation rate was 1.5% in 1970, so this equates to an absolute increase of 0.08 percentage points. By 2018, the difference in the agricultural innovation rates with and without climate change had risen to 10.3% (range 5.6-21.4%). This equates to an absolute increase of 0.09 ppts. on the counterfactual innovation rate of 1.0%. Beginning in 1970, this additional innovation would have cumulatively raised the level of agricultural productivity by about 5.1% by 2018 (range 2.8-10.8%).

However, as the middle left panel shows, the additional R&D has not fully compensated the negative effect of climate damages on overall agricultural productivity. Instead, this *net* agricultural technology index was 2.4% lower than in the counterfactual in 1970 (range 1.4-4.8%) and 3.6% lower in 2018 (2.0% to 6.8%). Nonetheless, this estimate should be compared with damages from Figure 4 of 8.2% in 2018 to demonstrate the effectiveness of innovation as an adaptation mechanism in our model, reducing the impact of climate change on agricultural productivity/yields.

Even after taking into account the adaptation mechanisms available in our model, we estimate that climate change has depressed agricultural output (middle right panel). In 2018, we estimate that it was about $63 billion (1.2%) lower than the counterfactual (range $27 to $132 billion; 2010 prices). The bottom row examines effects on world population and economy-wide GDP respectively. World population is lower as a result of climate change. In particular, we estimate that by 2018 world population was reduced by 82 million (1.1%) relative to the counterfactual (range 38 to 171 million). In our model, the mechanism bringing this about is an increase in the cost of feeding children, which affects fertility choices. World GDP was re-

[21] 36 million ha is closer to the amount of arable land currently in use in Argentina. Data on France and Argentina both from World Bank (2018).

Figure 5: Historical estimates of key model variables relative to counterfactual with no climate damages



(a) Arable land and permanent crops

(b) Growth rate of agricultural innovation

(c) Agricultural TFP

(d) Agricultural output

(e) Population

(f) Aggregate GDP

duced by \$1.1 trillion in 2018 (1.4%) relative to the counterfactual, with a range of \$0.4 to \$2.4 trillion.

5 Future projections

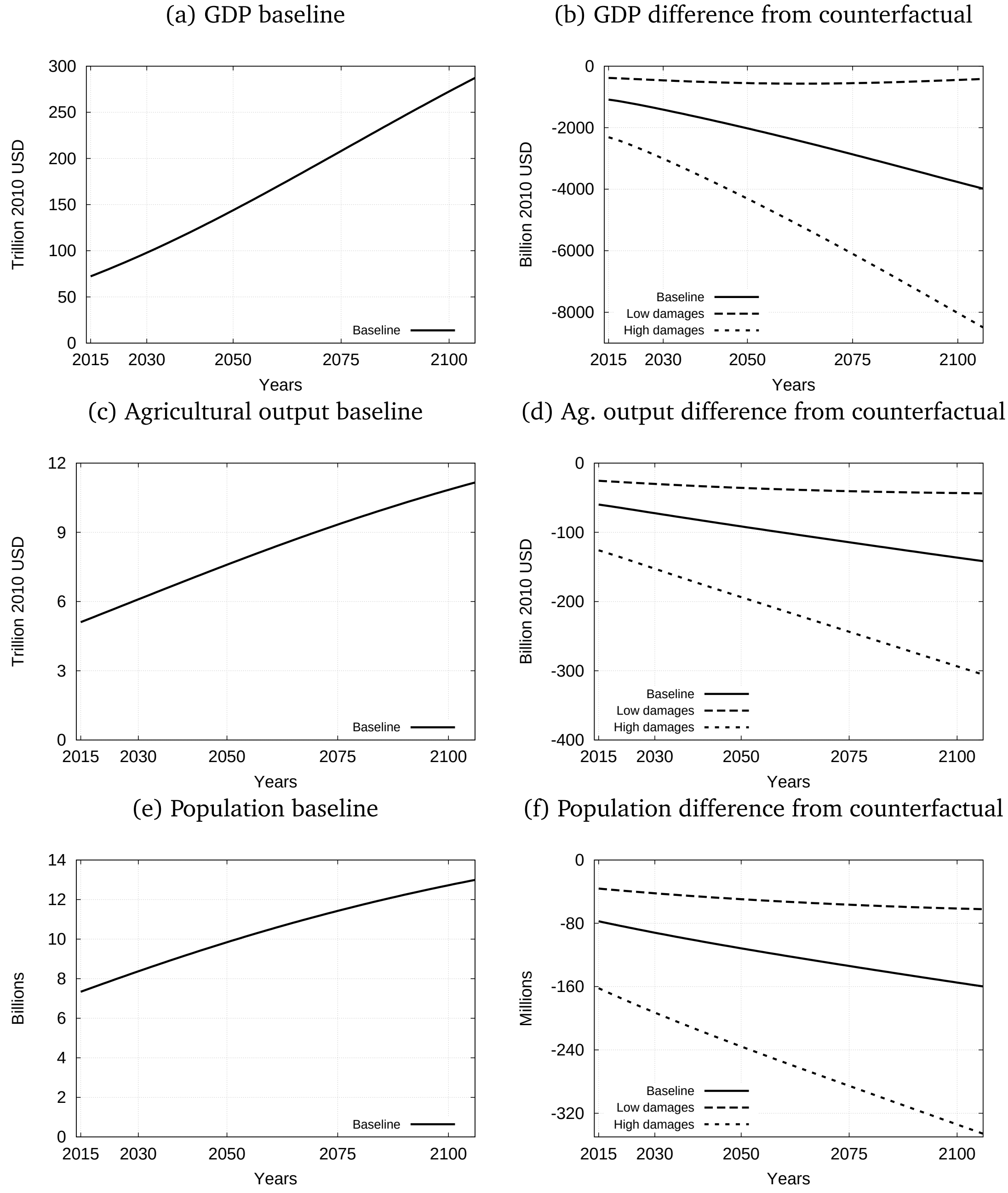
We now use the model to simulate the system over the rest of the 21st century. Our first set of projections is an extension of the comparison made in the previous section between the world in a changing climate and the counterfactual world absent climate change. This is under a continued, laissez faire emissions scenario, in which the climate-change externality is left uncorrected. Our second set of projections is of the optimal policy that internalizes climate damages.

5.1 Laissez faire equilibrium

Figure 6 reports our estimates of laissez faire output (both aggregate output and agricultural output specifically) and population in a changing climate. Panels (a), (c) and (e) plot the level of each. Despite climate change, baseline GDP increases nearly four-fold over the course of the century, from around \$80 trillion currently to \$277 trillion in 2100 (in year 2010 \$US). Agricultural output also increases, but only by a factor of two. Population increases from around 7.7 billion currently to 12.8 billion in 2100. Consistent with our previous work, population does not reach a steady state in the 21st century, but is on a path to do so after 2100 (Lanz et al., 2017a). Our estimate for 2100 is within the 95% confidence interval of the United Nations (2017) projections, which do not factor in future climate change. Panels (b), (d) and (f) report the differences in output and population with respect to the counterfactual and also include low and high damage specifications. We estimate that climate change will reduce GDP by \$3.8 trillion in 2100 relative to the counterfactual (-1.4%), with a range of \$0.4 to \$8.2 trillion (-0.1% to -2.9%). It will reduce agricultural output by \$138 billion in 2100 relative to the counterfactual (-1.3%), with a range of \$44 to \$298 billion (-0.4% to -2.7%). The corresponding reduction in population due to climate change is 157 million in 2100 (-1.2%), with a range of 62 to 338 million (-0.4% to -2.6%).

Figure 7 reports our estimates of laissez faire crop land and agricultural innovation (that is, the gross agricultural TFP index). Again, panels (a) and (c) report the level of each, while panels (b) and (d) report differences with the counterfactual, including low and high damage specifications. There is a modest amount of further crop land expansion over the course of the

Figure 6: Future estimates of baseline GDP and population, including relative to counterfactual with no climate damages

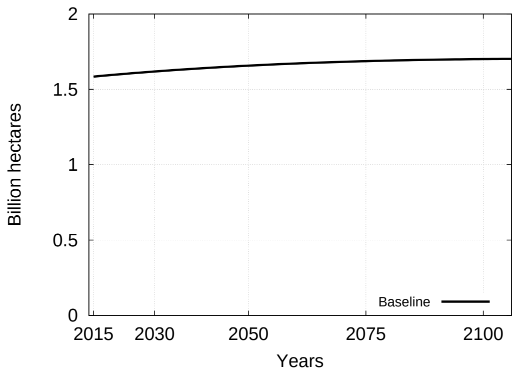


century, reaching 1.7 billion ha in 2100. In order to adapt to the changing climate, however, this constitutes a non-trivial 80 million ha increase relative to the counterfactual scenario (+4.9%), with a range of 46 to 162 million ha (+2.8% to +9.8%). Moreover panel (d) shows that much more effort is expended on agricultural R&D in a changing climate compared with the counterfactual, such that by 2100 gross agricultural TFP is more than 15% higher, with a range of 8-35%. This does not fully compensate climate damages, however, such that net TFP is lower than in the counterfactual (not shown).

