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Simon Dietz, Bruno Lanz

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Abstract

We study the capacity to meet food demand under conditions of climate change, economic and population growth. We take a novel approach to quantifying climate impacts, based on a model of the global economy structurally estimated on the period 1960 to 2015. The model integrates several features necessary to study the problem, including an explicit agriculture sector, endogenous fertility, directed technical change and fossil/renewable energy. We estimate the world economy is more than one trillion dollars smaller, and world population more than 80 million smaller, than would have been the case without climate change. This is despite substantial adaptation having taken place in general equilibrium through R&D and agricultural land expansion. Policy experiments with the model suggest that optimal GHG taxes are high and future temperatures held well below 2°C.

JEL-Codes: C510, O130, O440, Q540.

Keywords: adaptation, agricultural productivity, climate change, directed technical change, energy, food security, economic growth, population growth, structural estimation.

Simon Dietz
London School of Economics and Political Science / United Kingdom
s.dietz@lse.ac.uk

Bruno Lanz
University of Neuchâtel
Neuchâtel / Switzerland
bruno.lanz@unine.ch

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"[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 economic growth forecasters 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] Given the pressures coming from economic and population growth, evidence on how climate change affects agricultural production and in turn the wider economy is a central endeavor in climate economics (Dell et al., 2014).

In this paper, we develop a structural economic model to study how world food demand can be met under conditions of climate change, economic and population growth. We make three contributions to the literature. First, we develop a novel model structure, in which the world economy co-evolves with the climate system and in which the key drivers of food supply and demand are endogenous, i.e. fertility and technical change. Second, we extend recent developments using simulation methods to condition environmental macro-economic models on historical data (Acemoglu et al., 2016; Fried, 2018; Lanz et al., 2017).[3] We show that our

[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, defined as the ratio of crop production to harvested land area, are highly responsive to temperature, with a representative response of -5% per °C (local) warming (Challinor et al., 2014). Crop yields also respond positively to rainfall, except at very high levels (e.g. Schlenker and Roberts, 2009), and heightened atmospheric CO_2 (also see Challinor et al., 2014).

[3] In the micro-economic literature, this is referred to as structural estimation. In the macro-economic literature, this can be interpreted as model calibration without closed-form solutions.

model is able to closely replicate all the moments we target, namely 1960-2015 trajectories for world population, GDP, agricultural land use and total factor productivity (TFP) growth, and fossil and non-fossil energy use. We also show that the model reproduces stylized facts about a number of moments that we do not target, including agricultural yields, agriculture's share of GDP, per-capita consumption growth, sectoral and aggregate greenhouse gas (GHG) emissions, and the atmospheric GHG concentration. Third, we use the structurally estimated model to solve for counterfactual growth trajectories and thereby provide new estimates of the impact of *long-run* climate change, both in the past and future.[4] We also conduct policy experiments with the model, notably estimating the optimal Pigouvian tax on GHG emissions and increase in global temperatures.

The model builds on a number of seminal contributions to the economic growth literature. 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, but its evolution is constrained by the availability of food produced by an explicit agriculture sector (as per Strulik and Weisdorf, 2008; Vollrath, 2011; Sharp et al., 2012). It follows that agricultural productivity is a determinant of the cost of children. A second important determinant of the cost of children is economy-wide technical progress and the increasing requirements it places on education/skills, as emphasized in the economic literature on demographic transitions (Galor and Weil, 2000; Galor, 2005).

The manufacturing sector, which produces the consumption good, uses fossil energy and emits GHGs, but it can substitute fossil with carbon-free energy. Agricultural production also emits GHGs, not just from the use of fossil energy, but also directly from production and from land-use change. GHG emissions accumulate in the atmosphere and temperatures rise, which reduces productivity in both agriculture and manufacturing. Damages differ between agriculture and manufacturing, and have different welfare consequences, due to the role of food in sustaining population.

Another important element of the model is endogenous technical progress, which takes place in the final goods sectors (manufacturing and agriculture) and in energy intermediates (fossil vs. non-fossil). In each sector, 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, GHG emissions abatement is subject to directed technical change (Acemoglu et al., 2012). Second, technical progress in manufacturing and agriculture is a mechanism to compensate for climate

[4] In this way, our approach complements reduced-form econometric studies that exploit weather variability as a natural experiment, particularly where this is done over long time scales (Hsiang, 2016). While our approach requires estimates of the 'biophysical' impact of climate change as primitives, we are able to capture important general-equilibrium adaptation to these impacts, in a similar fashion to e.g. Desmet and Rossi-Hansberg (2015) and Costinot et al. (2016). In our case, R&D and agricultural land expansion are key mechanisms.

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., 2017).

We use our structurally-estimated model for three main purposes. First, we construct a counterfactual past *sans* climate change. This provides novel evidence about the impacts of climate change over the past 50 years. We find that climate change has reduced agricultural and manufacturing output, and population. In 2018, our central estimate is that world agricultural output was \$63 billion (1.2%) lower than it would have been in the absence of climate change, aggregate output was \$1.1 trillion (1.4%) lower, and world population was 82 million lower. We also show that macro-economic adjustments like crop land expansion and increased R&D have reduced climate damages substantially, but not wholly. Second, we make laissez-faire projections for the 21st century, with and without climate change. That is, we make future projections of the consequences of not acting globally to internalize the climate change externality. Our findings suggest that, without a Pigouvian tax on GHG emissions (or equivalent means of pricing those emissions), the model is able to sustain an increasing path of GDP and population that is not too far from the no-climate-damages counterfactual. However, we find that doing so comes at the cost of large-scale adaptation, including further cropland expansion and more agricultural R&D. Third, we solve the model to evaluate the optimal climate policy from 2015 onward; the Pigouvian GHG tax is high and significantly reduces GHG emissions, so that optimal global warming is well below 2°C in 2100. This implies that while macro-economic adaptation is effective in reducing climate impacts, it is costly, and welfare is improved by curbing GHG emissions.

We conduct extensive sensitivity analysis of the welfare impacts of future climate change. First, we analyze the mechanism by which the agricultural impacts of climate change affect welfare. To do so, we compare our main specification, in which climate change increases the cost of producing food and therefore implies lower population growth, with an alternative model, in which climate change only affects the manufactured, non-food consumption good. By keeping the economy-wide productivity loss the same in both specifications, we effectively compare our mechanism with the more standard approach in climate economics, which implicitly treats food and other consumption goods as perfect substitutes. We show that the optimal GHG tax is three to four times higher when climate impacts on agriculture affect population.

Second, we explore the effect of endogenizing fertility. To do this, we impose on the model an exogenous population trajectory, which we take from the United Nations (2017). Relative to our main specification of endogenous fertility, these projections happen to imply lower fertility and therefore higher per-capita consumption. Consequently the optimal GHG tax path starts lower, but increases much more steeply than in our main specification. This indicates that modeling of fertility/population is important in the debate about the shape of the optimal GHG tax path (initiated by Golosov et al., 2014).

Lastly we test the sensitivity of the optimal GHG tax and associated trajectories for GHG emissions, cropland and population to a number of parametric assumptions. We find that optimal trajectories are relatively robust to variations in most of the parameters we consider, including the elasticity of substitution between fossil and clean energy, the elasticity of substitution between land and other inputs in agriculture, and household time, consumption and fertility preferences. This illustrates how fitting the model to more than 50 years of data implies consistent policy implications across a range of plausible parameter values. The exceptions are the biophysical impact of climate change on agricultural yields and equivalent productivity damages in manufacturing, on which optimal trajectories depend sensitively.

1.1 Related literature

We contribute to quantitative research on how climate change and economic growth interact, in our case with a particular focus on the role of agriculture. This literature includes Integrated Assessment Models (IAMs), pioneered by William Nordhaus (e.g. Nordhaus, 1991; Nordhaus and Boyer, 2000; Nordhaus, 2017). Recent contributions include Golosov et al. (2014), Cai and Lontzek (2019) and Barrage (2019).[5] Like these studies, our empirical framework can be used to estimate the optimal GHG tax. Unlike previous IAM studies, our model is structurally estimated on more than 50 years of data. This enables us to constrain key parameters with limited evidential bases (Millner and McDermott, 2016, discuss the problems of not doing so), and conduct counterfactual analyses. Unlike existing IAMs, our model also contains a mechanism whereby climate change constrains population expansion, the omission of which has previously been described as "an elephant in the room" (Millner, 2013).[6]

An alternative approach is offered by reduced-form econometric studies, which use exogenous variation in past climate and weather as a natural experiment. Dell et al. (2014) and Carleton and Hsiang (2016) provide reviews. This literature comes closest to our model when it looks at the impact of changes in *long-run* climate; long differences. Our model does not substitute for this work, since we require estimates of the biophysical impact of climate change on crop yields, and of equivalent impacts on manufacturing, as primitives. Rather, it complements it by explicitly identifying general equilibrium effects, including how production factors are re-

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

[6] 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).

allocated across final goods, energy and R&D sectors globally to adapt to climate pressures. In doing so, our approach relates to recent work on climate change using structural models, such as Costinot et al. (2016) and Desmet and Rossi-Hansberg (2015). While these papers major on the geographical dimension, including the location of economic activities and trade patterns, we instead emphasize adaptation to climate change through R&D and land-use change.

As indicated above, our model applies and extends the literature on endogenous fertility in growth models, starting with Barro and Becker (1989). Ideas from unified growth theory are important, in particular that falling birth rates in the latter stages of the demographic transition are fundamentally driven by technological progress (Galor and Weil, 1999, 2000). Our framework also builds on endogenous growth models, in particular Schumpeterian models (Aghion and Howitt, 1992) and, within this class, growth models that do not exhibit a population scale effect (Aghion and Howitt, 1998; Dinopoulos and Thompson, 1998; Peretto, 1998; Young, 1998; Laincz and Peretto, 2006; Chu et al., 2013).[7] Since we model the choice between fossil and clean energy, our model also relates to previous work on directed technical change and the environment, notably Acemoglu (2002) and Acemoglu et al. (2012).[8]

The remainder of the paper is set out as follows. Section 2 briefly characterizes the data we target, as well as relevant future projections of growth, population, agriculture, energy and climate from other leading sources. Section 3 discusses our empirical strategy, including the structure of the model. In Section 4, we evaluate the goodness of fit of our model and construct counterfactual estimates of climate impacts over the 1960-2015 period, i.e. what has the impact of climate change already been? In Section 5, we turn to the future and derive projections for the 21st century both under a laissez-faire scenario and when GHG emissions are optimally controlled. Section 6 reports sensitivity analysis. Section 7 provides a discussion and concludes.

2 Data

Table 1 summarizes the data we target with our model over the period 1960 to 2015: world population (United Nations, 2017), aggregate GDP (World Bank, 2018), cropland area (FAO, 2018), and global fossil and non-fossil energy use (BP, 2017). Though we do not target these variables, for context we also report estimated global GHG emissions (Meinshausen et al., 2011) and mean temperature change (NASA-GISS, 2019). To these historical estimates we add 2050 projections, in some cases from alternative sources.

In the context of an historical population explosion, world population has grown not much

[7] 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.

[8] Also see Acemoglu et al. (2016), Fried (2018) and Acemoglu et al. (2019).

Table 1: Summary of global growth and climate data

	Observed data			Projected data	Source
	1960	1990	2015	2050	
Population (billion)	3.0	5.3	7.4	9.8	United Nations (2017)
GDP (trillion 2010 USD)	11.2	37.9	75.5	223.7	World Bank (2018), Christensen et al. (2018)
Agricultural land (billion ha)	1.4	1.5	1.6	1.7	FAO (2018), Alexandratos and Bruinsma (2012)
Fossil energy (Gt oil eq.)	2.7	7.2	11.3	24.6	BP (2017), EIA (2017)
Non-fossil energy (Gt oil eq.)	0.2	1.0	1.8	11.7	BP (2017), EIA (2017)
GHG emissions (Gt C eq.)	5.7	10.4	14.9	28	Meinshausen et al. (2011)
Temperature (°C relative to 1951-1980)	0	0.5	0.9	2.4	NASA/GISS; IPCC (2013)

Notes: This table provides estimates of a number of moments captured by our empirical framework. When two alternative sources are provided, the first refers to pre-2015 data and the second to post-2015 projections. The 2050 emissions and temperature projections relate to the IPCC's RCP8.5 scenario, which is a business-as-usual scenario compatible with the EIA energy projection.

more than arithmetically over the past half century, from just over 3 billion in 1960 to 7.4 billion in 2015. Between 1998 and 2011 alone, another billion people were added. The average annual growth rate was 2.5 percent between 1960 and 1990, and 1.5 percent between 1990 and 2015. Over the same period, GDP has grown nearly seven-fold, driving a well-documented increase in global living standards. The average annual growth rate was about eight percent between 1960 and 1990, and about four percent between 1990 and 2015. Future projections of both population and GDP show considerable further expansion. Central estimates suggest this will be at a continuing declining rate.

The global agricultural land area, as measured by arable land and permanent crops, has grown more slowly and there are indications that it may not expand much further over the course of this century. Historical research suggests global cropland roughly doubled in each of the 19th and 20th centuries (Klein Goldewijk et al., 2011). Between 1960 and 2015 it grew by about 15 percent, with the expansion concentrated in places such as tropical developing countries (Alexandratos and Bruinsma, 2012).[9] This did not constrain global food production, however. Alston and Pardey (2014) report that the value of global food production more than tripled from 1961 to 2011, corresponding to a growth rate of about 2.3 percent. This reflects significant productivity gains, yet Alston and Pardey (2014) also report a slowdown of agricultural productivity growth, with global average agricultural yields (the ratio of crop production to harvested land area) evoking Malthus by growing arithmetically.[10]

[9] In this paper we focus on cropland rather than crop *and* pasture land. Global pasture land increased by a factor of 2.5 in each of the 19th and 20th centuries. It expanded by 39% between 1950 and 2000 (Klein Goldewijk et al., 2011).

[10] For example, Alston and Pardey (2014) report a decline in the the global average annual growth rate of maize yields from 2.3 percent between 1961 and 1990 to 1.8 percent between 1990 and 2011, and corresponding figures of 2.7 percent and 1.1 percent for wheat yields, 2.1 percent and 1.1 percent for rice (paddy) yields, and so on (see also Alston et al., 2009).