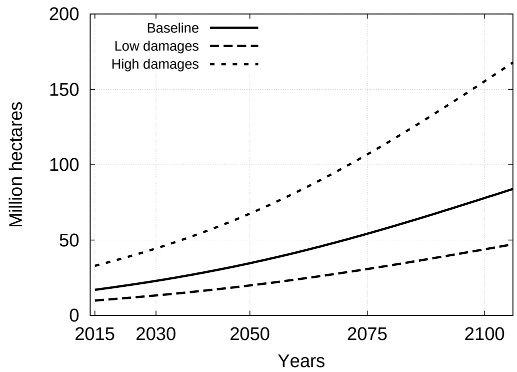
Consistent with our historical estimates, adaptation to climate change through factor reallocation is therefore effective in muting the impacts of climate change. This is exemplified by crop land expansion and especially by agricultural innovation, which compensate for yield losses due to climate change. It is striking that climate change has a smaller effect, in relative terms, on agricultural output than on aggregate output (Figure 6), despite gross productivity damages being much larger in agriculture according to the parametrization of Ω_{ag} and Ω_{mn}. That population is relatively impervious to climate change implies a strong preference for fertility in spite of rising costs. Below we test the robustness of these predictions to weaker preferences for fertility, lower substitutability of land in agriculture and lower substitutability of fossil/clean energy in industry, *inter alia*.

Figure 7: Future estimates of crop land and agricultural innovation, including relative to counterfactual with no climate damages

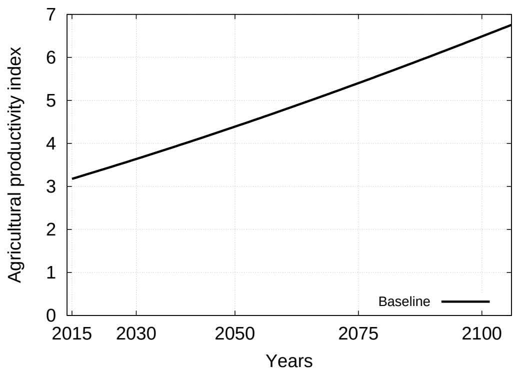
(a) Crop land baseline



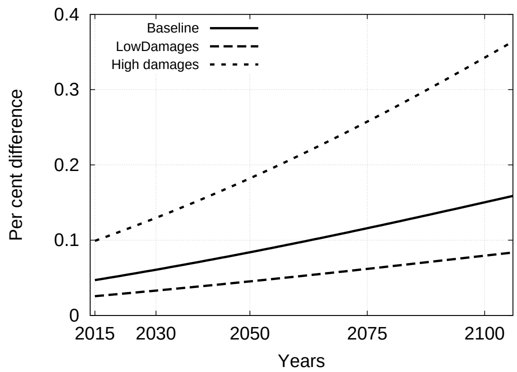
(b) Crop land difference from counterfactual



(c) Gross agricultural TFP baseline



(d) Gross agricultural TFP difference from counterfactual



5.2 Optimal policy

Figure 8 shows projections of the Pigouvian carbon tax,[22] resulting total GHG emissions, the atmospheric concentration of GHGs, atmospheric temperature, and damages to agriculture and manufacturing. The Pigouvian carbon tax is \$66/tCO_2eq in 2020 (in 2010 US dollars). This increases in real terms to \$81 in 2030 and \$182 in 2100 (we comment on the shape of this carbon tax trajectory in the following section). As a result, total GHG emissions are significantly reduced relative the baseline, laissez faire equilibrium under climate change. By 2030, optimal total GHG emissions are 7.3GtCeq, and emissions are held broadly constant at this level throughout the century. By contrast, laissez faire emissions rise steadily from 15GtCeq in 2019 to 33GtCeq in 2100, which means our baseline is close to IPCC's high-emissions 'RCP8.5' scenario (IPCC, 2014c).

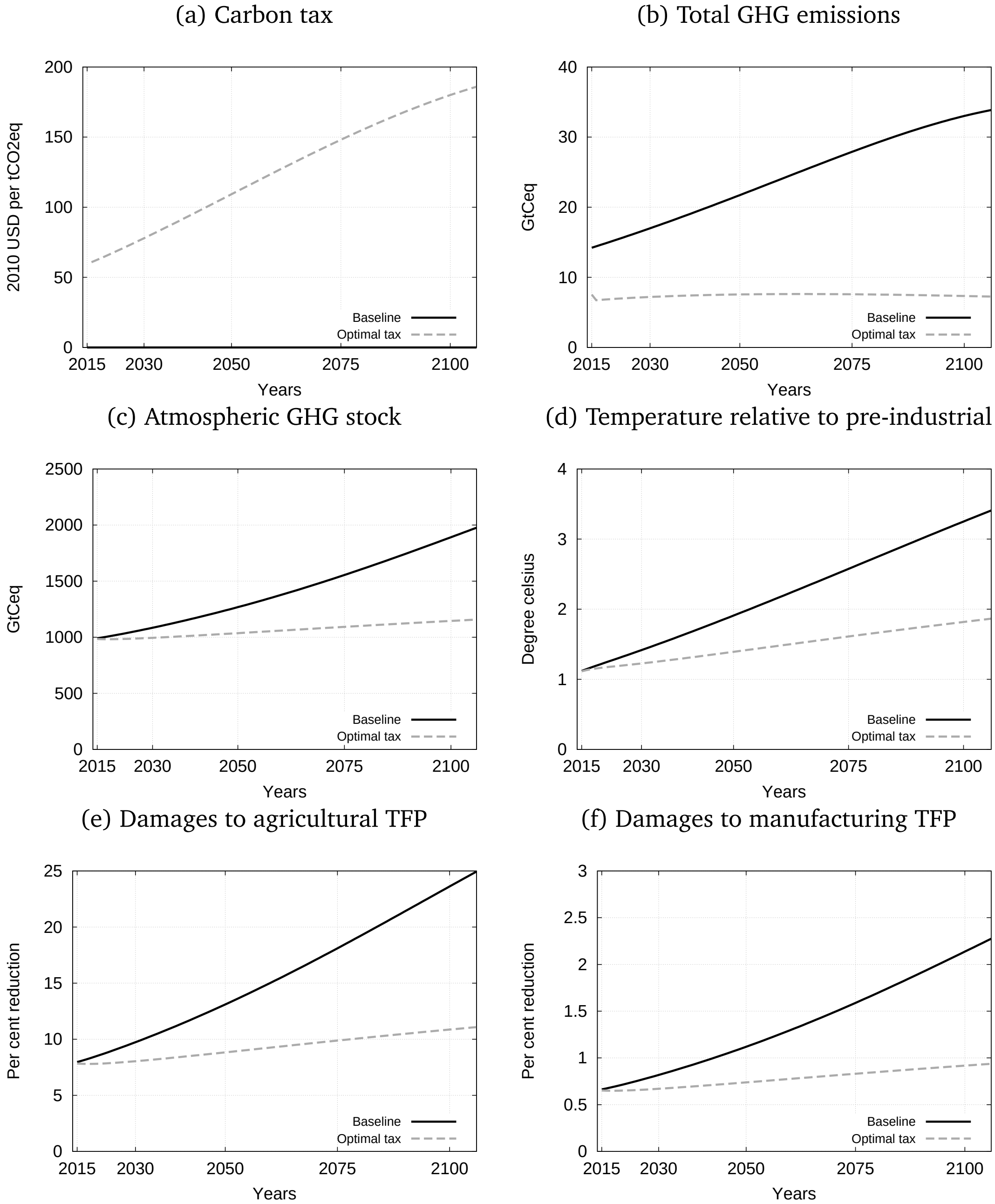
This large difference in emissions between the laissez faire equilibrium and the optimal policy translates into large differences in the atmospheric stock of GHGs and atmospheric temperatures. The optimal policy reduces the atmospheric stock of GHGs in 2100 by 40%. Although temperature plays no explicit 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.[23] The optimal policy reduces warming from 3.3°C in 2100 on the baseline path to only 1.8°C on the optimal path. This means optimal warming in 2100 according to our model is in agreement with the goal of the 2015 UN Paris Agreement on climate change to hold "the increase in the global average temperature to well below 2°C above pre-industrial levels".

Panels (e) and (f) in Figure 8 show that the optimal policy significantly reduces climate damages to both agriculture and manufacturing. Taking the year 2050 as an example, agricultural damages are equal to 13% of sectoral TFP in the laissez faire equilibrium, but only 8% on the optimal path. Manufacturing damages are 1% in the laissez faire equilibrium in 2050 and 0.6%

[22] This tax is implicitly levied not only on CO_2, but also on methane and nitrous oxide in proportion to their CO_2-equivalence.

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

Figure 8: Baseline and optimal paths for carbon prices, emissions, concentrations, temperatures and damages



on the optimal path. Below we test the sensitivity of the optimal path to alternative damage intensities.

Figure 9 brings together projections of energy inputs and also shows agricultural GHG emissions. Panel (a) shows that the carbon tax significantly reduces total global energy use. In 2050, the baseline world economy uses 26Gt oil eq, while on the optimal path energy use is only 12

Gt oil eq. Moreover panels (b) and (c) show that the carbon tax results in a significant shift away from dirty/fossil energy towards clean energy. Panel (d) shows that total GHG emissions from agriculture are significantly lower than on the baseline, about one third lower in 2030, for instance.

Figure 9: Baseline and optimal paths for energy and agricultural emissions

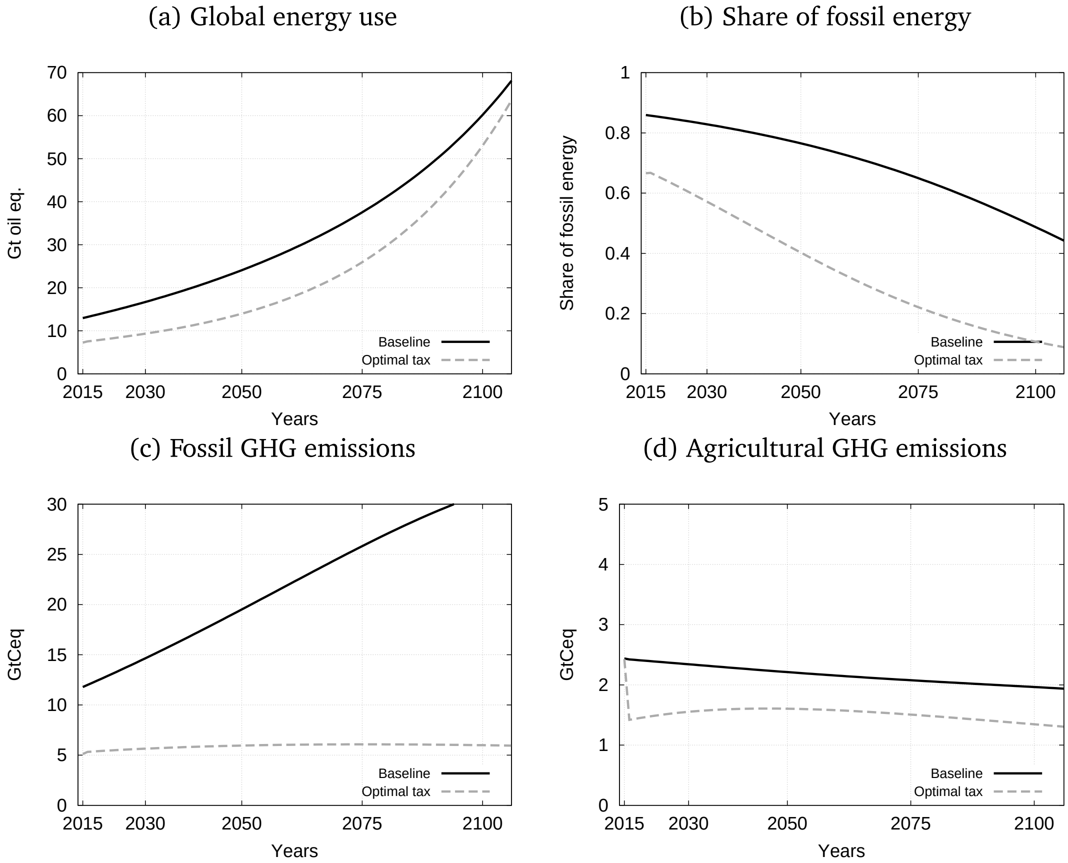
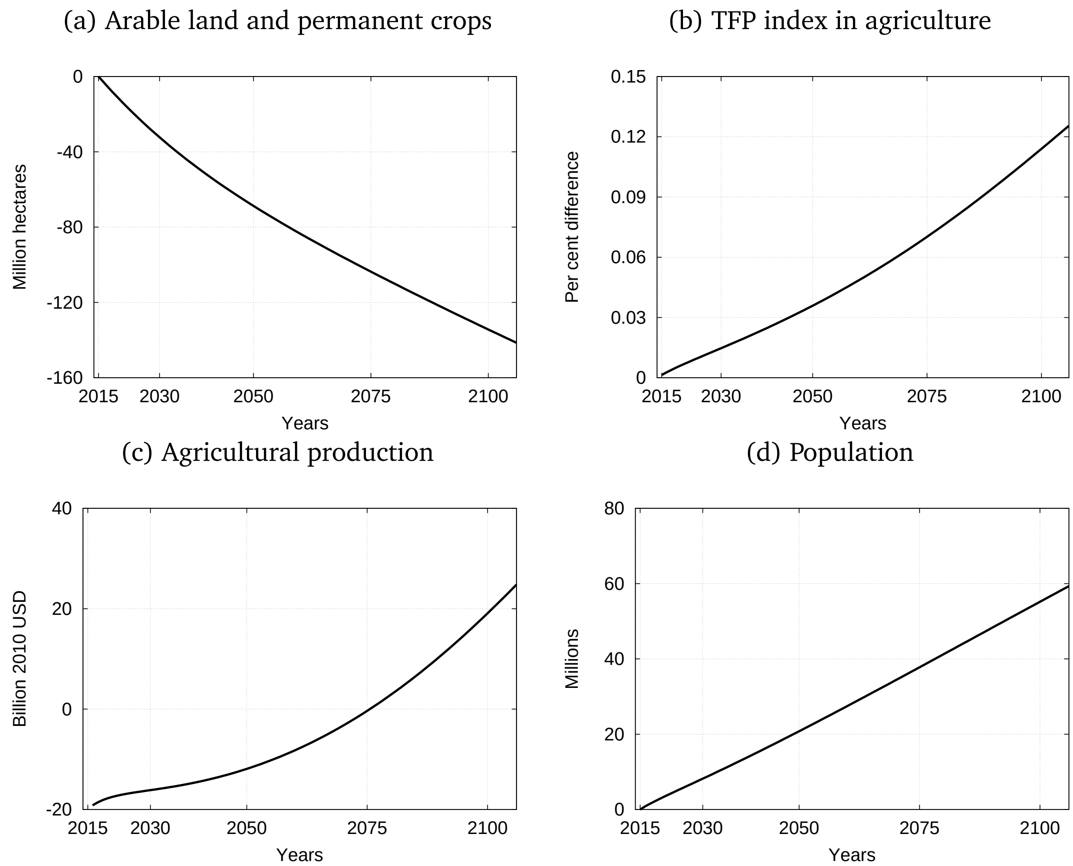


Figure 10 looks at what the baseline and optimal paths mean for the configuration of the agricultural system, and for population. On the optimal path, substantially less crop land is used. The difference is 72 million hectares in 2050 and 137 million ha in 2100 (-8%). This reflects two factors. First, land conversion results in CO_2 emissions; limiting agricultural land expansion thus avoids CO_2 emissions and the carbon tax. Second, climate damages are lower on the optimal path, necessitating less expansion in order to compensate for productivity/yield losses. Agricultural innovation is also higher on the optimal path, as panel (b) shows. The difference is about 12% in 2100. Under pressure from the carbon tax to use comparatively less land and to abate emissions from the capital-labor-energy composite, the agricultural system strives to increase productivity through R&D.

Panel (c) shows that agricultural output is initially lower on the optimal path than on the baseline, by \$16 billion in 2030 for instance, but around 2075 the situation is reversed and by 2100 agricultural output on the optimal path is \$21 billion higher. In effect there is an optimal investment in long-term agricultural production, with an up-front cost. Panel (d) shows that the optimal path sustains a larger world population than the baseline path. The world population is 22 million higher in 2050 and 57 million higher in 2100.

Figure 10: The agricultural system and population on the optimal path relative to the baseline



6 Sensitivity analysis of future projections

Table 2 reports a sensitivity analysis of our future projections, focusing on the optimal policy. We report the sensitivity of four key variables: the carbon tax, total GHG emissions, crop land and population, each for three representative points in time. We explore three issues. First, we compare our main damage specification with an alternative specification, in which total economy-wide damages are the same, but climate change does not directly impact food supply, and food and other consumption goods are implicitly perfect substitutes in welfare. This is a way of imitating how climate damages are modeled in standard IAMs and allows us to examine what difference it makes to optimal policies to incorporate a separate channel through which agricultural damages impact welfare, namely via the role of food in sustaining population. To construct this alternative, we set $\Omega_{ag} = 0$ and $\Omega_{mn} = 2.612\mathrm{E}^{-4}$.[24]

It is clear that the specification of damages, specifically how damages to the agricultural sector impact welfare, matters a great deal. Take the optimal carbon tax for instance. If the impact of climate change is concentrated on the manufacturing sector, the optimal carbon tax is only \$18/tCO_2eq in 2020, 72% lower than in our main specification. Consequently optimal GHG emissions are significantly higher, roughly double in the second half of the century. With increased substitution between food and other consumption goods, the difference in crop land between the optimal policy and the baseline is small and without a food constraint the difference in population is negligible.