To accompany the great expansion of the global economy, energy use has increased by a factor of around five over the period 1960 to 2015. The vast majority of that energy has been derived from fossil-fuel combustion, with non-fossil sources having been trivial until the last decade or two. Nonetheless the share of non-fossil energy reached 12% in 1990 and 14% in 2015. Energy use has grown more slowly than GDP due to improvements in energy efficiency. Energy intensity, defined as energy use per unit of GDP, fell by about one third between 1970 and 2010 (IPCC, 2014c). What happens to energy use this century depends centrally on policy choices across the world. A business-as-usual or laissez faire projection sees fossil energy use more than doubling to nearly 25 gigatonnes of oil equivalent in 2050, but non-fossil energy use increases even more strongly to 11.7 Gt oil eq. in 2050, a 32% share.

Fossil-fuel combustion is the primary source of GHG emissions and so the four-fold increase in fossil energy between 1960 and 2015 has resulted in a substantial increase in annual global GHG emissions, from 5.7 gigatonnes of carbon equivalent in 1960 to 14.9 Gt C eq. in 2015. The slower rate of increase relative to fossil energy reflects reductions in the carbon intensity of energy and that other sources of GHGs such as land-use change have increased more slowly (IPCC, 2014c). Climate science unequivocally attributes the increase in the global mean temperature over the period 1960-2015 to anthropogenic GHG emissions (IPCC, 2013). The global mean temperature in 2015 was already 0.9°C above the 1951-1980 average. Along a high-emissions scenario it is projected to be 2.4°C above the 1951-1980 average in 2050.

In a nutshell, world population and GDP have expanded significantly, albeit at a decreasing rate. Agricultural productivity has so far more than kept up with this growth, resulting in declining relative food prices (Alston and Pardey, 2014) and undernourishment (World Bank, 2018), but a slowdown of productivity growth is raising concerns about the capacity of agriculture to keep pace (Alston et al., 2009; Godfray et al., 2010). These concerns come in part from rising global temperatures, driven by agricultural land expansion, but most especially by fossil energy use. We now move to developing a structural model of this co-evolving system.

3 Empirical strategy

This section starts by motivating our empirical approach. We then present a structural economic model that can be used to quantify general equilibrium impacts of climate change on food production. Finally, we discuss how we take the model to the data.

3.1 Motivation

This paper asks: can a growing world population be fed under changing climatic conditions? The pessimistic, Neo-Malthusian emphasizes limits to the availability of natural resources that are essential inputs to agriculture, especially under climate change. The optimistic view focuses on technological progress in agriculture and substitution away from finite natural resources, enabling farmers and the agricultural system to adapt. It follows from these contrasting perspectives that a structured assessment of the question must consider the joint evolution of the world economy and the climate, and integrate the key drivers of food supply and demand, such as fertility choices, land as a primary factor and technological progress. It must also consider the potential role of policies to internalize the climate-change externality.

Accordingly, we formulate a dynamic, general-equilibrium model that allows us to endogenously determine the joint evolution of the world economy, including agriculture, and the climate system. The model is intended to be 'canonical' in the specific sense of being as simple as possible, while integrating all the structure necessary to study the problem. Building on Acemoglu et al. (2016) and Lanz et al. (2017), we then employ a simulated method-of-moments procedure to discipline the parameters, which does not require solving the model in closed form, something that is impossible given the variety of drivers at play. Intuitively, estimation requires solving the model a large number of times, and selecting the parameters so as to minimize a measure of the distance between simulated trajectories and those observed over the period 1960 to 2015.[11] This approach implies that estimands 'rationalize' observed trajectories conditional on the structure of the model and a set of imposed parameters.

Given our focus on the external cost of climate change, and since simulation-based estimation requires us to compute the model for a large set of candidate estimates, we formulate the model as a discrete-time planning problem.[12] Specifically, our solution concept maximizes the preferences of a representative household, expressed from the perspective of the dynastic head, subject to technological and feasibility constraints. It follows that, when studying optimal paths that internalize the climate change externality, the objective function can be interpreted as a social welfare function (SWF). As we discuss further below, our baseline objective function belongs to the class of number-dampened, critical-level utilitarian SWFs (Asheim and Zuber, 2014).

Nevertheless, it is important to appreciate our structural estimation procedure implies the model fits observed trajectories, and therefore rationalizes a laissez-faire equilibrium too.[13] In this case, trajectories derived from the estimated model account for pre-existing market im-

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

[12] As we show below, a social planner formulation affords a number of simplifications, including reducing the number of state variables that need to be computed. Moreover, we use a primal formulation, so that we only compute quantities, while prices are implicitly given by Lagrange multipliers and can be retrieved at the solution point. Finally, this formulation allows us to exploit efficient solvers for non-linear mathematical programs.

[13] 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.

perfections in the economy, such as tax distortions, despite the planner representation. One implication, however, is that estimands cannot be interpreted as representing technology parameters for a representative household or firm. In line with this, we do not seek to interpret the value of estimates, or carry-out statistical inference.

3.2 A structural economic model of global agriculture climate change

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

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 $E_{t,mn}$:

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

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 $\Sigma_i \vartheta_i < 1$.[14]

Manufacturing output is also a function of the climate state variable S_t, the atmospheric GHG concentration. This is a reduced-form simplification that was introduced by Golosov et al. (2014) and made possible by the fact that temperature responds almost instantaneously to GHG emissions (Dietz and Venmans, 2019). As we describe below, GHG emissions from energy, agricultural production and land use increase S_t and this in turn reduces TFP in manufacturing. The scale of climate damages in manufacturing is measured by the parameter $\Omega_{mn} > 0$. This should be an estimate of the primal impact of climate change on manufacturing productivity, i.e. prior to adaptation through the mechanisms we identify.

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

[14] This is a plausible representation of substitution patterns in the long run (conditional on Hicks-neutral technological progress; see Antràs, 2004). For short- and medium-run analyses, it may be more appropriate to use a constant-elasticity-of-substitution function, in which the elasticity of substitution between energy and other inputs is less than unity (Fried, 2018; Hassler et al., 2016b). 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.

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 a gross agricultural TFP index 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).[15] As in manufacturing, climate change affects aggregate productivity through the parameter Ω_{ag}. This is the biophysical impact of climate change on crop yields, in essence.

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):

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

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 (Stern, 2012; Papageorgiou et al., 2017).

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

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

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:

$$\overline{R} \geq \sum_0^T E_{t,dt} \quad (5)$$

[15] 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.

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

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. (2017), the evolution of land available for agricultural production is given by

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

where $\delta_X > 0$ is a 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.

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 $\lambda_j = (1+s_j)^{I_j} - 1$.[16] 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.

[16] 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.

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

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

where $\mu_j \in (0,1)$ is a labor productivity parameter that captures the duplication of ideas among researchers (Jones and Williams, 2000). One important feature of this representation is that we dispose of the population scale effect by dividing the labor force in R&D by total population N_t. 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.[17]

Population dynamics

Population, described by state variable N_t, is endogenous in the model. We make the usual assumption that population equals the total labor force,[18] 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.

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

[17] 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).

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

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.[19]

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 – 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.

[19] 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).

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.

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:[20]

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

Because population is endogenous in our model and one of our core aims is to evaluate the Pigouvian GHG 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 captures 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

[20] 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 $\Pi_{\tau=0}^{t} b(\tilde{n}_\tau)\tilde{n}_\tau = (N_t/N_0)^{(1-\eta)}$.

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 A 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:[21]

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

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.

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:

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

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

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

time t are given by

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

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.[22] $\pi_{E,NCO2}$ 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.[23]

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 activities, subject to technological constraints. Given the parameter restrictions, the ensuing mathematical programming problem is convex, which ensures

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

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

a global optimum.

We formulate the numerical problem with the algebraic modeling language GAMS, and solve it with the KNITRO package (Byrd et al., 2006). This combination allows us to rely on analytical expressions for the Jacobian and Hessian matrices associated with the optimization problem, and use these in a solver that flexibly alternates between an interior point type algorithm, looking for an optimum of the objective function in the feasible region defined by the constraints, and an active set algorithm, which stays at the boundary of the feasible region.[24] Appendix B contains a formal statement of the primal optimization problem, and discusses some further computational considerations.

3.3 Estimation

In this section we describe how we take the model to the data. Our approach builds on Acemoglu et al. (2016) and Lanz et al. (2017) and proceeds in two steps. First, a number of model parameters are imposed on the estimation procedure. These include parameters determining households' preferences and firms' technology (Table 2). Most parameter values are either standard in the literature, or set to match external sources, and a discussion of parameter selection is relegated to Appendix C.[25] We also discuss how we calibrate initial values of the eleven state variables so as to initialize the model on observed quantities at the start of the estimation period in 1960.

In a second step, conditional on imposed parameter values and initial values of the state variables, we use a simulated method-of-moments procedure developed in Lanz et al. (2017) to identify the vector comprising the remaining nine parameters: $\Theta = \{\chi, \zeta, \omega, \psi, \varepsilon, \mu_{mn}, \mu_{ag}, \mu_{cl}, \mu_{dt}\}$. Intuitively, we select values for the elements of the vector that jointly minimize the distance between targeted variables over the 1960-2015 period and corresponding trajectories simulated by the model. We now discuss the set of individual parameters together with targeted quantities.

First, parameters determining the cost of incremental labor units, χ and ζ, and those driving the cost of technological progress in the production of the consumption good, μ_{mn} and ω (i.e. the drivers of the demographic transition), are identified from the joint evolution of global population (United Nations, 2017) and aggregate GDP World Bank (2018). The corresponding

[24] Note that, for the numerical solution, the domain of per-capita consumption is constrained to be strictly greater than one, so that per-period utility is positive for any possible values (see Jones and Schoonbroodt, 2010, for a discussion). This restriction does not affect the actual solution of the problem, since per-capita consumption is initialized above one and grows thereafter. Therefore, this additional constraint only serves the purpose of avoiding bad function calls by the solver, which could compromise the optimization algorithm.

[25] Appendix C also reports parametrization of the climate module by Joos et al. (2013).

Table 2: Parameters imposed for estimation

Parameter value	Definition	Source
Preferences and population		
$\beta = \{0.99, 0.97\}$	Discount factor	Giglio et al. (2015)
$\gamma = \{2, 1\}$	Intertemporal elasticity of substitution	Guvenen (2006)
$u = 1$	Critical level of utility	Calibrated
$\eta = \{0.001, 0.5\}$	Parental altruism	Calibrated
$\kappa = 0.25$	Food income elasticity	Thomas and Strauss (1997)
$\xi = 0.4$	Unit food demand	Echevarria (1997)
$\delta_N = 0.022$	Mortality rate	Calibrated
Manufacturing and capital accumulation		
$\vartheta_K = 0.3$	Capital share	Various
$\vartheta_E = 0.04$	Energy share	Golosov et al. (2014)
$\delta_K = 0.1$	Capital depreciation	Various
$\Omega_{mn} = \{1.66E^{-5}, -0.8E^{-5}, 3.73E^{-5}\}$	Manufacturing damage intensity	Nordhaus and Moffat (2017)
Agricultural sector		
$\sigma_X = \{0.6, 0.2\}$	Substitutability of land in agriculture	Wilde (2013)
$\theta_K = 0.25$	Capital share	Various
$\theta_X = 0.3$	Land share	Lanz et al. (2017)
$\theta_E = 0.04$	Energy share	Golosov et al. (2014)
$\delta_X = 0.02$	Land depreciation	Calibrated
$\overline{X} = 3$	Land reserves (billion ha)	Alexandratos and Bruinsma (2012)
$\Omega_{ag} = \{0.000207, 0.00015, 0.000415\}$	Agricultural damage intensity	Nelson et al. (2014)
Energy sector and R&D activities		
$\sigma_E = \{1.5, 0.95\}$	Substitutability of energy intermediates	Stern (2012)
$\vartheta_D = 0.65$	Dirty intermediates share	Golosov et al. (2014)
$\overline{R} = 5000$	Dirty energy (Gt oil eq)	Rogner (1997)
$\lambda_j = 0.05$	Innovation size in R&D	Fuglie (2012)

Notes: This table reports model parameters imposed during the estimation of the model. For parameters considered in the sensitivity analysis we report multiple values, starting with our baseline assumption. See also Appendix C for a discussion.

quantities in the model are N_t and $Y_{t,mn} + Y_{t,ag}$.[26]

Second, the parameter driving labor productivity in agricultural R&D, μ_{ag}, is pinned down by data on the evolution of agricultural TFP growth (Martin and Mitra, 2001; Fuglie, 2012).[27] Importantly, because observed agricultural TFP is based on data on agricultural output, it includes potential impacts of climate change. We therefore identify the parameter μ_{ag} by minimizing the distance between agricultural TFP (in levels) and agricultural TFP derived from the model, as measured by $A_{t,ag} \cdot \exp(-\Omega_{ag}\left[S_t - \overline{S}\right])$.

[26] Note that investment in land conversion and sectoral TFP should in principle be included in aggregate GDP, since they are not used in production. These activities, however, represent a very small share of total output, and for simplicity we exclude these from the calculations.

[27] We note that TFP estimates vary across sources and are subject to a number of caveats, and here we assume that global agricultural TFP has grown 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). See Lanz et al. (2017) for further discussion.

Third, parameters determining labor productivity in land clearing for agriculture (ψ and ε) are used to minimize the distance between X_t in the model and observed data on agricultural land area from FAO (2018). Lastly, μ_{cl} and μ_{dt}, which determine labor productivity in R&D activities for clean and dirty energy intermediates, are selected to fit global fossil and non-fossil energy use, respectively, using data from BP (2017).