Second, we compare our main specification, in which population is endogenous, with a model run in which we impose exogenous population growth from 2015, based on the UN projections (United Nations, 2017, medium fertility variant). This generates a world population in 2100 of 11.2 billion, compared with 12.8 billion in our main specification. Unable to satisfy their preferences for fertility, households in this model variant increase their consumption of manufactured goods instead (see Appendix C). This demand is met by expansion of the manufacturing sector, and the resulting optimal carbon tax has a markedly different trajectory to our main specification, starting lower but increasing at a much faster rate to end the century more than 2.5 times higher. A corollary of this finding is that the relatively flat carbon tax path in our main specification fundamentally derives from endogenous population and its prediction of relatively strong population growth. Previous findings that carbon taxes increase rapidly, either at or above the rate of growth of GDP per capita (Golosov et al., 2014; Rezai and van der

[24] Using the estimated damages to agricultural and manufacturing output from the main specification of $\Omega_{ag} = 0.000207$ and $\Omega_{mn} = 1.66\mathrm{E}^{-5}$ respectively, weighted by the respective shares of agricultural and manufacturing (i.e. non-agricultural) output, 5% and 95%.

Ploeg, 2016; Dietz and Venmans, 2019), may not be robust to assumptions about population and preferences for population.

Third, we analyze the robustness/sensitivity of the optimal policy in our main damage specification to variation in seven parameters: the joint intensity of agricultural and manufacturing damages Ω_{ag} and Ω_{mn}; the elasticity of substitution between clean and dirty energy σ_E; the elasticity of substitution between land and the capital-labor-energy composite in agriculture σ_X; the elasticity of marginal utility with respect to fertility η; the discount factor β; and the inverse of the elasticity of intertemporal substitution γ.

Table 2: Sensitivity of key variables to parameter variations

	2020	2050	2100	2020	2050	2100
	Carbon tax ($/tCO$_2$eq)			Total GHG emissions (GtCeq)		
Main spec.	66.23	112.47	182.02	6.93	7.58	7.31
Alternative damages	18.27	32.56	63.98	11.92	14.45	16.13
Exogenous population	39.33	100.87	485.09	8.87	15.19	16.30
Parameter variations						
Ω_{ag}, Ω_{mn} low	26.04	41.83	61.54	10.63	13.23	16.67
Ω_{ag}, Ω_{mn} high	127.03	220.14	353.19	3.55	4.26	3.92
$\sigma_E = 0.95$	66.28	114.23	190.15	7.09	8.68	10.68
$\sigma_X = 0.2$	73.16	124.20	198.52	7.31	7.43	6.63
$\eta = 0.5$	54.74	87.16	131.10	7.87	8.67	8.52
$\beta = 0.97$	37.07	64.25	115.59	9.62	11.94	12.82
$\gamma \approx 1$	59.95	88.72	139.46	7.19	8.65	9.41
	Δ crop land from baseline (mn ha)			Δ population from baseline (mn)		
Main spec.	-13.52	-71.83	-136.72	3.43	22.12	56.56
Alternative damages	-2.20	-11.60	-20.77	0.11	0.07	-2.39
Exogenous population	-14.62	-83.63	-199.73	n/a	n/a	n/a
Parameter variations						
Ω_{ag}, Ω_{mn} low	-5.11	-26.42	-48.16	1.24	7.19	14.45
Ω_{ag}, Ω_{mn} high	-31.62	-164.04	-300.88	8.07	56.04	149.84
$\sigma_E = 0.95$	-13.62	-71.31	-130.73	2.96	18.50	44.97
$\sigma_X = 0.2$	-9.52	-53.72	-126.93	3.90	26.76	66.85
$\eta = 0.5$	-13.19	-70.31	-132.99	3.31	29.33	88.68
$\beta = 0.97$	-14.38	-76.72	-157.76	3.03	24.76	90.29
$\gamma \approx 1$	-14.92	-81.50	-151.75	5.47	36.11	90.73

One clear finding is that the optimal path is highly sensitive to the intensity of damages, and generally less sensitive to variations in the other parameters. Higher damages imply much higher carbon taxes, much lower GHG emissions, bigger differences in crop land and population relative to the baseline, and *vice versa*. By contrast, the optimal path is much less sensitive to variation in σ_E and σ_X, although an exception to this is the difference in crop land relative to the baseline initially. When land is less substitutable with other inputs in agriculture, it becomes harder for the economy to adapt to changing climatic conditions by varying the amount of crop land. Accordingly, the difference between the area of crop land on the baseline and optimal paths is only 9.5 million hectares in 2020 when $\sigma_X = 0.2$, compared with 13.5 million ha when $\sigma_X = 0.6$. However, by the end of the century this effect of lower substitutability of land is greatly ameliorated, as the economy has had time to adapt.

With less weight placed on future utility, a higher utility discount rate ($\beta = 0.97$) yields lower optimal carbon taxes, higher optimal GHG emissions, but little difference in crop land and population. Increasing the elasticity of intertemporal substitution results in a somewhat lower optimal carbon price than the main specification, higher GHG emissions, a slightly larger difference in crop land relative to the baseline, and a large difference in population relative to the baseline. Reducing γ reduces the marginal value of population relative to consumption,[25] which results in higher consumption per capita, lower population and greater sensitivity of population to climate policy.

Given the difficulty of calibrating this parameter, it is particularly noteworthy that the optimal path is relatively robust to the value of η. Placing a lower value on fertility in household decision-making does lead to a 17% reduction in the optimal carbon price initially, leading to emissions that are 14% higher. As intuition would dictate, doing so also leads to smaller population differences between the baseline and optimal paths, and in turn differences in crop land. The effect of varying η on the difference in population and crop land is small, however.

7 Discussion

The aim of this paper has been to construct a model of the world economy that serves as a laboratory for experiments on the relationship between climate change, population growth and

[25] Supressing time subscripts, $\frac{\partial \text{MRS}(N,c)}{\partial \gamma} = -\frac{t(\eta-1)(c-uc^{\gamma})}{(\gamma-1)^2 N} - \frac{t(\eta-1)uc^{\gamma}\ln(c)}{(\gamma-1)N}$, which is positive over the domains of c, N, η and γ that we consider when $u = 1$. So when γ is reduced from 2 to c. 1, MRS(N, c) falls.

food security, both in the past and in the future. Our argument is that these need to be tightly integrated in a dynamic modeling framework and one that emphasizes the role of growth and innovation/technology. We build on 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). This ensure that key variables are endogenous, rather than exogenous as in many of the literatures we span (e.g. population and technology in climate-economy models, and food demand in agro-economic models). We include a climate model that follows best practice in the physical-science literature on carbon stock dynamics (Joos et al., 2013).

The model structure, combined with our estimation approach using more than half a century of data on key aggregates, constitutes a novel way of estimating damages from long-run climate change. It may be compared with recent empirical work on 'long differences' (Dell et al., 2012). The two approaches have advantages and disadvantages. One possible advantage of our approach is that it its application to future climate change involves less – but still some – extrapolation out of sample.[26]

In a nutshell, we estimate that the effects of climate change on the world economy and population have been and will be large, particularly when it comes to the agricultural system. We find climate change has already substantially depressed agricultural yields *ceteris paribus* and would do so much more in a laissez faire future. However, we estimate that this has not led to equivalently large reductions in agricultural output, or in turn population, mainly due to macro-economic adjustments such as agricultural land expansion and R&D. In our model, market mechanisms make the world economy highly adaptive to climate change. In turn this limits the climate costs of agricultural and manufacturing production, so that household consumption and fertility patterns are notably stable across scenarios.

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 carbon tax, which implies the welfare cost of a laissez faire future is large, despite the adjustments

[26] While the structural estimation ensures future trajectories are to some extent conditioned on past trends, the model is far from fully constrained to reproduce the past. Climate damages, for instance, are calibrated on simulation models that explicitly look at future temperatures and their effects on crop yields (Nelson and Shively, 2014).

projected to take place. Our estimates naturally rest to an extent on uncertain parameters, but our sensitivity analysis implies these qualitative conclusions are fairly robust, notably to variations in the marginal utility of fertility.

We can sense-check some of our model projections by comparing them with others in the literature. The United Nations (2017) population projections are often regarded as the benchmark in demography. Our population projections are within their 95% confidence interval, towards the upper end. In any case, low population projections typically depend on the assumption of relatively rapid convergence to replacement fertility levels, which the data do not clearly support (Strulik and Vollmer, 2015). Conversely we project average GDP per capita growth between 2015 and 2100 of around 1%. This is within the 90% confidence interval of expert forecasts reported in Christensen et al. (2018), towards the lower end, but below the 10th percentile of the statistical forecast reported in the same paper. We can generate much higher GDP growth per capita in a scenario with an exogenous population projection based on the United Nations medium fertility variant. Our projection of global crop land in 2050 is almost identical to that of the FAO (Alexandratos and Bruinsma, 2012). As mentioned above, our laissez faire GHG emissions scenario closely tracks the IPCC's RCP8.5 scenario, as does our estimated atmospheric GHG concentration.[27]

The high level of adaptability displayed by our model economy deserves further comment. A number of elements are at play here, including endogenous innovation in agriculture and manufacturing, which can compensate for climate damages. The model suggests this is particularly true of agriculture. On the other hand, our model does not include any adjustment costs to re-allocating capital or labor, which may overstate the economy's adaptability, particularly in relation to labor and issues such as migration and re-skilling. The lack of explicit capital stocks in the innovation sectors – for tractability reasons – also means that we are unable to interpret the model's labor shares literally and compare them with observed values.

While we estimate a high optimal carbon tax, our model still misses some elements that could render it higher still. These include the fact that our damage functions are smooth and continuous. Tipping points in the climate system or in the socio-economic response to climatic changes

[27] This can be verified by comparing Figure 8 panel (c) with Figure 12.43 of Collins et al. (2013), noting that the conversion rate between ppm and GtC is 2.13.

would probably increase the optimal carbon tax. So would consideration of the consequences of GHG emissions for air quality, and the consequences of climate change and agricultural land expansion for biodiversity, so-called ‘co-benefits’ of reducing GHG emissions.

Appendix A Optimization problem and quantitative implementation

The model optimization problem can be stated formally as:

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

Direct optimization methods cannot explicitly accommodate an infinite horizon.[28] Therefore we approximate an infinite horizon with a long but finite horizon. For the structural estimation, the model is initialized in 1960 and solved up to 2260. For future projections, the model is initialized in 2015 and solved up to 2315. Our interest is in projections up to 2100, so this

[28] An infinite horizon could be accommodated using dynamic programming, but dynamic programming is subject to the curse of dimensionality and we have many state variables.

approach ensures 21st century estimates are not unduly affected by agents anticipating the end of the horizon.

As mentioned in Section 2, our parametrization of the model involves dividing parameters into three classes. First, there is a class of imposed parameters, based on values used in other studies, or on our own judgement. Second, there is a class of parameters that can be calibrated on empirical data. Third, there is a class of parameters that are structurally estimated by fitting the model to observed data from 1960 to 2015. All the parameter values are reported in Tables 3-5. Here we offer some additional commentary on some of the more important choices.

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 a potential GHG abatement channel in our model, we consider $\sigma_X = 0.2$ as an alternative. In the energy sector, we set the elasticity of substitution between clean and dirty intermediates $\sigma_E = 1.5$, drawing on evidence from inter-fuel substitution by Stern (2012). We also use $\sigma_E = 0.95$ in sensitivity analysis (following Golosov et al., 2014). The income elasticity of food consumption is $\kappa = 0.25$, calibrated on econometric estimates reported in Thomas and Strauss (1997) and Beatty and LaFrance (2005).

We set the discount factor $\beta = 0.99$, which corresponds with a utility discount rate of 1%, consistent with the recent survey of economists by Drupp et al. (2018), as well as empirical work on very long-run investments by Giglio et al. (2015). We also consider $\beta = 0.97$ in sensitivity analysis. The inverse of the elasticity of intertemporal substitution $\gamma = 2$, consistent with the macro-economic estimates reported in Guvenen (2006). For reasons of tractability, logarithmic utility ($\gamma \approx 1$) is often used instead. We consider this alternative as a robustness test.

The two remaining imposed preference parameters are η and u. We set $\eta = 0.001$, which implies a strong preference for children. In previous work, we found the model was a better fit of the targeted historical variables when $\eta = 0.001$ than when it took higher values (Lanz et al., 2017a). With $\eta = 0.001$, we also approximate classical/total utilitarianism when the model is given a social-planner interpretation,[29] which has the benefit of being consistent with most

[29] We avoid setting $\eta = 0$ to ensure that the problem remains convex, although numerically the difference is negligible.

previous integrated climate-economy modeling (e.g. Nordhaus' DICE model), thereby aiding comparability. However, we also consider $\eta = 0.5$ as a robustness test.[30] We set the critical level of utility $u = 1$. Given $\gamma = 2$, this implies the critical consumption level that makes incremental population units desirable is 1,000 US dollars (2010 prices), and in fact all the solution points we consider are above the critical level anyway.[31]

The extent of climate damages is determined by the parameters Ω_{ag} and Ω_{mn}. We calibrate Ω_{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[32] of 15.4 per cent in 2050 (range 8.9 to 28.5 per cent), relative to a reference scenario without climate change. 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 $\Omega_{ag} = 0.000207$ (range 0.000115 to 0.000415). We calibrate manufacturing damages on the best estimate in the recent meta-analysis by Nordhaus and Moffat (2017),[33] giving $\Omega_{mn} = 1.66\text{E}^{-5}$ (range -0.8E^{-5} to 3.73E^{-5}).[34]

The structural estimation procedure for the class of unobserved parameters involves minimizing a measure of the distance between trajectories estimated with the model and those observed in the data, for a set of variables $Z_{\tau,k}$, where $\tau \in [1960, 2015]$, k indexes the variable (i.e. population, GDP, cropland area, agricultural TFP, dirty and clean energy use, total GHG emissions and the atmospheric GHG concentration), and the vector of parameters to be estimated is Θ.

For each variable, we compute the squared relative error between observed and simulated

[30] We find a model solution does not exist for $\eta > 0.5$.

[31] From a practical point of view, $u = 1$ also ensures our model is consistent with logarithmic utility as a limiting case.

[32] This is an unweighted average across the four combinations of global circulation models and crop models, seven AgMIP models and 5 crop types.

[33] We note there remains large uncertainty about this parameter and concern has been expressed that, in effect, all estimates included in Nordhaus and Moffat (2017) may be biased downwards (Stern, 2013; Weitzman, 2013). Implicitly the same criticism applies to the agricultural modeling estimates.

[34] This is after having stripped out the contribution of agriculture, using the corresponding estimate of Ω_{ag} and based on agriculture having a 5% share of global GDP currently.

values:

$$e_{k,\Theta} = \sum_{\tau} [(Z_{\tau,k}^{model,\Theta} - Z_{\tau,k}^{data})/Z_{\tau,k}^{data}]^2. \tag{23}$$

Our estimand $\hat{\Theta}$ then solves

$$\min_{\Theta} \sum_{k} e_{k,\Theta} \,. \tag{24}$$

Our estimation procedure defines bounds on all the parameters to be estimated and simulates the model for randomly drawn vectors of parameters. Based on the ensuing relative error, we gradually refine the bounds on the parameters to improve the objective.

Table 3: Imposed parameters (values used for sensitivity analysis in parenthesis)

Parameter/value	Definition	Source
$\vartheta_K = 0.3$	Capital share in manufacturing	Various
$\vartheta_E = 0.04$	Energy share in manufacturing	Golosov et al. (2014)
$\theta_K = 0.25$	Capital share in agriculture	Various
$\theta_E = 0.04$	Energy share in agriculture	Golosov et al. (2014)
$\theta_X = 0.3$	Land share in agriculture	Lanz et al. (2017a)
$\delta_K = 0.1$	Capital depreciation rate	Various
$\delta_X = 0.02$	Reconversion rate for agricultural land	Assumed
$\delta_N = 0.022$	Inverse of the expected working lifetime	Assumed
$\vartheta_D = 0.65$	Dirty intermediates share in energy sector	Golosov et al. (2014)
$\lambda_j = 0.05$	Scale parameter for labor in R&D sector	Fuglie (2012)
$\beta = 0.99\ (0.97)$	Discount factor	Drupp et al. (2018); Giglio et al. (2015)
$\gamma = 2\ (\approx 1)$	Elasticity of marginal utility of consumption	Guvenen (2006)
$u = 1$	Critical level of utility	Assumed
$\eta = 0.001\ (0.5)$	Elasticity of utility w.r.t. population increments	Assumed
$a_0 = 0.217$	Share of CO_2 going to geological re-absorption	Joos et al. (2013)
$a_1 = 0.224$	Share of CO_2 going to deep ocean	“
$a_2 = 0.282$	Share of CO_2 going to biospheric uptake and ocean thermocline	“
$a_3 = 0.276$	Share of CO_2 going to rapid biospheric uptake and ocean mixed layer	“
$\delta_{S,0} = 1\mathrm{E}^{-6}$	Geological re-absorption rate	“
$\delta_{S,1} = 0.00254$	Deep ocean invasion/equilibriation rate	“
$\delta_{S,2} = 0.0325$	Biospheric uptake/ocean thermocline invasion rate	“
$\delta_{S,3} = 0.232$	Rapid biospheric uptake/ocean mixed layer invasion rate	“
$\Omega_{ag} = 0.000207$ (0.00015,0.000415)	Agricultural damage intensity	Nelson et al. (2014)
$\Omega_{mn} = 1.66\mathrm{E}^{-5}$ $(-0.8\mathrm{E}^{-5}, 3.73\mathrm{E}^{-5})$	Manufacturing damage intensity	Nordhaus and Moffat (2017)