Formally, for a given vector of candidate estimates Θ_v, with esimated parameters indexed by v, we solve the model to obtain simulated trajectories for the set of k targeted quantities $Z_{\tau,k}^{model,\Theta_v}$, where τ indexes years from 1960 to 2015. Denoting the observations of each targeted quantity k by $Z_{\tau,k}^{data}$, we measure the error-distance e_{k,Θ_v} associated with Θ_v as the squared relative deviation summed over the estimation period:

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

The vector of estimated parameters $\hat{\Theta}$ is then selected to minimize total model error:

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

Note that total model error refers to one instance of the model, and therefore results from solving the model with the vector of parameters Θ_v, *plus* all other fixed parameters. In other words, parameters are jointly estimated, which requires running the solution algorithm once for all vectors of candidate estimates.

In order to find a solution to Eq. 24, we use an iterative procedure. We start with a vector Θ_v^1 of parameters that coarsely approximates observed trajectories, and solve the model for 1,000 vectors randomly drawn from a uniform distribution around Θ_v^1. This allows us to identify a subset of parameter values that improves the objective function, and we repeat the sampling process for a vector of estimates Θ_v^2, solving the model again for 1,000 draws. This procedure leads us to gradually update the distribution of parameters considered until we converge to the set of estimates reported in Table 3.

Because estimation results and ensuing simulations with the model are conditioned by the value of fixed parameters, we evaluate the sensitivity of our results with respect to a number of alternative assumptions about these fixed parameters. These include, for example, the discount factor, the intensity of damages in manufacturing and agriculture, and the substitutability between clean and dirty energy intermediates, etc. These alternative values are reported in Table 2, and discussed in Appendix C.

In practice, sensitivity analysis requires updating one of the fixed parameters (e.g. the discount factor), keeping all the other parameters at their baseline values, and re-estimating the model in order to fit 1960-2015 trajectories. Estimates supporting sensitivity analysis are re-

Table 3: Parameters estimated with simulated method of moments

Parameter estimates	Definition
$\chi = 0.123$	Labor productivity in fertility and education
$\zeta = 0.509$	Elasticity of labor productivity in fertility and education
$\omega = 0.071$	Elasticity parameter for technology in fertility and education
$\psi = 0.083$	Labor productivity in agricultural land conversion
$\varepsilon = 0.2535$	Elasticity of labor productivity in agricultural land conversion
$\mu_{mn} = 0.298$	Elasticity of labor productivity in manufacturing R&D
$\mu_{ag} = 0.431$	Elasticity of labor productivity in agricultural R&D
$\mu_{cl} = 0.077$	Elasticity of labor productivity in clean energy R&D
$\mu_{dt} = 0.159$	Elasticity of labor productivity in dirty energy R&D

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

ported in Appendix D. Importantly, estimates derived under an alternative set of imposed parameters provide a different rationalization of the observed past, resulting in very similar laissez-faire projections from 2015 forward. However, this is not necessarily the case for policy simulations.

4 Estimation results and counterfactual analysis

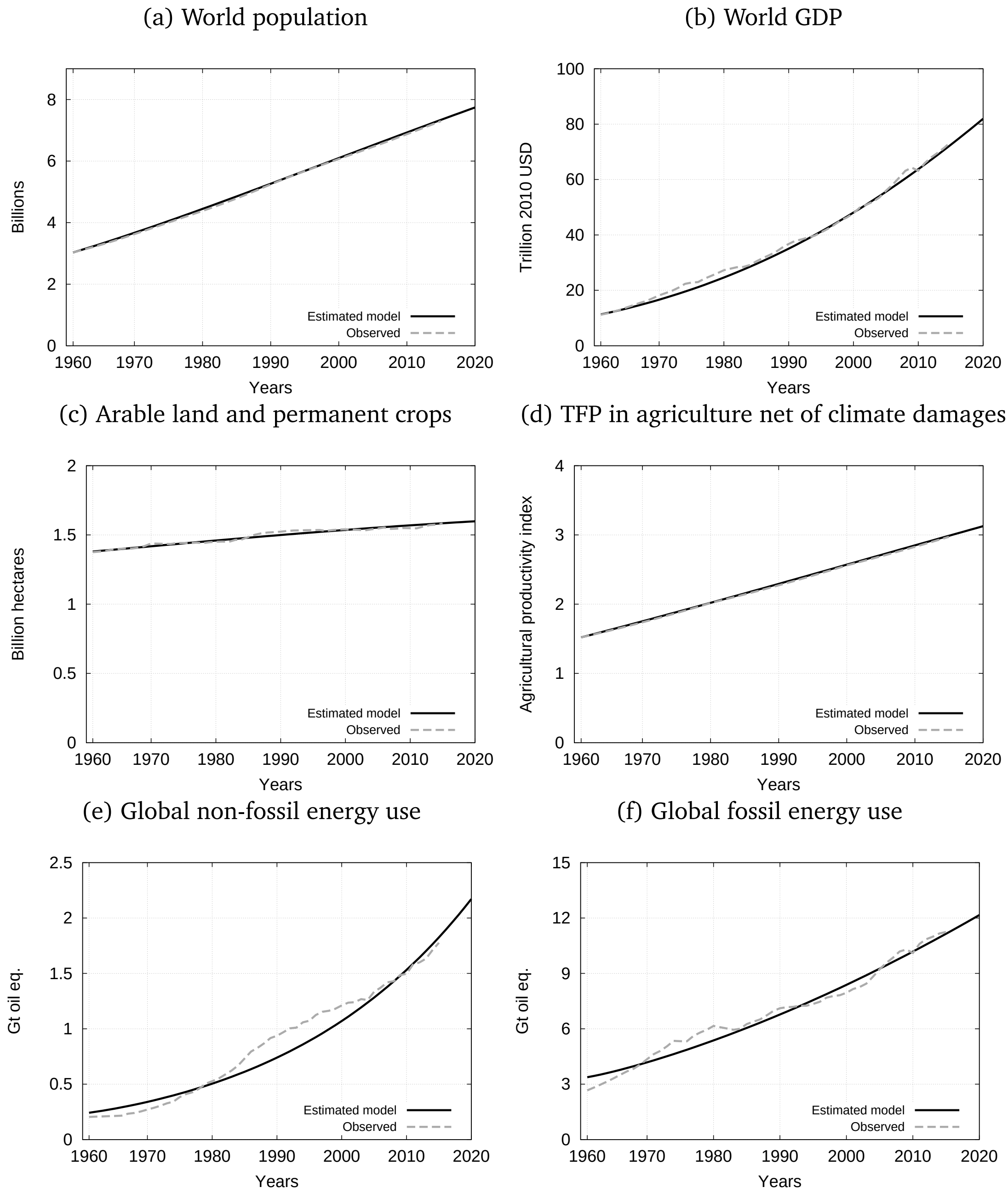
This section focuses on the period from 1960 to 2015. First, we document how well the model is able to track the evolution of observed outcomes. Second, we use the model to provide evidence on the impact of climate change in the recent past.

4.1 Estimated model: goodness of fit

Figure 1 reports simulated trajectories for the variables targeted in our structural estimation procedure: world population (panel a); world GDP (b); total agricultural land area (c); agricultural TFP (net of climate damages, i.e. $A_{t,ag} \cdot \exp(-\Omega_{ag}\left[S_t - \overline{S}\right])$, panel d); and global fossil and non-fossil energy use (e and f respectively). These trajectories result from solving the model with the baseline parameter values listed in Table 2, 1960 values of the state variables (Appendix C, Table C1), and structurally estimated parameters reported in Table 3. We also include observed trajectories of these variables in the figure.

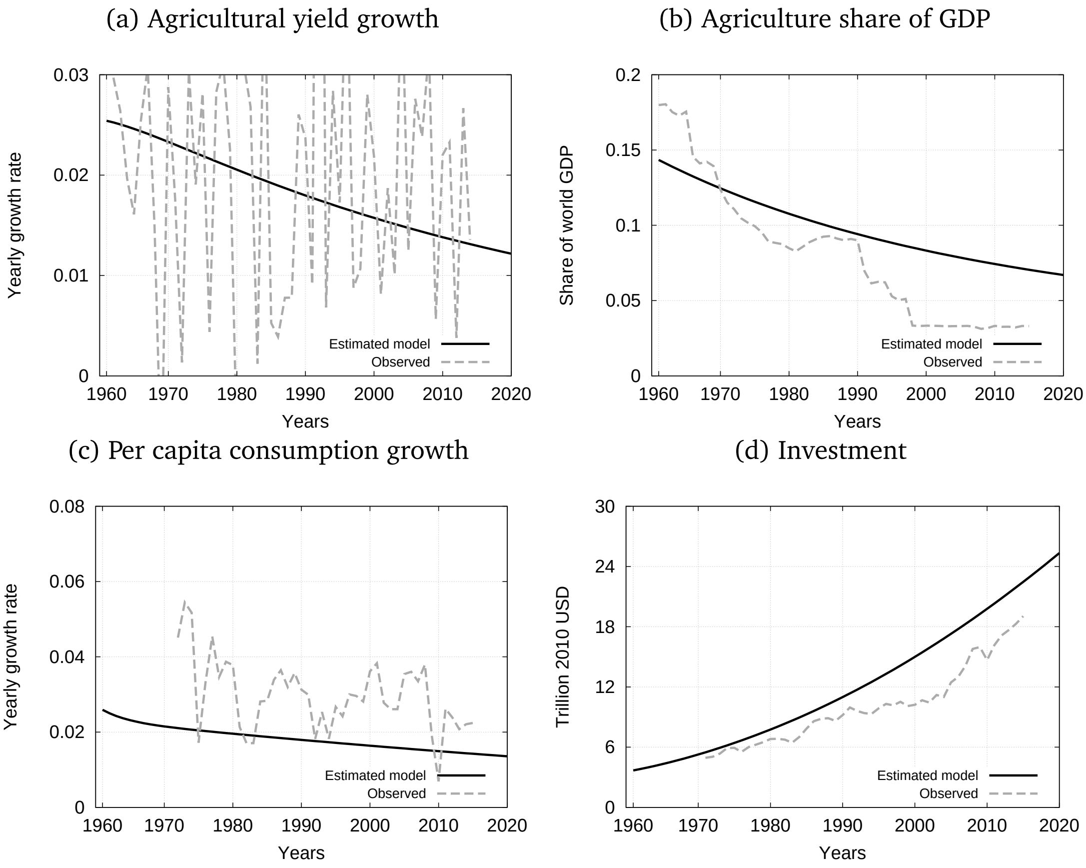
The comparison shows the model is able to replicate observed trajectories quite closely. Absolute percentage deviations are largest for clean and dirty energy use, with 13.6% and 6.0% average errors over the estimation period respectively, which reflect relatively high variability of these two variables. The average deviation of world GDP is 3.8 percent, while those for population, agricultural land, and agricultural TFP are all below one percent.

Figure 1: Estimation results for targeted variables



A more stringent test of the model's goodness of fit is provided by comparing trajectories from the estimated model with data on untargeted quantities. Figure 2 panel (a) reports simulated trajectories for the growth rate of agricultural yields, together with observed data from FAO (2018). Using data from the World Bank (2018), panel (b) compares the share of agriculture in total GDP derived from the model with observations, panel (c) makes the same comparison for per-capita consumption growth, and panel (d) focuses on investment (gross fixed capital

Figure 2: Estimation results for untargeted variables



formation, see World Bank, 2018).[28]

In general, the model fits the untargeted moments reasonably well, without of course capturing the short-run volatility inherent in empirical data. The slowdown in agricultural yield growth, which has resulted in an approximately linear trend in absolute yields (e.g. Alston and Pardey, 2014), is captured by our model with a declining trend in agricultural yield growth. Similarly, the historical decrease in agriculture's share of GDP is also qualitatively replicated by the model, although the decline is somewhat underestimated. Similarly, the model exhibits the declining per-capita consumption growth found in the data, but the growth rate itself is somewhat underestimated. This is related to the model somewhat overestimating the historical growth in investment.

We next consider the fit of the model to the emissions/climate variables, also untargeted.

[28] 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, and it in part driven by the demand for food.

Figure 3: Estimation results for climate dynamics

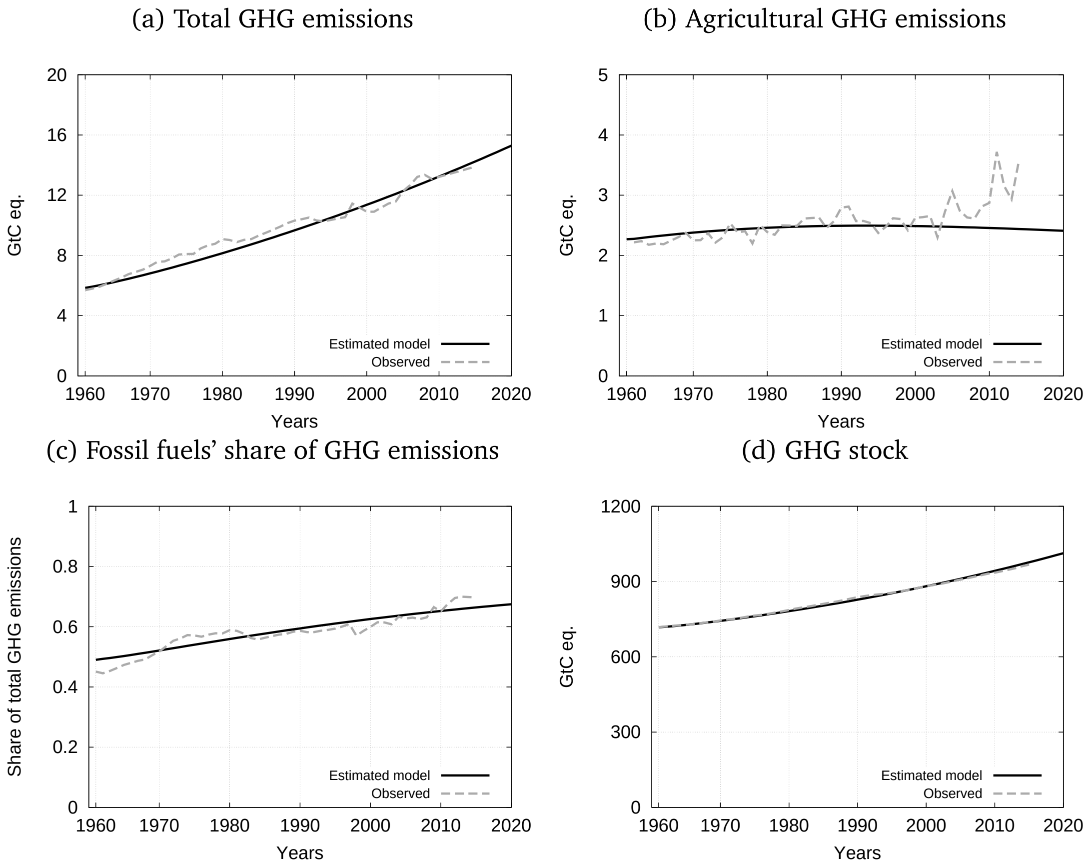
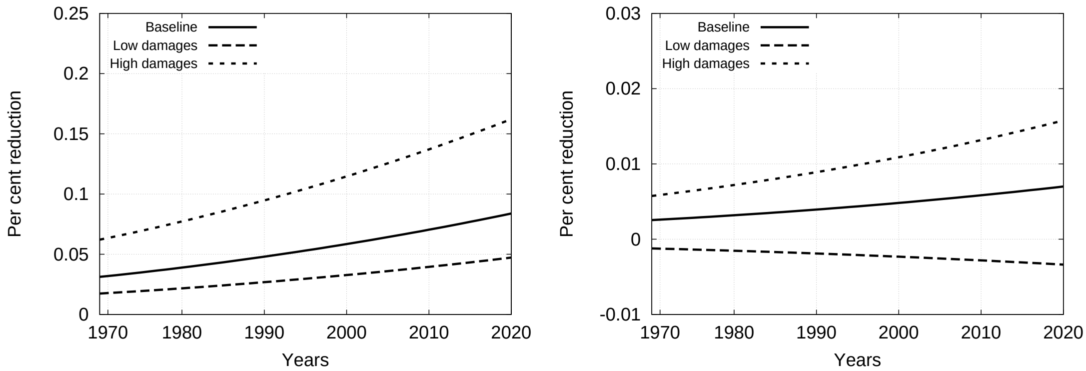