Table 4: Parameters calibrated on empirical data (values used for sensitivity analysis in parenthesis)

Parameter/value	Definition	Source
$\sigma_X = 0.6\ (0.2)$	Elasticity of substitution between land and capital-labor-energy in agriculture	Wilde (2013)
$\sigma_E = 1.5\ (0.95)$	Elasticity of substitution between clean and dirty energy	Stern (2012)
$\overline{R} = 5000$	Global reserves of dirty energy fuels (Gt oil eq)	Rogner (1997)
$\overline{X} = 3$	Stock of natural land that can be converted (billion ha)	Alexandratos and Bruinsma (2012)
$\xi = 0.4$	Scale parameter in the demand for food	Echevarria (1997)
$\kappa = 0.25$	Income elasticity of food consumption	Thomas and Strauss (1997); Beatty and LaFrance (2005)
$\pi_{E,CO2} = 0.858$	Unit CO_2 emissions from dirty energy (Gt C per Gt oil eq)	Boden et al. (2017)
$\pi_{E,NCO2} = 0.211$	Unit non-CO_2 emissions from dirty energy (Gt C eq per Gt oil eq)	Meinshausen et al. (2011); World Bank (2018)
$\pi_X = 350.685$	Unit emissions from agricultural land expansion (Gt C per bn ha)	Le Quéré et al. (2018)
$\pi_{ag} = 0.747$	Unit emissions from application of the capital-labor -energy composite in agriculture (Gt C eq per unit)	Meinshausen et al. (2011); World Bank (2018)
$A_{0,mn} = 6.2$	Initial TFP in manufacturing	Calibrated on 1960 world GDP, share of agricultural
$A_{0,ag} = 1.52$	Initial TFP in agriculture	output in 1960 world GDP, and assumed
$K_0 = 22.38$	Initial stock of capital (trillion 2010 USD)	capital depreciation
$A_{0,cl} = 22.021$	Initial TFP in clean energy	Calibrated on 1960 fossil and non-fossil
$A_{0,dt} = 68.764$	Initial TFP in dirty energy	energy use
$X_0 = 1.38$	Agricultural cropland in 1960 (billion ha)	FAO (2017)
$N_0 = 3.03$	World population in 1960 (billion)	United Nations (2017)
$S_{0,0} = 28.115$	Stock of carbon in reservoir 0 in 1960 (GtC eq)	Obtained by initializing model in pre-industrial
$S_{0,1} = 29.570$	Stock of carbon in reservoir 1 in 1960 (GtC eq)	conditions and running forward to 1960 with
$S_{0,2} = 16.017$	Stock of carbon in reservoir 2 in 1960 (GtC eq)	reported parameters
$S_{0,3} = 6.257$	Stock of carbon in reservoir 3 in 1960 (GtC eq)	”
$\overline{S} = 590$	Pre-industrial stock of atmospheric carbon (GtC eq)	IPCC (2013))

Table 5: Structurally estimated parameters

Parameter/value	Definition
$\mu_{mn} = 0.298$	Elasticity parameter for labor in manufacturing R&D
$\mu_{ag} = 0.431$	Elasticity parameter for labor in agricultural R&D
$\mu_{cl} = 0.077$	Elasticity parameter for labor in clean energy R&D
$\mu_{dt} = 0.159$	Elasticity parameter for labor in dirty energy R&D
$\psi = 0.083$	Scale parameter for labor in land conversion
$\varepsilon = 0.254$	Elasticity parameter for labor in land conversion
$\omega = -0.071$	Elasticity parameter for technology in child-rearing
$\chi = 0.123$	Scale parameter for labor in fertility and education
$\zeta = 0.509$	Elasticity parameter for labor in fertility and education

Appendix B A sketch of the ethical properties of number-dampened critical-level utilitarianism

Our SWF is

$$W = \sum_{t=0}^{\infty} \beta^t N_t^{1-\eta} \frac{(C_t/N_t)^{1-\gamma}}{1-\gamma} - u,$$

where $\eta \in (0, 1)$. As such it is a so-called (discounted) number-dampened critical-level utilitarian social welfare ordering (NDCLU: see Asheim and Zuber, 2014). An NDCLU SWF multiplies average utility, minus the critical level, by a positive-valued function of population size.

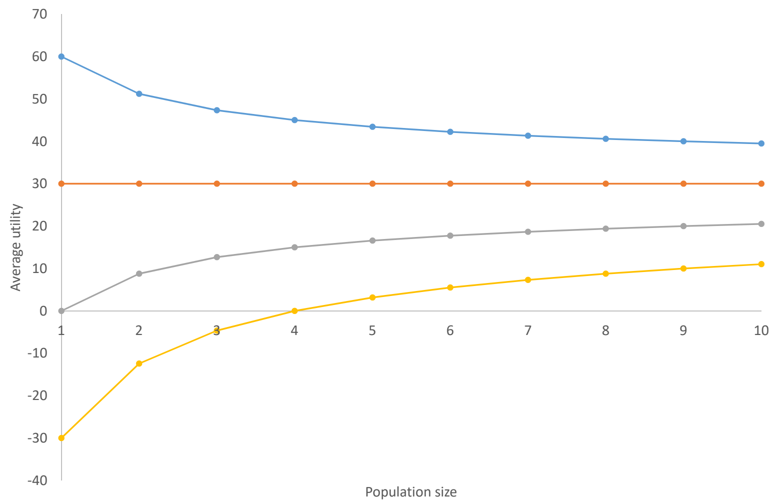
A number of well-known SWFs are sub-classes of NDCLU. These include critical-level utilitarianism (CLU) if $\eta = 0$, classical or total utilitarianism (CU) if $\eta = u = 0$, and average utilitarianism (AU) if $\eta = 1$ and $u = 0$.

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 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 corresponds with our SWF, where $\beta = 1$, $\eta = 0.5$ 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.

Figure 11: Critical-level number-dampened utilitarianism



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. CU satisfies existence independence, negative expansion and priority for lives worth living, but does not avoid Parfit's (1984) repugnant conclusion. AU avoids the repugnant conclusion and satisfies priority for lives worth living, but neither existence independence nor negative expansion. CLU avoids the repugnant conclusion and satisfies existence independence as well as negative expansion, but now priority for lives worth living is not satisfied.

References

Acemoglu, Daron, Philippe Aghion, Leonardo Bursztyn, and David Hemous, "The environment and directed technical change," *American Economic Review*, 2012, *102* (1), 131–66.

_ , **Ufuk Akcigit, Douglas Hanley, and William R. Kerr**, "Transition to clean technology," *Journal of Political Economy*, 2016, *124 (1)*, 52–104.

Aghion, P. and H. Howitt, *Endogenous Growth Theory*, MIT University Press, Cambridge MA, 1998.

Aghion, Philippe and Peter Howitt, "A model of growth through creative destruction," *Econometrica*, 1992, *60 (2)*, 323 – 351.

Alexandratos, Nikos and Jelle Bruinsma, "World agriculture towards 2030/2050: the 2012 revision," ESA Working Paper 12-03, FAO, Rome, Italy June 2012.

Alston, J.M. and P.G. Pardey, "Agriculture in the global economy," *Journal of Economic Perspectives*, 2014, *28 (1)*, 121 – 146.

Antràs, P., "Is the U.S. aggregate production function Cobb-Douglas? New estimates of the elasticity of substitution," *Contributions to Macroeconomics*, 2004, *4(1)*, 1–34.

Asheim, Geir B and Stéphane Zuber, "Escaping the repugnant conclusion: Rank-discounted utilitarianism with variable population," *Theoretical Economics*, 2014, *9* (3), 629–650.

Ashraf, Q. H., A. Lester, and D.N. Weil, "When does improving health raise GDP?," in D. Acemoglu, K. Rogoff, and M. Woodford, eds., *NBER Macroeconomics Annual*, University of Chicago Press 2008, pp. 157 – 204.

Baqaee, D. and E. Farhi, "The macroeconomic impact of microeconomic shocks: beyond Hultens's theorem," 2018. NBER working paper 23145.

Barro, Robert J. and Gary S. Becker, "Fertility choice in a model of economic growth," *Econometrica*, 1989, *57*, 481 – 501.