Figure 3 reports total GHG emissions (panel a), agricultural GHG emissions (b), the share of GHG emissions from fossil fuels (c), and the atmospheric GHG stock (d). Observed emissions data are taken from Boden et al. (2017), FAO (2018), Janssens-Maenhout et al. (2017) and Le Quéré et al. (2018), while estimates of the GHG stock are from Meinshausen et al. (2011).

Results suggest that the model closely tracks observed quantities. Aggregate GHG emissions almost triple over the estimation period, 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. 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, 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.

Figure 4: Climate damages since 1970; reduction in TFP relative to a counterfactual with no climate damage

(a) Agriculture (b) Manufacturing



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 reduced-form empirical studies looking mainly at short-run climate variability, imply this observed warming has already affected productivity in agriculture and the rest of the economy (see Dell et al., 2014; Carleton and Hsiang, 2016). We now use our estimated model to provide novel evidence on how much, and quantify the role of possible adjustment channels for the economy and population. This is achieved by simulating a counterfactual global economy in the absence of climate change. The counterfactual is constructed by taking the model estimated when climate damages to agriculture and manufacturing are included, and then re-running it – without re-estimation – with damages 'turned off', that is when $\Omega_{ag} = \Omega_{mn} = 0$.

Figure 4 plots historical climate damages derived from the estimated model, that is, estimates of Ω_{ag} (panel a) and Ω_{mn} (panel b).[29] It is important to remember that 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.

We estimate climate damages equal to a 3.2% reduction in agricultural TFP in 1970, 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 C for further details of the parameter values). By 2018, rising temperatures caused agricultural damages to rise to 8.2%, with a range of 4.6-16.0%. In the rest of the economy,

[29] 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.

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 document climate impacts by differencing a world with a changing climate and a counterfactual world absent climate change, taking general equilibrium effects and 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 employing more agricultural land. We estimate that by 2018 an additional 19 million hectares of arable/cropland 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 cropland currently in use in France.[30]

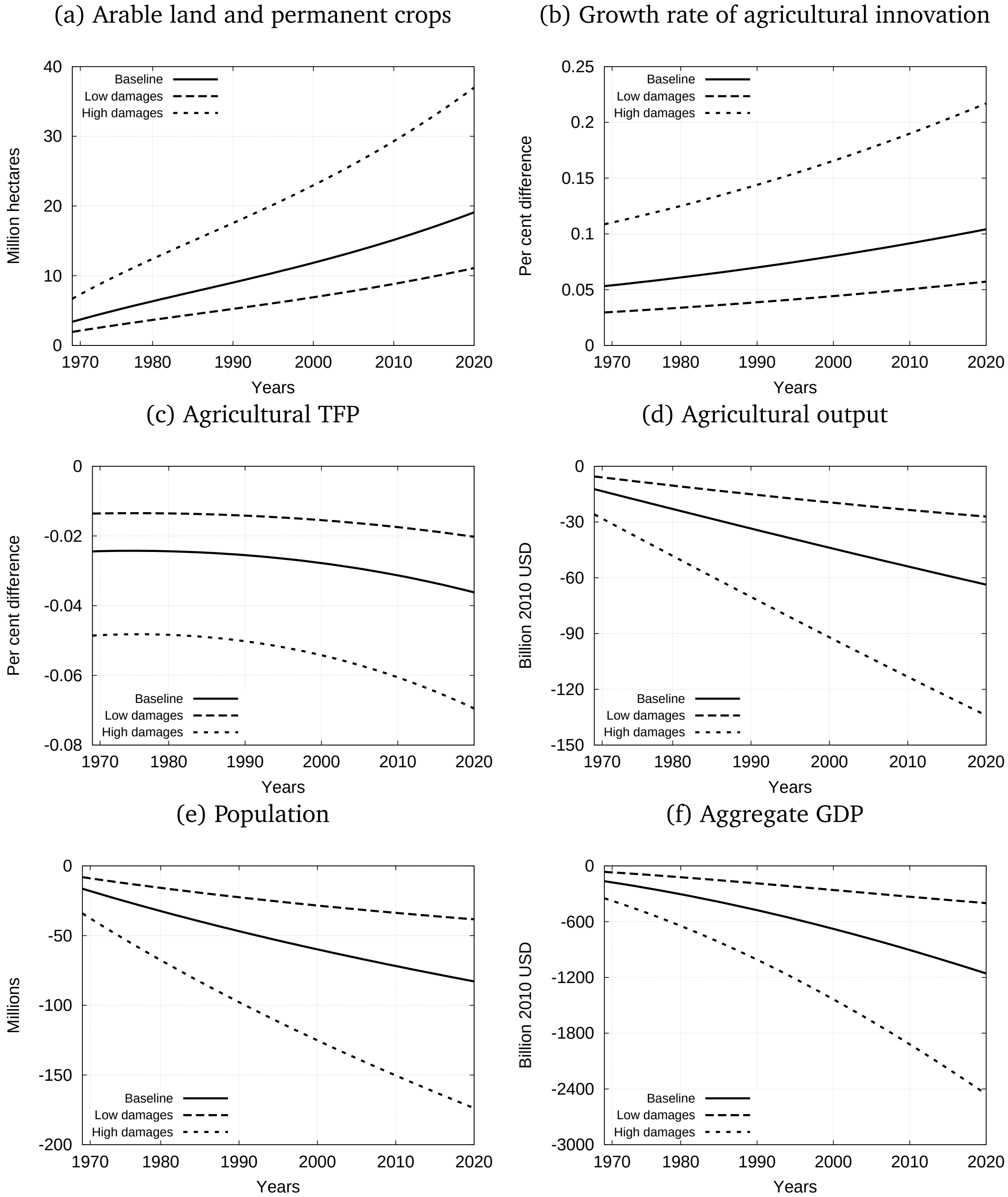
Climate change has also increased agricultural innovation, as measured by the growth rate of the gross technology index $A_{t,ag}$. We estimate that in 1970 the innovation rate for global agriculture was 5.4% higher than in the absence of climate change (range 3.0-11.0%). To put this in context, the 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

[30] 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 climate change impacts relative to a counterfactual with no climate damages



an increase in the cost of feeding children, which affects fertility choices. World GDP was reduced 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 and policy simulations

We now use the model to produce projections 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. Finally, we present results from a sensitivity analysis.

5.1 Laissez-faire equilibrium

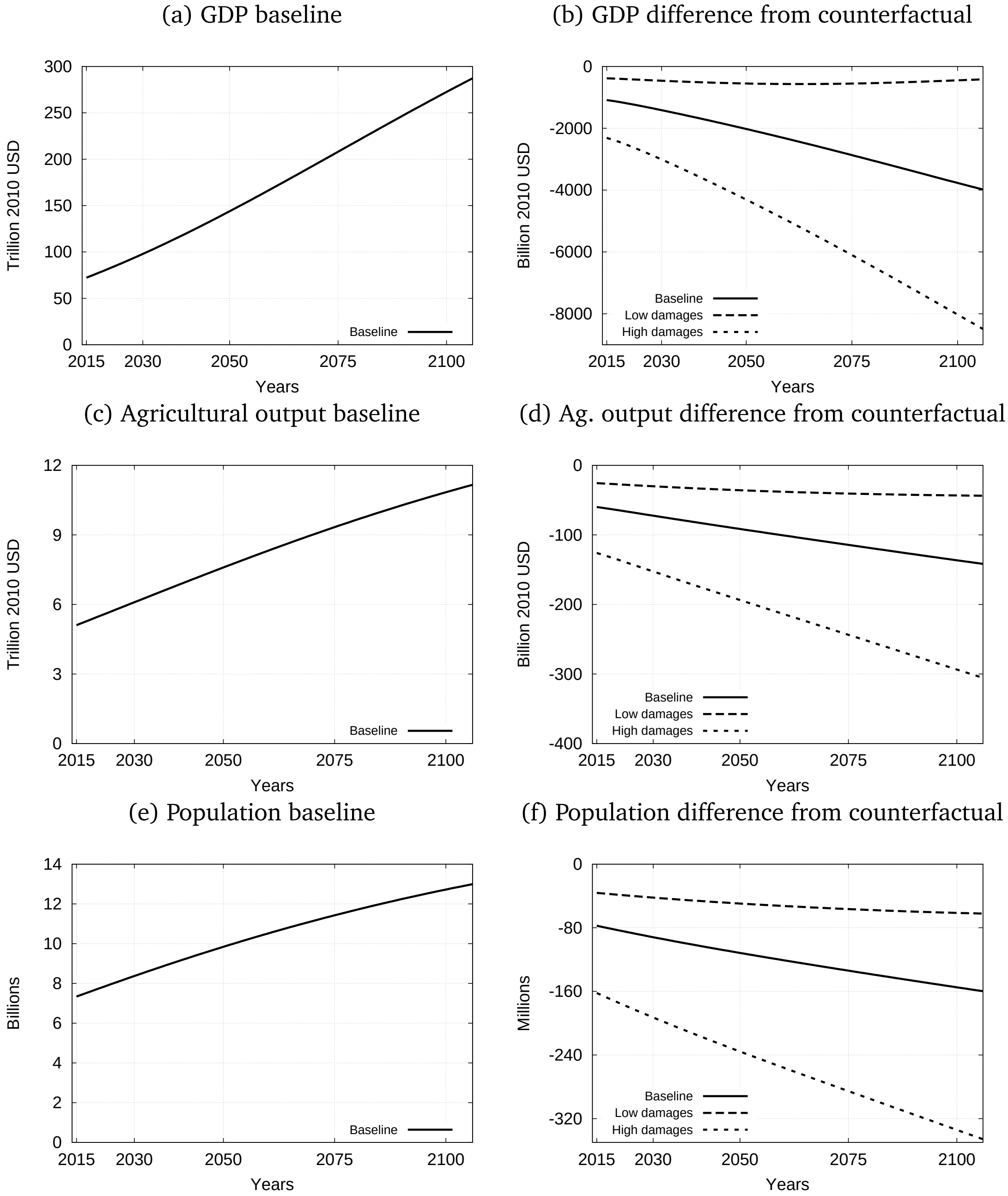
Figure 6 reports our estimates of laissez-faire output (both aggregate output and agricultural output specifically) and population in a changing climate. Panels (a), (c) and (e) plot the level of each. Despite climate change, baseline GDP increases nearly four-fold over the course of the century, from 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. 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 laissez-faire cropland 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. Projections suggest a modest amount of further cropland expansion over the course of the 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).