Barro, Robert J and Xavier Sala i Martin, *Economic Growth*, 2nd ed., MIT Press, 2004.

Beatty, Timothy K. M. and Jeffrey T. LaFrance, "United States Demand for food and nutrition in the twentieth century," *American Journal of Agricultural Economics*, 2005, *87 (5)*, 1159 – 1166.

Becker, Gary S., "An economic analysis of fertility," in Ansley J. Coale, ed., *Demographic and Economic Change in Developed Countries*, Princeton, NJ: Princeton University Press, 1960.

Blackorby, Charles, Walter Bossert, and David Donaldson, *Population Issues in Social Choice Theory, Welfare Economics, and Ethics* Econometric Society Monographs, Cambridge, UK: Cambridge University Press, 2005.

Boden, T.A., G. Marland, and R.J. Andres, "Global, regional, and national fossil-fuel CO2 emissions," 2017. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tenn., U.S.A.

Böhringer, Christoph, Andreas Löschel, and Thomas F Rutherford, "Decomposing the integrated assessment of climate change," *Journal of Economic Dynamics and Control,* 2007, *31* (2), 683–702.

BP, "Statistical Review of World Energy 2017," 2017. London, UK.

Bretschger, Lucas, "Population growth and natural resource scarcity: long-run development under seemingly unfavourable conditions," *Scandinavian Journal of Economics*, 2013, *115 (3)*, 722 – 755.

Cai, Yongyang, Jevgenijs Steinbuks, Joshua Elliott, and Thomas Hertel, "The Effect of Climate and Technological Uncertainty in Crop Yields on the Optimal Path of Global Land Use," 2014. World Bank Policy Research Working Paper 7009.

Calel, Raphael and David A Stainforth, "On the physics of three integrated assessment models," *Bulletin of the American Meteorological Society*, 2017, *98* (6), 1199–1216.

Carleton, Tamma A and Solomon M Hsiang, "Social and economic impacts of climate," *Science*, 2016, *353* (6304), aad9837.

Challinor, Andrew J, J Watson, DB Lobell, SM Howden, DR Smith, and Netra Chhetri, "A meta-analysis of crop yield under climate change and adaptation," *Nature Climate Change*, 2014, *4* (4), 287–291.

Christensen, Peter, Kenneth Gillingham, and William Nordhaus, "Uncertainty in forecasts of long-run economic growth," *Proceedings of the National Academy of Sciences*, 2018, *115* (21), 5409–5414.

Chu, Angus, Guido Cozzi, and Chih-Hsing Liao, "Endogenous fertility and human capital in a Schumpeterian growth model," *Journal of Population Economics*, 2013, *26*, 181 – 202.

Collins, M., R. Knutti, J. Arblaster, J.-L. Dufresne, T. Fichefet, P. Friedlingstein, X. Gao, W.J. Gutowski, T. Johns, G. Krinner, M. Shongwe, C. Tebaldi, Weaver A.J., and M. Wehner, "Long-term climate change: projections, commitments and irreversibility," in T.F. Stocker, C. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, and P.M. Midgeley, eds., *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge, UK: Cambridge University Press, 2013.

Darwin, Roy, Marinos E Tsigas, and Jan Lewandrowski, "World Agriculture and Climate Change: Economic Adaptations," Technical Report, United States Department of Agriculture Economic Research Service Agricultural Economic Report Number 703 1995.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken, "Temperature shocks and economic growth: Evidence from the last half century," *American Economic Journal: Macroeconomics*, 2012, *4* (3), 66–95.

_ , _ , and _ , "What do we learn from the weather? The new climate-economy literature," *Journal of Economic Literature*, 2014, *52* (3), 740–98.

Dietz, Simon and Frank Venmans, "Cumulative carbon emissions and economic policy: in search of general principles," *Journal of Environmental Economics and Management*, 2019, *96*, 108–129.

Dinopoulos, E. and P. Thompson, "Scale effects in Schumpeterian models of economic growth," *Journal of Evolutionary Economics*, 1999, *9*, 157 – 185.

Dinopoulos, Elias and Peter Thompson, "Schumpeterian growth without scale effects," *Journal of Economic Growth*, 1998, *3*, 313 – 335.

Drupp, Moritz A, Mark C Freeman, Ben Groom, and Frikk Nesje, "Discounting disentangled," *American Economic Journal: Economic Policy*, 2018, *10* (4), 109–34.

Echevarria, C., "Changes in sectoral composition associated with economic growth," *International Economic Review*, 1997, *38 (2)*, 431 – 452.

FAO, "The future of food and agriculture: trends and challenges," Technical Report, Food and Agriculture Organization of the United Nations 2017.

FAO, "FAOSTAT Database," 2018. Food and Agriculture Organization of the United Nations, Rome.

Fried, Stephie, "Climate policy and innovation: A quantitative macroeconomic analysis," *American Economic Journal: Macroeconomics*, 2018, *10* (1), 90–118.

Fuglie, Keith O., "Productivity Growth and Technology Capital in the Global Agricultural Economy," in Keith O. Fuglie, Sun Ling Wang, and V. Eldon Ball, eds., *Productivity Growth in Agriculture: An International Perspective*, Wallingford, U.K.: CAB International, 2012, pp. 335 – 368.

Galor, O., "From stagnation to growth: unified growth theory," in P. Aghion and S. Durlauf, eds., *Handbook of Economic Growth Vol 1A*, Elsevier, Amsterdam 2005.

Galor, Oded and David N Weil, "From Malthusian stagnation to modern growth," *American Economic Review*, 1999, *89* (2), 150–154.

_ **and David N. Weil**, "Population, technology, and growth: from Malthusian stagnation to the demographic transition and beyond," *American Economic Review*, 2000, *90 (4)*, 806 – 828.

Geoffroy, Olivier, David Saint-Martin, Dirk JL Olivié, Aurore Voldoire, Gilles Bellon, and Sophie Tytéca, "Transient climate response in a two-layer energy-balance model. Part I: Analytical solution and parameter calibration using CMIP5 AOGCM experiments," *Journal of Climate*, 2013, *26* (6), 1841–1857.

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Andreas Weber, "Climate change and long-run discount rates: Evidence from real estate," Technical Report, National Bureau of Economic Research Working Paper 21767 2015.

Goldin, Claudia and Lawrence Katz, "The origins of technology-skill complementarity," *Quarterly Journal of Economics*, 1998, *113*, 693 – 732.

Golosov, Mikhail, John Hassler, Per Krusell, and Aleh Tsyvinski, "Optimal taxes on fossil fuel in general equilibrium," *Econometrica*, 2014, *82* (1), 41–88.

Guvenen, F., "Reconciling conflicting evidence on the elasticity of intertemporal substitution: A macroeconomic perspective," *Journal of Monetary Economics*, 2006, *53*, 1451 – 1472.

Hansen, Gary D. and Edward C. Prescott, "Malthus to Solow," *American Economic Review*, 2002, *92 (4)*, 1204 – 1217.

Hassler, J., P. Krusell, and C. Olovsson, "Directed technical change as a response to natural-resource scarcity," 2016. Working paper.

Hertel, Thomas W and David B Lobell, "Agricultural adaptation to climate change in rich and poor countries: current modeling practice and potential for empirical contributions," *Energy Economics*, 2014, *46*, 562–575.

IPCC, "Summary for Policymakers," in T.F. Stocker, D. Qin et al., eds., *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge, UK and New York, NY, USA: Cambridge University Press, 2013.

IPCC, *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Geneva, Switzerland: IPCC, 2014.

IPCC, "Summary for Policymakers," in C.B. Field, V.R. Barros et al., eds., *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge, UK and New York, NY, USA: Cambridge University Press, 2014.

IPCC, "Summary for Policymakers," in O. Edenhofer, R. Pichs-Madruga et al., eds., *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge, UK and New York, NY, USA: Cambridge University Press, 2014.

IPCC, "Summary for Policymakers," in V. Masson-Delmotte, P. Zhai et al., eds., *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty*, In press, 2018.

Janssens-Maenhout, Greet, Monica Crippa, Diego Guizzardi, Marilena Muntean, Edwin Schaaf, Frank Dentener, Peter Bergamaschi, Valerio Pagliari, JGJ Olivier, JAHW Peters et al., "EDGAR v4. 3.2 Global atlas of the three major greenhouse gas emissions for the period 1970–2012," *Earth Syst. Sci. Data Discuss*, 2017, *2017*, 1–55.

Jones, C. and J. Williams, "Too much of a good thing? The economics of investment in R&D," *Journal of Economic Growth*, 2000, *5*, 65 – 85.

Jones, C. I., "Time series tests of endogenous growth models," *Quarterly Journal of Economics*, 1995, *110*, 495 – 525.

Jones, L. and A. Schoonbroodt, "Complements versus substitutes and trends in fertility choice in dynastic models," *International Economic Review*, 2010, *51 (3)*, 671 – 699.

Joos, Fortunat, Raphael Roth, JS Fuglestvedt, GP Peters, IG Enting, W von Bloh, V Brovkin, EJ Burke, M Eby, NR Edwards et al., "Carbon dioxide and climate impulse response functions for the computation of greenhouse gas metrics: a multi-model analysis," *Atmospheric Chemistry and Physics*, 2013, *13* (5), 2793–2825.

Kane, Sally, John Reilly, and James Tobey, "An empirical study of the economic effects of climate change on world agriculture," *Climatic Change*, 1992, *21* (1), 17–35.

Knight, F., *Risk, Uncertainty and Profit*, Boston: Houghton Mifflin, 1921.

Kremer, Michael, "Population growth and technological change: one million B.C. to 1990," *Quarterly Journal of Economics*, 1993, *108 (30)*, 681 – 716.

Laincz, Christopher A. and Pietro F. Peretto, "Scale effects in endogenous growth theory: an error of aggregation not specification," *Journal of Economic Growth*, 2006, *11*, 263 – 288.

Lanz, B., S. Dietz, and T. Swanson, "Global population growth, technology, and land conversion: a quantitative growth theoretic perspective," *International Economic Review*, 2017, *58 (3)* (973-1006).

Lanz, Bruno, Simon Dietz, and Tim Swanson, "Global economic growth and agricultural land conversion under uncertain productivity improvements in agriculture," *American Journal of Agricultural Economics*, 2017, *100* (2), 545–569.

_ , _ , **and** _ , "The expansion of modern agriculture and global biodiversity decline: an integrated assessment," *Ecological Economics*, 2018, *144*, 260–277.

Le Quéré, Corinne, Robbie M. Andrew et al., "Global carbon budget 2018," *Earth System Science Data*, 2018.

Martin, Will and Devashish Mitra, "Productivity growth and convergence in agriculture versus manufacturing," *Economic Development and Cultural Change*, 2001, *49 (2)*, 403 – 422.

Mattauch, Linus, Richard Millar, Rick van der Ploeg, Armon Rezai, Anselm Schultes, Frank Venmans, Nico Bauer, Simon Dietz, Ottmar Edenhofer, Niall Farrell et al., "Steering the climate system: an extended comment," *CESifo Working Paper no. 7414*, 2018.

Meinshausen, Malte, Steven J Smith, K Calvin, John S Daniel, MLT Kainuma, Jean-Francois Lamarque, Km Matsumoto, SA Montzka, SCB Raper, K Riahi et al., "The RCP greenhouse gas concentrations and their extensions from 1765 to 2300," *Climatic change*, 2011, *109* (1-2), 213.

Mierau, J. O. and S.J. Turnovsky, "Capital accumulation and the sources of demographic changes," *Journal of Population Economics*, 2014, *27 (3)*.

Millner, Antony, "On welfare frameworks and catastrophic climate risks," *Journal of Environmental Economics and Management*, 2013, *65*, 310–325.

Moav, O., "Cheap children and the persistence of poverty," *Economic Journal*, 2005, *115*, 88 – 110.

Müller, Ulrich K and Mark W Watson, "Measuring uncertainty about long-run predictions," *Review of Economic Studies*, 2016, *83* (4), 1711–1740.

Mundlak, Yair, *Agriculture and economic growth: theory and measurement*, Harvard University Press, Cambridge M.A., 2000.

Nelson, Gerald C. and Gerald E. Shively, "Modeling climate change and agriculture: an introduction to the special issue," *Agricultural Economics*, 2014, *45*, 1–2.

Nelson, Gerald C, Dominique Mensbrugghe, Helal Ahammad, Elodie Blanc, Katherine Calvin, Tomoko Hasegawa, Petr Havlik, Edwina Heyhoe, Page Kyle, Hermann Lotze-Campen et al., "Agriculture and climate change in global scenarios: why don't the models agree," *Agricultural Economics*, 2014, *45* (1), 85–101.

Ngai, L. Rachel and Christopher A. Pissarides, "Structural Change in a Multisector Model of Growth," *American Economic Review*, 2007, *97 (1)*, 429 — 443.

Nordhaus, William D, "To slow or not to slow: the economics of the greenhouse effect," *Economic Journal*, 1991, *101* (407), 920–937.

Nordhaus, William D., "Revisiting the social cost of carbon," *Proceedings of the National Academy of Sciences*, 2017, *114* (7), 1518–1523.

Nordhaus, William D and Andrew Moffat, "A survey of global impacts of climate change: replication, survey methods, and a statistical analysis," Technical Report, National Bureau of Economic Research Working Paper 23646 2017.

_ **and Joseph Boyer**, *Warming the World: Economic Models of Global Warming*, MIT Press (MA), 2000.

Parfit, Derek, *Reasons and Persons*, Oxford: Oxford University Press, 1984.

Peretto, Pietro F., "Technological change and population growth," *Journal of Economic Growth*, 1998, *3*, 283 – 311.

Peretto, Pietro F and Simone Valente, "Growth on a finite planet: resources, technology and population in the long run," *Journal of Economic Growth*, 2015, *20* (3), 305–331.

Rezai, Armon and Frederick van der Ploeg, "Intergenerational inequality aversion, growth, and the role of damages: Occam's rule for the global carbon tax," *Journal of the Association of Environmental and Resource Economists*, 2016, *3* (2), 493–522.

Rogner, H.-H., "An assessment of world hydrocarbon resources," *Annual Review of Energy and the Environment*, 1997, *22*, 217–262.

Rose, Steven K, Delavane B Diaz, and Geoffrey J Blanford, "Understanding the social cost of carbon: a model diagnostic and inter-comparison study," *Climate Change Economics*, 2017, *8* (02), 1750009.

Rosenzweig, Cynthia and Martin L Parry, "Potential impact of climate change on world food supply," *Nature*, 1994, *367* (6459), 133–138.

Schelling, T.C., "Some economics of global warming," *American Economic Review*, 1992, *82* (1), 1–14.

Schlenker, Wolfram and Michael J Roberts, "Nonlinear temperature effects indicate severe damages to US crop yields under climate change," *Proceedings of the National Academy of Sciences*, 2009, *106* (37), 15594–15598.

Sharp, P., H. Strulik, and J. Weisdorf, "The determinants of income in a Malthusian equilibrium," *Journal of Development Economics*, 2012, *97*, 112 – 117.

Stern, David I, "Interfuel substitution: a meta-analysis," *Journal of Economic Surveys*, 2012, *26* (2), 307–331.

Stern, Nicholas, "The structure of economic modeling of the potential impacts of climate change: grafting gross underestimation of risk onto already narrow science models," *Journal of Economic Literature*, 2013, *51* (3), 838–859.

Strulik, Holger and Jacob Weisdorf, "Population, food, and knowledge: a simple unified growth theory," *Journal of Economic Growth*, 2008, *13*, 195 – 216.

_ **and Sebastian Vollmer**, "The fertility transition around the world," *Journal of Population Economics*, 2015, *28 (1)*, 31 – 44.

Subramanian, S. and A. Deaton, "The demand for food and calories," *Journal of Political Economy*, 1996, *104 (1)*, 132 – 162.

Thomas, Duncan and John Strauss, "Health and wages: evidence on men and women in urban Brazil," *Journal of Econometrics*, 1997, *77 (1)*, 159 – 185.

Tilman, David, Christian Balzer, Jason Hill, and Belinda L. Befort, "Global food demand and the sustainable intensification of agriculture," *Proceedings of the National Academy of Sciences*, 2011, *108* (50), 20260–20264.

United Nations, *World Population Prospects: the 2017 Revision*, United Nations, Department of Economic and Social Affairs, Population Division, 2017.

Vollrath, D., "The agricultural basis of comparative development," *Journal of Economic Growth*, 2011, *16*, 343 – 370.

von Lampe, Martin, Dirk Willenbockel, Helal Ahammad, Elodie Blanc, Yongxia Cai, Katherine Calvin, Shinichiro Fujimori, Tomoko Hasegawa, Petr Havlik, Edwina Heyhoe et al., "Why do global long-term scenarios for agriculture differ? An overview of the AgMIP Global Economic Model Intercomparison," *Agricultural Economics*, 2014, *45* (1), 3–20.

Weitzman, Martin L, "Tail-hedge discounting and the social cost of carbon," *Journal of Economic Literature*, 2013, *51* (3), 873–82.

Wilde, Joshua, "How substitutable are fixed factors in production? evidence from pre-industrial England," 2013. Working paper 0113, University of South Florida, Department of Economics.

World Bank, *World Development Indicators*, Washington, D.C.: The World Bank., 2018.

World Economic Forum, "The Global Risks Report 2018: 13th Edition," Technical Report, World Economic Forum 2018.

Young, Alwyn, "Growth without scale effects," *Journal of Political Economy*, 1998, *106*, 41 – 63.