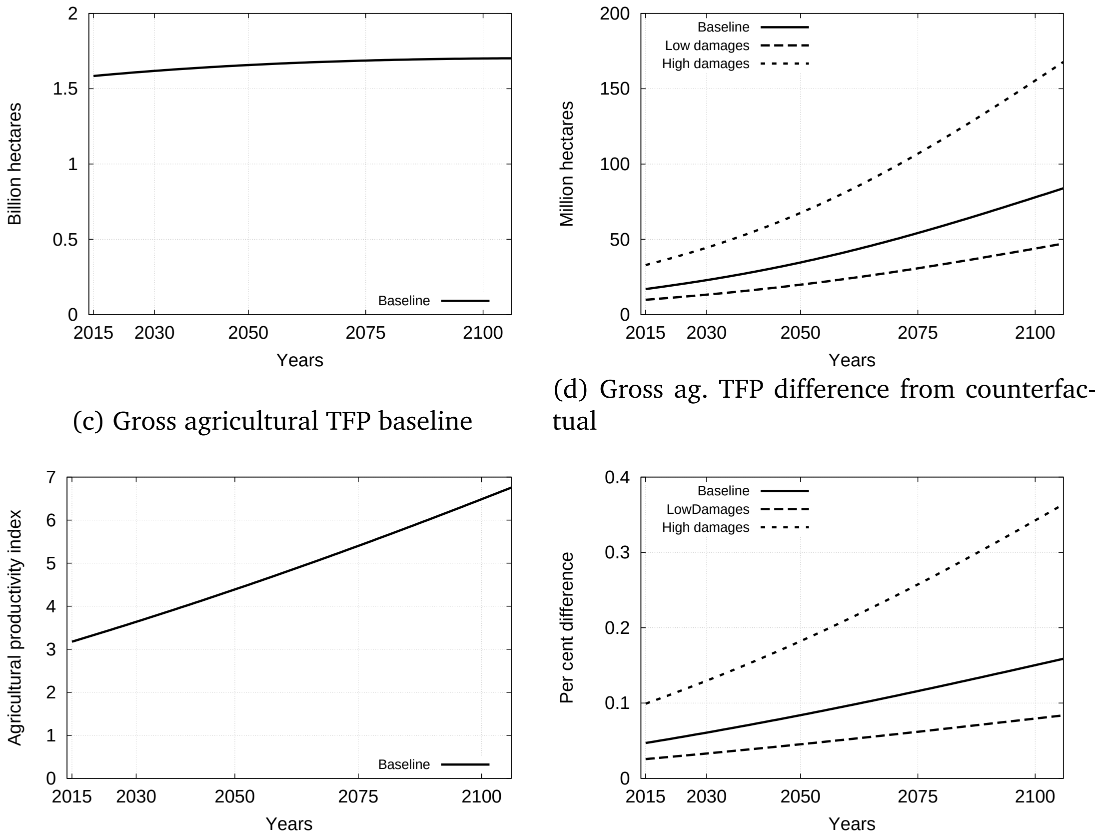
Consistent with our historical estimates, adaptation to climate change through general equilibrium factor reallocation is therefore effective in mitigating the impacts of climate change. This

Figure 6: Future projections and estimates of future climate change impacts on output and population relative to a counterfactual with no climate damages



is exemplified by cropland 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

Figure 7: Future estimates of cropland and agricultural innovation, and and estimates of future climate change impacts relative to counterfactual with no climate damages



(a) cropland baseline

(b) cropland difference from counterfactual

(c) Gross agricultural TFP baseline

(d) Gross ag. TFP difference from counterfactual

preferences for fertility, lower substitutability of land in agriculture and lower substitutability of fossil/clean energy in industry, *inter alia*.

5.2 Optimal policy

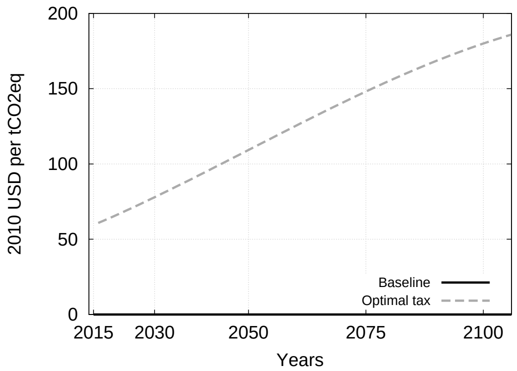
Figure 8 shows projections of the Pigouvian GHG tax (panel a),[31] resulting total GHG emissions (b), the atmospheric concentration of GHGs (c), atmospheric temperature (d), and damages to agriculture and manufacturing (e and f).

The Pigouvian GHG 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 GHG 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

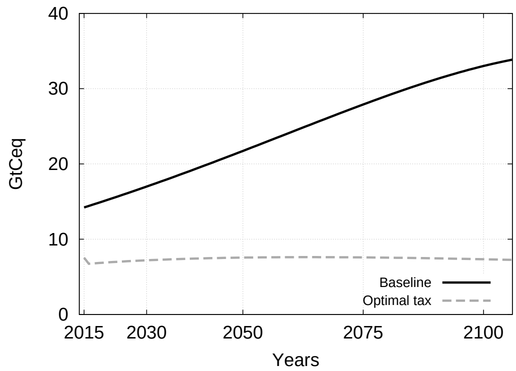
[31] This tax is implicitly levied not only on CO_2, but also on methane and nitrous oxide in proportion to their CO_2-equivalence.

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

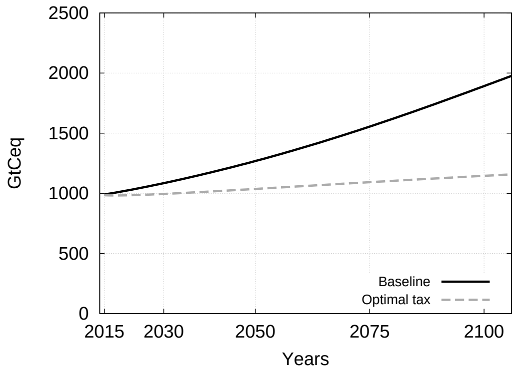
(a) GHG tax



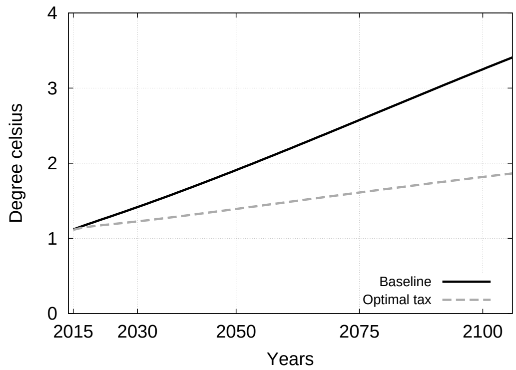
(b) Total GHG emissions



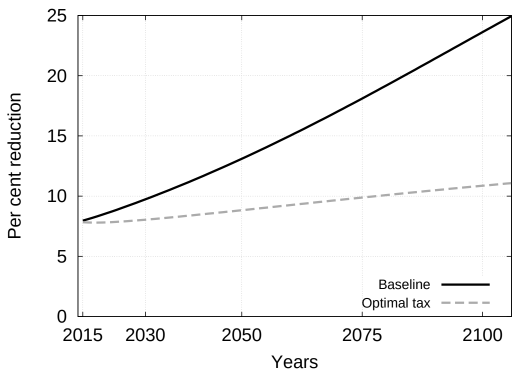
(c) Atmospheric GHG stock



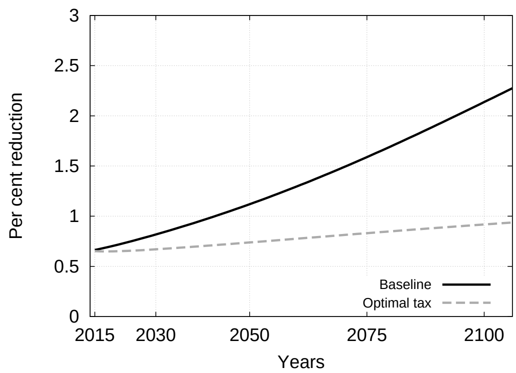
(d) Temperature relative to pre-industrial



(e) Damages to agricultural TFP



(f) Damages to manufacturing TFP



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.[32] 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".

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

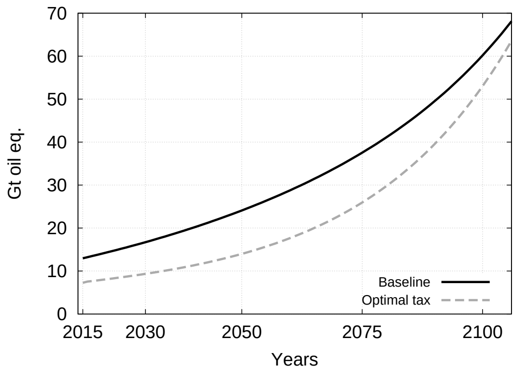
Figure 9 brings together projections of energy inputs and also shows agricultural GHG emissions. Panel (a) shows that the GHG tax significantly reduces total global energy use. In 2050, the baseline world economy uses 26Gt oil eq, while on the optimal path energy use is only 12 Gt oil eq. Moreover panels (b) and (c) show that the GHG 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 10 looks at what the baseline and optimal paths mean for agriculture (panels a, b and c), population (panel d) and consumption (panels e and f). On the optimal path, substantially less cropland 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 GHG 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. The difference is about 12% in 2100. Under pressure from the GHG tax to use comparatively less land and to abate associated agricultural emissions, increased agricultural R&D compensates through higher productivity growth. 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. The optimal path sustains a larger world population than the baseline path. The world population is 22

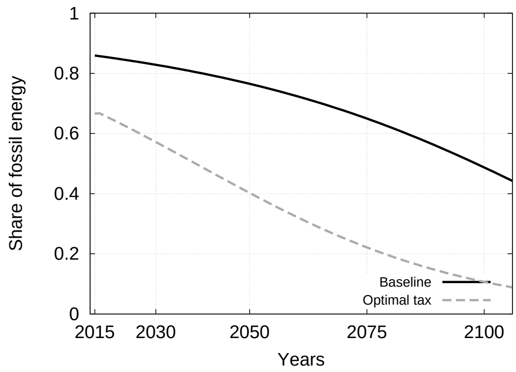
[32] As we feed not only CO_2 emissions into the model of Geoffroy et al. (2013), but also methane and nitrous oxide (in tCO_2eq), we make a bias correction of -0.372°C to the level of temperature in all years, which corresponds with the difference between the model projection of warming in 2005 relative 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 9: Baseline and optimal paths for energy and agricultural emissions

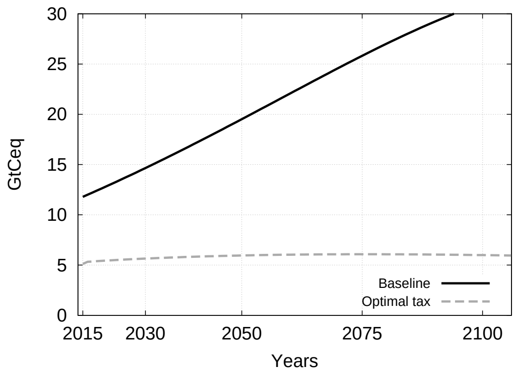
(a) Global energy use



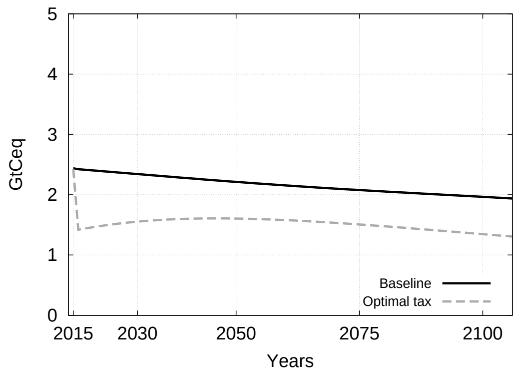
(b) Share of fossil energy



(c) Fossil GHG emissions



(d) Agricultural GHG emissions



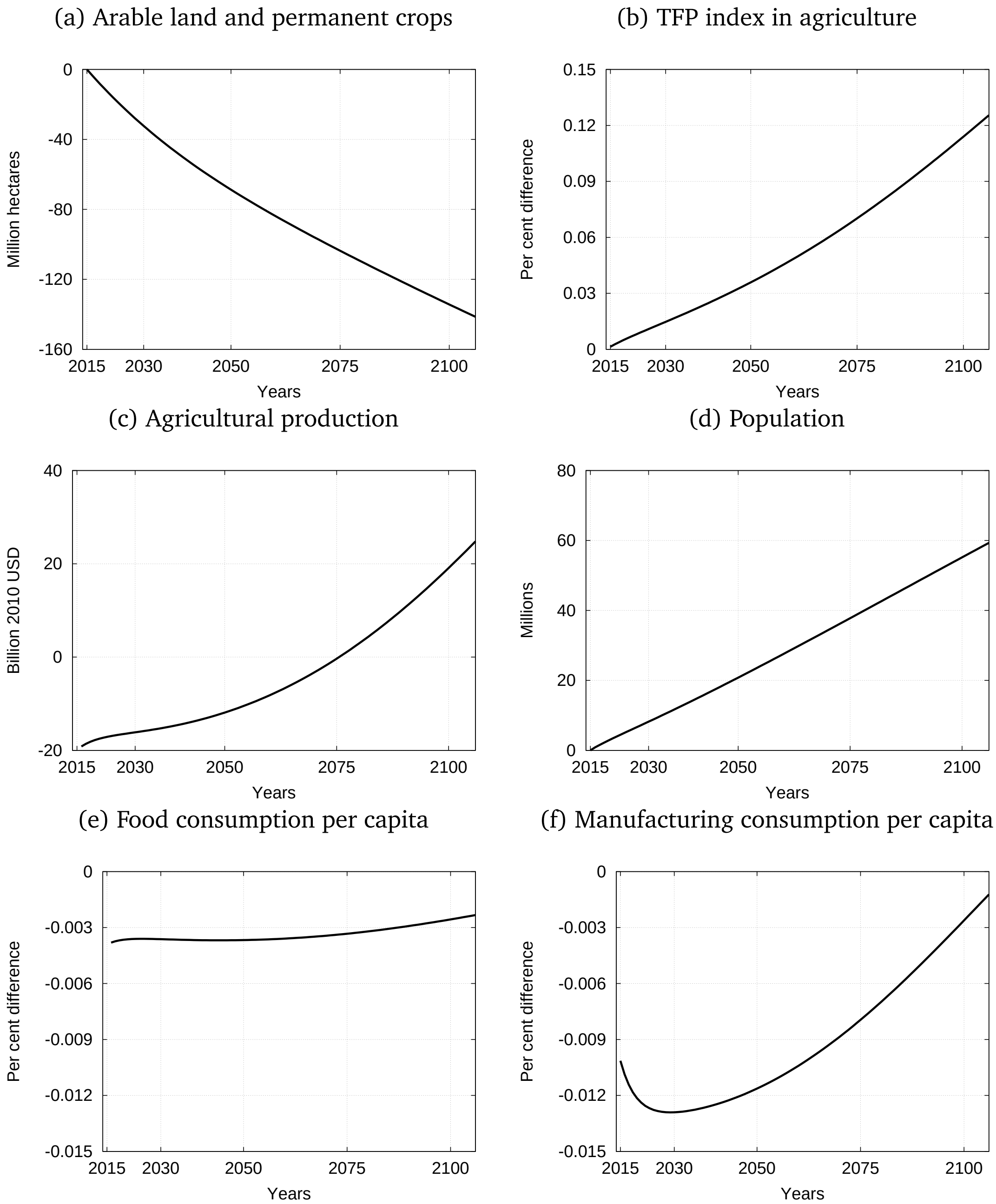
million higher in 2050 and 57 million higher in 2100. Per-capita consumption of food and the manufactured good are both fractionally lower on the optimal path, although consumption of the manufactured good is higher than on the baseline path after 2100.

6 Sensitivity analysis

Table 4 reports a sensitivity analysis of our future projections, focusing on the optimal policy. We report the sensitivity of four key variables: the GHG tax, total GHG emissions, cropland and population, each for three representative points in time. We explore three issues. First, we consider the welfare impacts of food-related climate change damages. Second, we document the effect of population growth by integrating UN population projections in our model. Third, we test the robustness of our results with respect to the parameters used in the model. We now discuss each set of results in turn, and provides underlying trajectories in Appendix E.

Starting with our main damage specification, we compare it with results derived from a model in which total economy-wide damages are the same, but climate change does not directly impact food supply. This allows us to quantify the impact of incorporating a separate channel

Figure 10: Optimal paths for agriculture, population and consumption relative to the baseline



through which agricultural damages impact welfare, namely via the role of food in sustaining population, with how climate climate damages are modeled in standard IAMs (treating food and other consumption goods as perfect substitutes in welfare). To construct this alternative, we set $\Omega_{ag} = 0$ and $\Omega_{mn} = 2.612\text{E}^{-4}$.[33]

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

Table 4: Sensitivity of key variables to parameter variations

	2020	2050	2100	2020	2050	2100
	GHG 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
$\beta = 0.97$	37.07	64.25	115.59	9.62	11.94	12.82
$\gamma = 1$	59.95	88.72	139.46	7.19	8.65	9.41
$\eta = 0.5$	54.74	87.16	131.10	7.87	8.67	8.52
	Δ cropland 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
$\beta = 0.97$	-14.38	-76.72	-157.76	3.03	24.76	90.29
$\gamma = 1$	-14.92	-81.50	-151.75	5.47	36.11	90.73
$\eta = 0.5$	-13.19	-70.31	-132.99	3.31	29.33	88.68

It is clear that the specification of damages, specifically how damages to the agricultural sector impact welfare, matters a great deal. Take the optimal GHG tax for instance. If the impact of climate change is concentrated on the manufacturing sector, the optimal GHG tax is only \$18/tCO$_2$eq 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. Given smaller incentives to reduces emissions, agricultural land area declines significantly less than in the baseline. And given a lack of climate damages in agriculture, the cost of population increments does not rise as in the baseline, which in turn implies that 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 E.2). This demand is met by expansion of the manufacturing sector, and the resulting optimal GHG 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 GHG tax path in our main specification fundamentally derives from endogenous population and its prediction of relatively strong population growth. Previous findings that GHG taxes increase rapidly, either at or above the rate of growth of GDP per capita (Golosov et al., 2014; Rezai and van der Ploeg, 2016; Dietz and Venmans, 2019), may not be robust to assumptions about population and/or 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. Changing these parameters necessitates re-estimating the models, with ensuing estimates reported in Appendix D.

One 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 GHG taxes, much lower GHG emissions, bigger differences in cropland 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 cropland 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 cropland. Accordingly, the difference between the area of cropland 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, adaptation implies that land-use change is very similar to our baseline specification.

With less weight placed on future utility, a higher utility discount rate ($\beta = 0.97$) yields lower optimal GHG taxes, higher optimal GHG emissions, but little difference in cropland 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 cropland 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,[34] 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 cropland. The effect of varying η on the difference in population and cropland is small, however.

7 Discussion and conclusion

In this paper, we have proposed a structural model of the world economy as a laboratory to study the relationship between climate change, population growth and food security, both in the past and in the future. Our approach builds 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). We also 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.[35] In particular, our structural approach allows us to quantify the extent of adaptation to climate change, in the form of agricultural land expansion and R&D investments, as a way to compensate reduced agricultural productivity. Our work therefore complements recent empirical work on the issue, especially estimates derived from long differences (Dell et al., 2012; Hsiang, 2016).

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 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 general equilibrium

[34] 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.

[35] 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).

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 GHG tax, which implies the welfare cost of a laissez-faire future is large, despite the adjustments 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 cropland 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.[36]

We close by emphasizing that our model has necessarily made a number of simplifying assumptions, which suggests a number of avenues open for future research. In particular, the high level of adaptability displayed by our model economy deserves further comment. 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 reskilling. The lack of explicit sectoral capital stocks in energy and R&D – for tractability reasons – also means that we are unable to interpret the model's labor shares literally and compare them with observed values. Our framework could therefore be augmented with sectoral and geographical constraints to factor mobility, which are likely to increase the expected cost of coping with climate change.

[36] 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.

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

Our SWF is given by

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

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

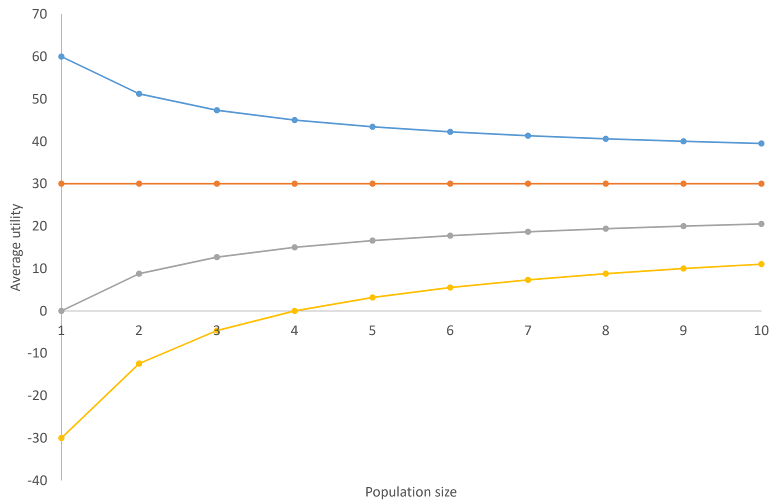
Here we sketch the ethical properties of NDCLU for $0 < \eta < 1$, following closely the expositional approach and terminology of Blackorby et al. (2005, chapter 5, part A). A formal treatment has been provided by Asheim and Zuber (2014). First, since average utility is multiplied by a positive-valued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

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

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

It is an impossibility theorem in population ethics that no SWF satisfies all four of these axioms. See Blackorby et al. (2005) for a full discussion. Classical/total utilitarianism satisfies existence independence, negative expansion and priority for lives worth living, but does

Figure A1: Critical-level number-dampened utilitarianism



not avoid Parfit's (1984) repugnant conclusion. Average Utilitarianism avoids the repugnant conclusion and satisfies priority for lives worth living, but neither existence independence nor negative expansion. Critical-level utilitarianism avoids the repugnant conclusion and satisfies existence independence as well as negative expansion, but now priority for lives worth living is not satisfied.

Appendix B Optimization problem

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

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

This problem falls in the class of infinite horizon non-linear optimal control problem, and we can rely on efficient mathematical programming solvers to search for an optimum in the intertemporal welfare function subject to the set of technological constraints and feasibility constraints. Numerically, however, direct optimization methods cannot explicitly accommodate an infinite horizon: the problem includes both an infinite number of terms in the objective function and an infinite number of constraints, which can only be approximated when working with limited computer memory.[37]

Our approximation relies on the presence of a discount factor $\beta < 1$, which implies that

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

only a finite number of terms matter for the numerical solution. We therefore approximate the solution to the infinite horizon problem by truncating the time-horizon to the first T years. One implication of this approach is that shadow values for state variables drop to zero in period T, and we therefore need to select a value for T that is large enough to avoid that these terminal effect influence the solution over the period of interest. In our context, since we are interested in outcomes up to 90 periods after initialization (i.e. up to 2100 when the model is initialized in 2015), we select $T = 300$ based on evidence that an increase in T does not affect 2100 outcomes by more than 0.1 percent.

Concretely, the ensuing numerical mathematical program includes eleven continuous state variables, and for estimation and estimation of past climate change impacts we initialize the model to match observations in 1960, and solve it up to year 2260. For future projections and optimal climate policy runs, the model is re-initialized in 2015 based on optimal values determined in the corresponding 1960 solution, and solved up to year 2315. Once appropriately scaled, the nonlinear program solves in a matter of seconds, which is particularly important for the simulation-based estimation.

Finally, in order to solve for a laissez-faire allocation, we employ the decomposition procedure by Böhringer et al. (2007). Specifically, to computing a laissez-faire equilibrium in which the planner does not act to reduce climate damages, we set the stock of GHGs entering the damage function in equations 1 and 2 as fixed and exogenous. Doing so, however, creates a potential discrepancy between the GHG stock determining economic damages, which is exogenous, and the GHG stock resulting from emissions, which is controlled by the planner.

To reconcile both stocks, we follow the iterative procedure described in Böhringer et al. (2007), we sequentially update the exogenous stock variable entering climate damages with the GHG stock resulting from the decisions by the planner.[38] Our experience with the model suggests that, after two iterations, the exogenous GHG stock entering climate damages approximates the GHG stock resulting from emissions with an accuracy of 0.1 percent.

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

Appendix C Selection of parameter values

This section provides a discussion for some of the key parameters of the model, reported in Table 2. Starting with households preferences, we set the discount factor $\beta = 0.99$, which corresponds with a utility discount rate of 1%. This is consistent with empirical evidence on very long-run investments by Giglio et al. (2015), and with a recent survey of economists by Drupp et al. (2018). As an alternative, we also consider $\beta = 0.97$ in sensitivity analysis, which corresponds to a utility discount rate of 3%. The inverse of the elasticity of intertemporal substitution $\gamma = 2$ is consistent with the macro-economic estimates reported in Guvenen (2006). For reasons of tractability, logarithmic utility ($\gamma \to 1$) is often used instead, and we consider this alternative in the sensitivity analysis.

The two remaining preference parameters are u and η, which represent the critical level of utility and the elasticity of marginal utility with respect to fertility. We calibrate $u = 1$, so that the consumption level that makes incremental population units desirable is 1,000 US dollars (given $\gamma = 2$). This is broadly in line with the definition of a poverty level by the World Bank, and it also implies that our model is consistent with logarithmic utility as a limiting case. Further, in our baseline model we set $\eta = 0.001$ so that the SWF approximates (critical-level) classical utilitarianism, which is consistent with most previous analysis of optimal GHG taxes in the context of IAMs (e.g. Nordhaus, 2017; Golosov et al., 2014; Lemoine and Traeger, 2014; Cai and Lontzek, 2019).[39] Evidence reported in Lanz et al. (2017) suggest that a model with $\eta = 0.001$ is able to provide a better representation of the demographic transition as compared to higher values, although one implication is that the marginal utility of children is (almost) constant as the number of children increases. Despite this, we also consider $\eta = 0.5$ as a robustness test.[40]

In the food constraint, the income elasticity of food consumption is $\kappa = 0.25$, which matches econometric estimates reported in Thomas and Strauss (1997, see also Beatty and LaFrance, 2005). The scale parameter $\xi = 0.4$ is calibrated such that 1960 food consumption represents around 15 percent of world GDP, which is in line with Echevarria (1997). The last parameter determining population dynamics is the mortality rate $\delta_N = 0.022$, which is calibrated so that expected working lifetime of agents in the model is 45 years (United Nations, 2013).

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

In agriculture, we take the elasticity of substitution between land and the capital-labor-energy composite from long-run econometric evidence reported in Wilde (2013), which suggests $\sigma_X = 0.6$. Because there is uncertainty about this parameter, and because land use is an

[39] We avoid setting $\eta = 0$ to ensure that the objective function of the problem remains strictly concave.

[40] Experimentation with the model suggests that increasing the value of η substantially increases computational burden, which makes simulation-based estimation impractical for values above $\eta = 0.5$.

important GHG abatement channel in our model, we consider $\sigma_X = 0.2$ in the sensitivity analysis. Share parameters for capital and land are respectively $\theta_K = 0.3$ and $\theta_X = 0.25$, which is consistent with the work of Ashraf et al. (2008), and we set $\theta_E = 0.04$ to be in line with Golosov et al. (2014). Taken together, this implies that our agricultural technology is broadly in line with factor shares reported in the aggregate database of Hertel et al. (2012). The reconversion rate for agricultural land $\delta_X = 0.02$ is set so that agricultural land reverts back to natural land over a period of 50 years (Lanz et al., 2017), and the stock of natural land that can be converted is $\overline{X} = 3$ billion hectares (as discussed in Alexandratos and Bruinsma, 2012).

In the energy sector, we set the elasticity of substitution between clean and dirty intermediates $\sigma_E = 1.5$, drawing on evidence from inter-fuel substitution by Stern (2012). This assumption is also consistent with empirical evidence for non-electric energy reported in Papageorgiou et al. (2017). In the sensitivity analysis, we consider a case with lower substitution possibilities, and use $\sigma_E = 0.95$ as an alternative estimate (following Golosov et al., 2014). The share parameter for dirty energy $\vartheta_D = 0.65$ is also taken from Golosov et al. (2014), and total reserves for dirty energy is set to $\overline{R} = 5,000$ Gt of oil equivalent, in line with Rogner (1997). Note that the latter estimate takes into account all fossil fuels, as well as technological progress and new discoveries (this estimate is also used in Golosov et al., 2014; Acemoglu et al., 2016). The last parameter is $\lambda_j = 0.05$, which can be interpreted as the maximum feasible rate of yearly TFP growth.

The extent of sectoral climate damages is determined by the parameters 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 of 15.4 percent in 2050 (range 8.9 to 28.5 percent), relative to a reference scenario without climate change.[41] Using IPCC (2014a), we estimate the atmospheric GHG concentration (CO_2, methane and nitrous oxide) in the RCP8.5 scenario will be 1399 GtCeq in 2050, yielding $\Omega_{ag} = 0.000207$ (sensitivity range: 0.000115 to 0.000415). We lack estimates of the pre-adaptation or gross damages from climate change on manufacturing productivity. As a pragmatic approach we therefore calibrate manufacturing damages on the best estimate in the recent meta-analysis by Nordhaus and Moffat (2017), giving $\Omega_{mn} = 1.66\text{E}^{-5}$ (sensitivity range: -0.8E^{-5} to 3.73E^{-5}).[42] 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.

In Table C1, we report initial values for the stock variables. We set population in 1960 $N_0 = 3.03$ billion (United Nations, 2017) and cropland is $X_0 = 1.38$ billion hectares (FAO,

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

[42] 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.

2018). By contrast, initial values for sectoral TFP and capital are not observed, and we target the following moments. First, we use 1960 world GDP of USD 11.19 trillion (2010 prices) from World Bank (2018), and target agricultural output (assumed to be 15 percent of GDP, as discussed above) and manufacturing output (the remaining 85 percent). Second, based on evidence reported in Caselli and Feyrer (see 2007), we set the marginal product of capital in 1960 to 15 percent. Third, for energy intermediates, we use 1960 data from BP (2017) on non-fossil energy use (0.2 Gt of oil equivalent) and fossil energy use (2.67 Gt of oil equivalent). Taken together, this gives $A_{0,mn} = 6.2$, $A_{0,ag} = 1.52$, $A_{0,cl} = 22.02$, $A_{0,dt} = 68.76$, and $K_0 = 22.38$.

Last, Table C1 also provides parameter values for the climate module of Joos et al. (2013). We note that initial values of the unobserved carbon stocks $S_{0,i}$ are obtained by feeding estimated GHG emissions from 1750 to 1960 (Boden et al., 2017; FAO, 2018; Janssens-Maenhout et al., 2017; Le Quéré et al., 2018; Meinshausen et al., 2011) into the carbon-cycle model (20)-(22) under a pre-industrial parametrization (Millar et al., 2017). From 1960 onwards, the model is re-parametrized to match the contemporary response of carbon sinks to CO_2 accumulating in the atmosphere (again see Millar et al., 2017).

Table C1: Starting values and parameters for the climate module

Parameter value	Definition	Source
State variable: Initial values		
$N_0 = 3.03$	World population in 1960 (billion)	United Nations (2017)
$X_0 = 1.38$	Agricultural cropland in 1960 (billion ha)	FAO (2018)
$A_{0,mn} = 6.20$	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
$A_{0,cl} = 22.02$	Initial TFP in clean energy	Calibrated on 1960 fossil and non-fossil
$A_{0,dt} = 68.76$	Initial TFP in dirty energy	energy use
$S_{0,0} = 28.115$	Stock of carbon in reservoir 0 in 1960 (GtC eq)	Obtained by initializing model in pre-industrial
$S_{0,1} = 29.570$	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)	”
Parameters for the climate module		
$\overline{S} = 590$	Pre-industrial stock of atmospheric carbon (GtC eq)	IPCC (2013))
$\pi_{E,CO2} = 0.858$	Dirty energy CO_2 emissions factor (GtC eq. per Gt oil eq.)	Boden et al. (2017)
$\pi_{E,NCO2} = 0.211$	Dirty energy non-CO_2 emissions factor (GtC eq. per Gt oil eq.)	Meinshausen et al. (2011); World Bank (2018)
$\pi_X = 350.685$	Land use change emissions factor (Gt C eq. per bn ha)	Le Quéré et al. (2018)
$\pi_{ag} = 0.747$	Agricultural emissions factor (Gt C eq. per unit of input)	Meinshausen et al. (2011); World Bank (2018)
$a_0 = 0.217$	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 / ocean thermocline	“
$a_3 = 0.276$	Share of CO_2 going to rapid biospheric uptake / ocean mixed layer	“
$\delta_{S,0} = 1E^{-6}$	Geological re-absorption rate	“
$\delta_{S,1} = 0.00254$	Deep ocean invasion/equilibration 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	“

Appendix D Parameter estimates for sensitivity analysis

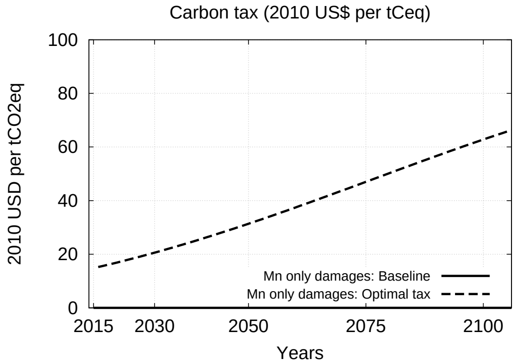
Table D1: Structurally estimated parameters

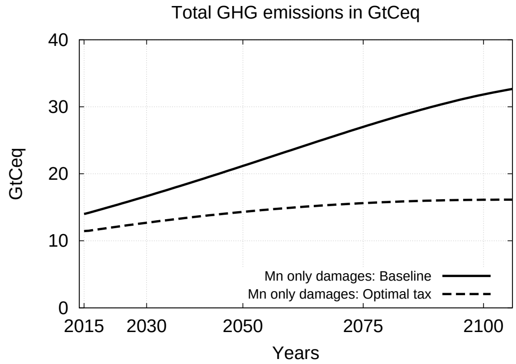
Parameter	Baseline	Alternative damages	Ω_{ag}, Ω_{mn} low	Ω_{ag}, Ω_{mn} high	$\sigma_E = 0.95$	$\sigma_X = 0.2$	$\beta = 0.97$	$\gamma = 1$	$\eta = 0.5$
χ	0.123	0.122	0.123	0.123	0.123	0.123	0.133	0.168	0.202
ζ	0.509	0.508	0.508	0.508	0.509	0.509	0.509	0.577	0.392
ω	0.071	0.07	0.072	0.072	0.071	0.071	0.067	0.225	0.123
ψ	0.083	0.084	0.083	0.083	0.083	0.075	0.08	0.081	0.073
ε	0.2535	0.2525	0.2535	0.2535	0.2535	0.228	0.245	0.233	0.262
μ_{mn}	0.298	0.297	0.301	0.294	0.298	0.298	0.378	0.696	0.691
μ_{ag}	0.431	0.43863	0.433	0.428	0.431	0.456	0.369	0.464	0.511
μ_{cl}	0.077	0.077	0.077	0.077	0.062	0.077	0.069	0.121	0.114
μ_{dt}	0.159	0.159	0.159	0.159	0.127	0.159	0.142	0.257	0.229

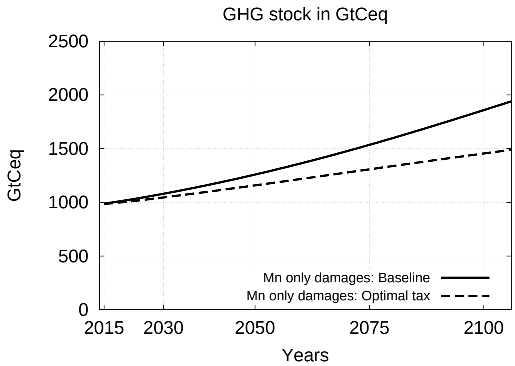
Notes: This table reports parameters estimated for the baseline model and sensitivity runs.

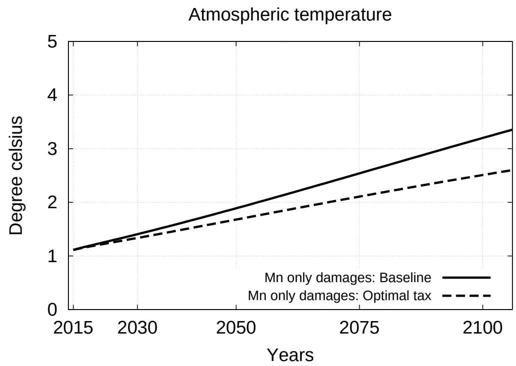
Appendix E Sensitivity analysis: Further results

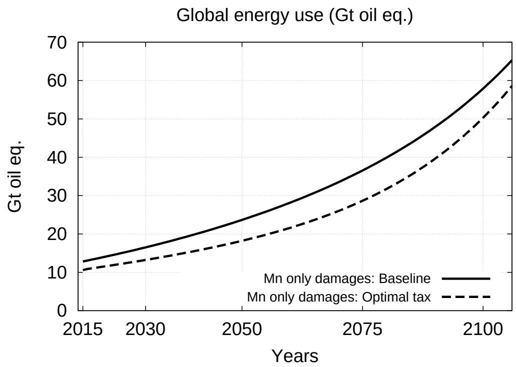
Appendix E.1 Alternative damages

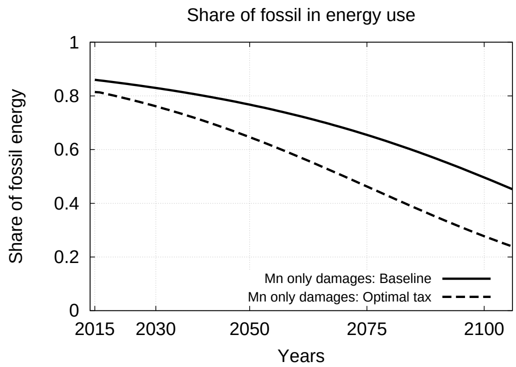


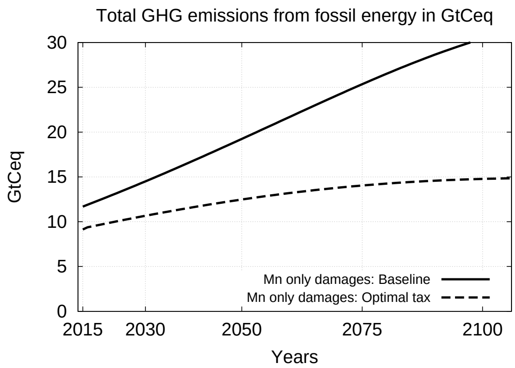


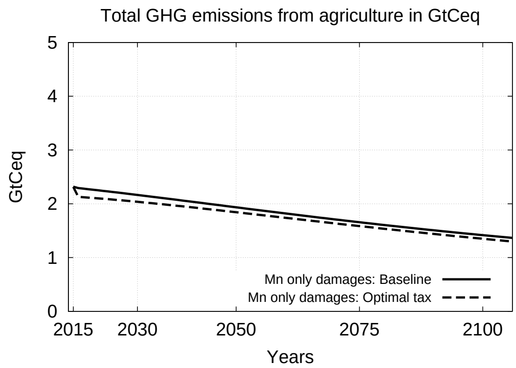


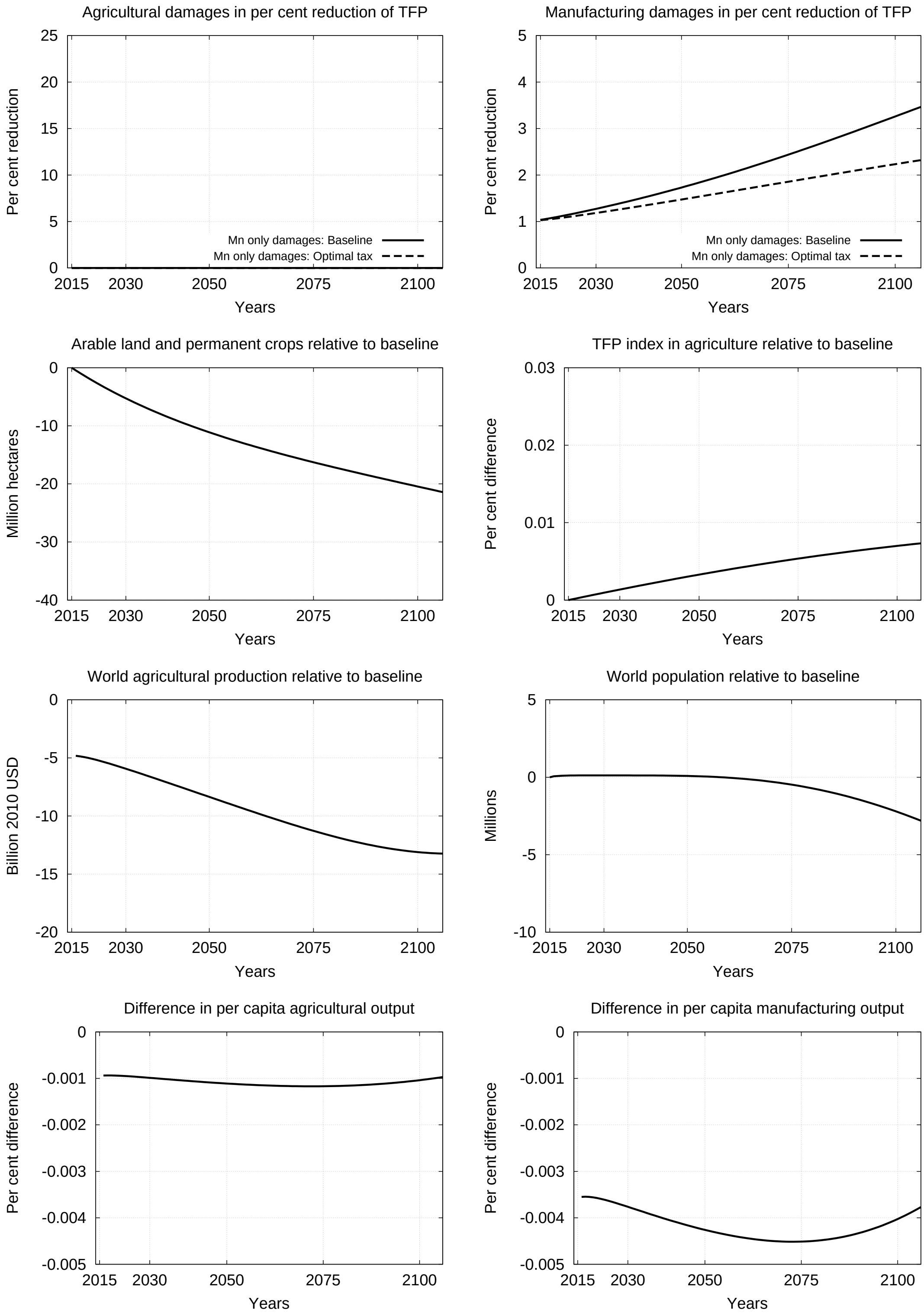




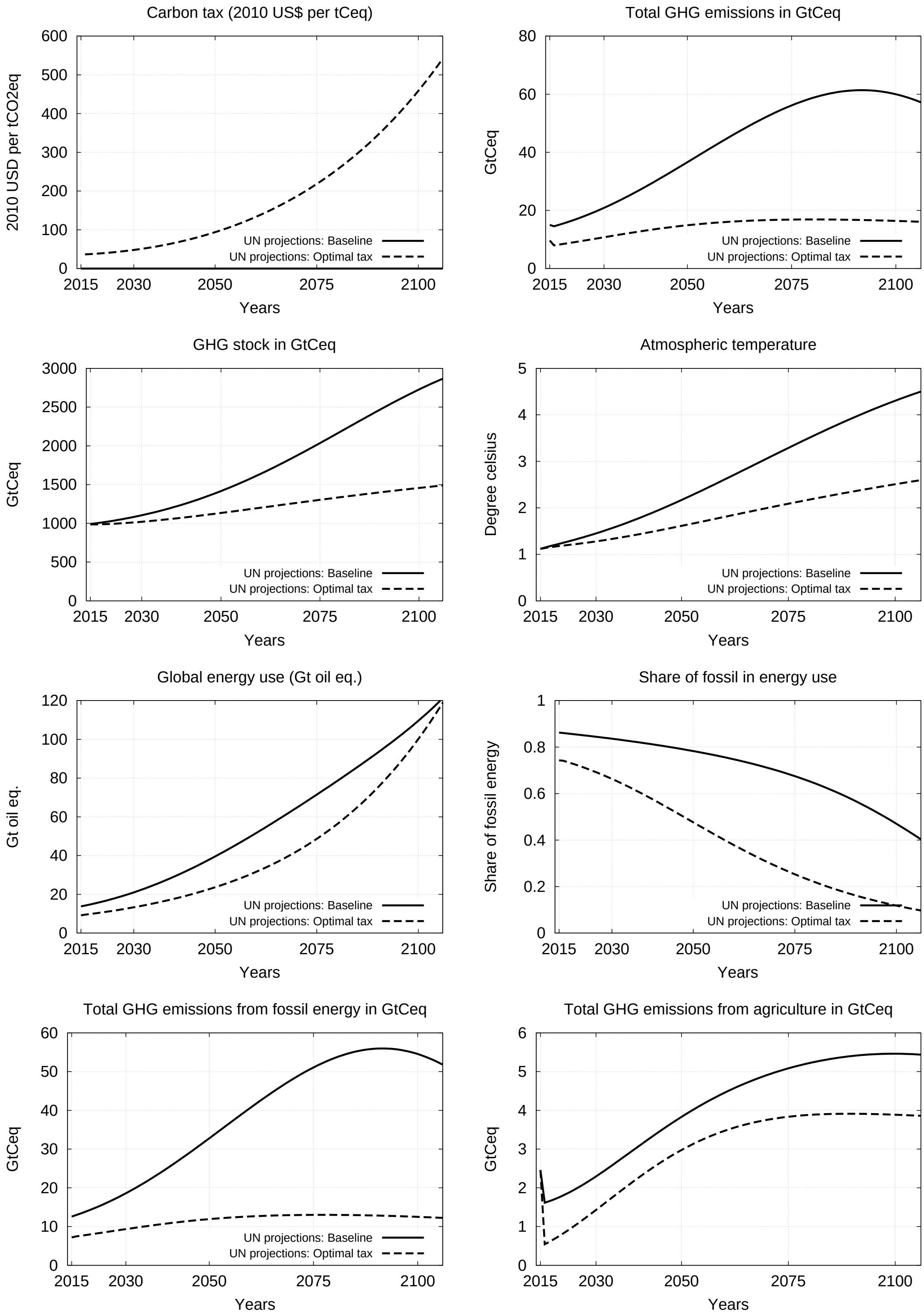


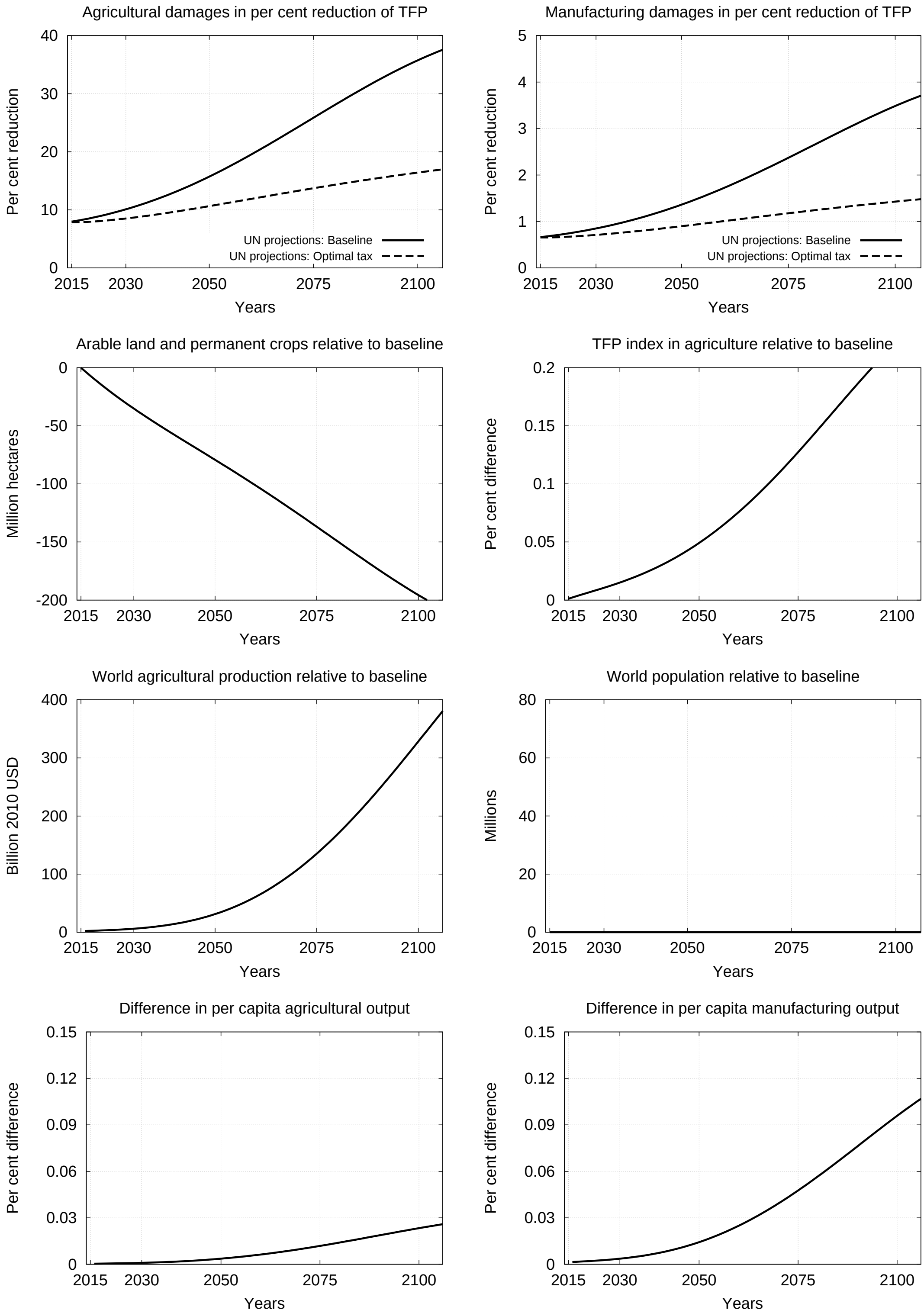




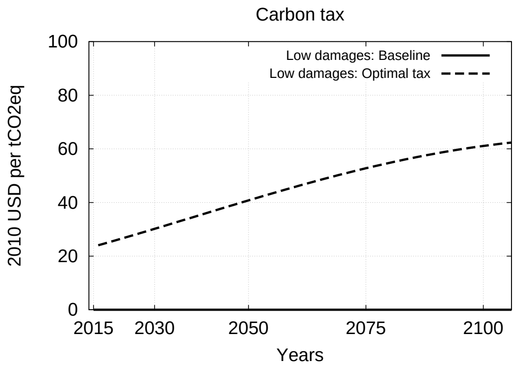

Agricultural damages in per cent reduction of TFP
Per cent reduction
Mn only damages: Baseline
Mn only damages: Optimal tax
Years
Manufacturing damages in per cent reduction of TFP
Per cent reduction
Mn only damages: Baseline
Mn only damages: Optimal tax
Years
Arable land and permanent crops relative to baseline
Million hectares
Years
TFP index in agriculture relative to baseline
Per cent difference
Years
World agricultural production relative to baseline
Billion 2010 USD
Years
World population relative to baseline
Millions
Years
Difference in per capita agricultural output
Per cent difference
Years
Difference in per capita manufacturing output
Per cent difference
Years

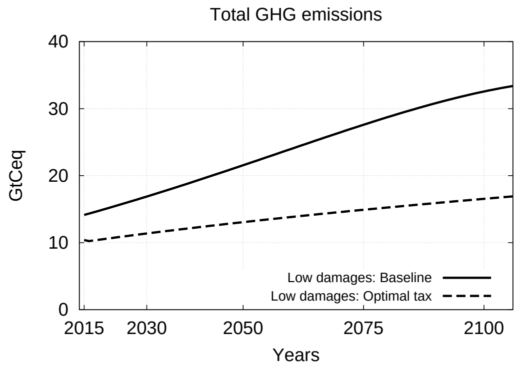
Appendix E.2 Exogenous population

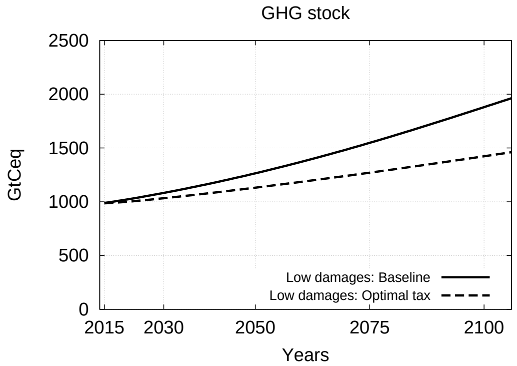


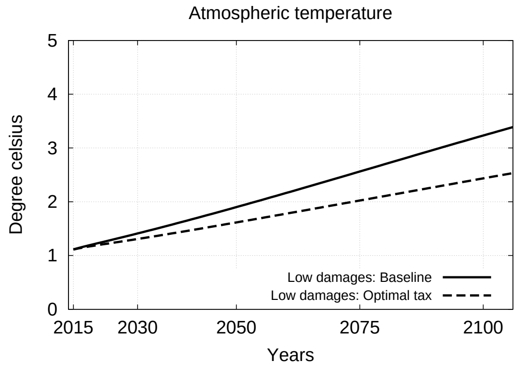

Agricultural damages in per cent reduction of TFP
Per cent reduction
UN projections: Baseline
UN projections: Optimal tax
Years
Manufacturing damages in per cent reduction of TFP
Per cent reduction
UN projections: Baseline
UN projections: Optimal tax
Years
Arable land and permanent crops relative to baseline
Million hectares
Years
TFP index in agriculture relative to baseline
Per cent difference
Years
World agricultural production relative to baseline
Billion 2010 USD
Years
World population relative to baseline
Millions
Years
Difference in per capita agricultural output
Per cent difference
Years
Difference in per capita manufacturing output
Per cent difference
Years

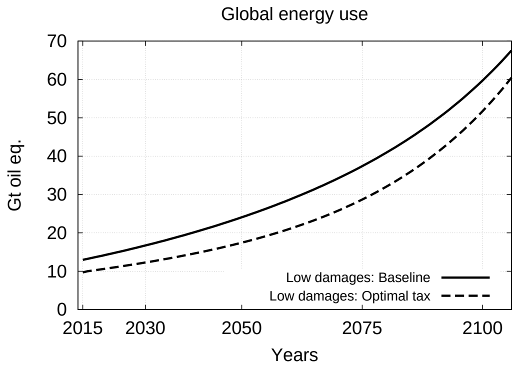
Appendix E.3 Low damages

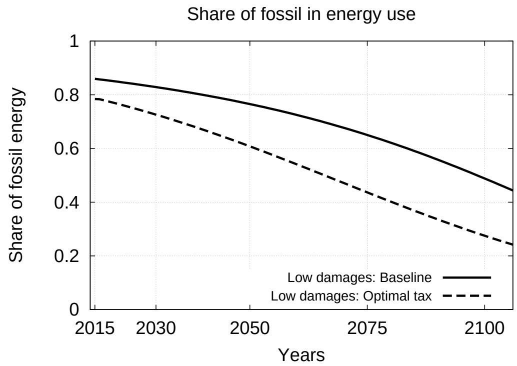


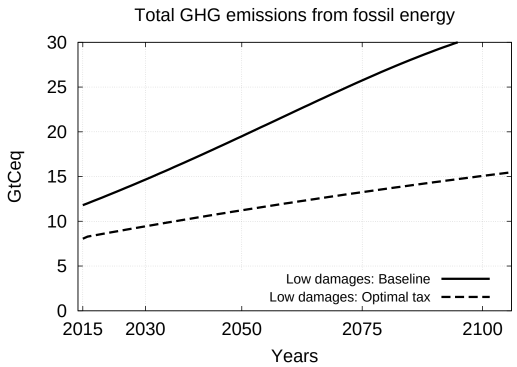


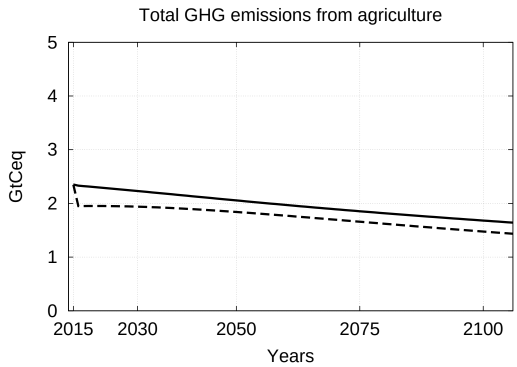


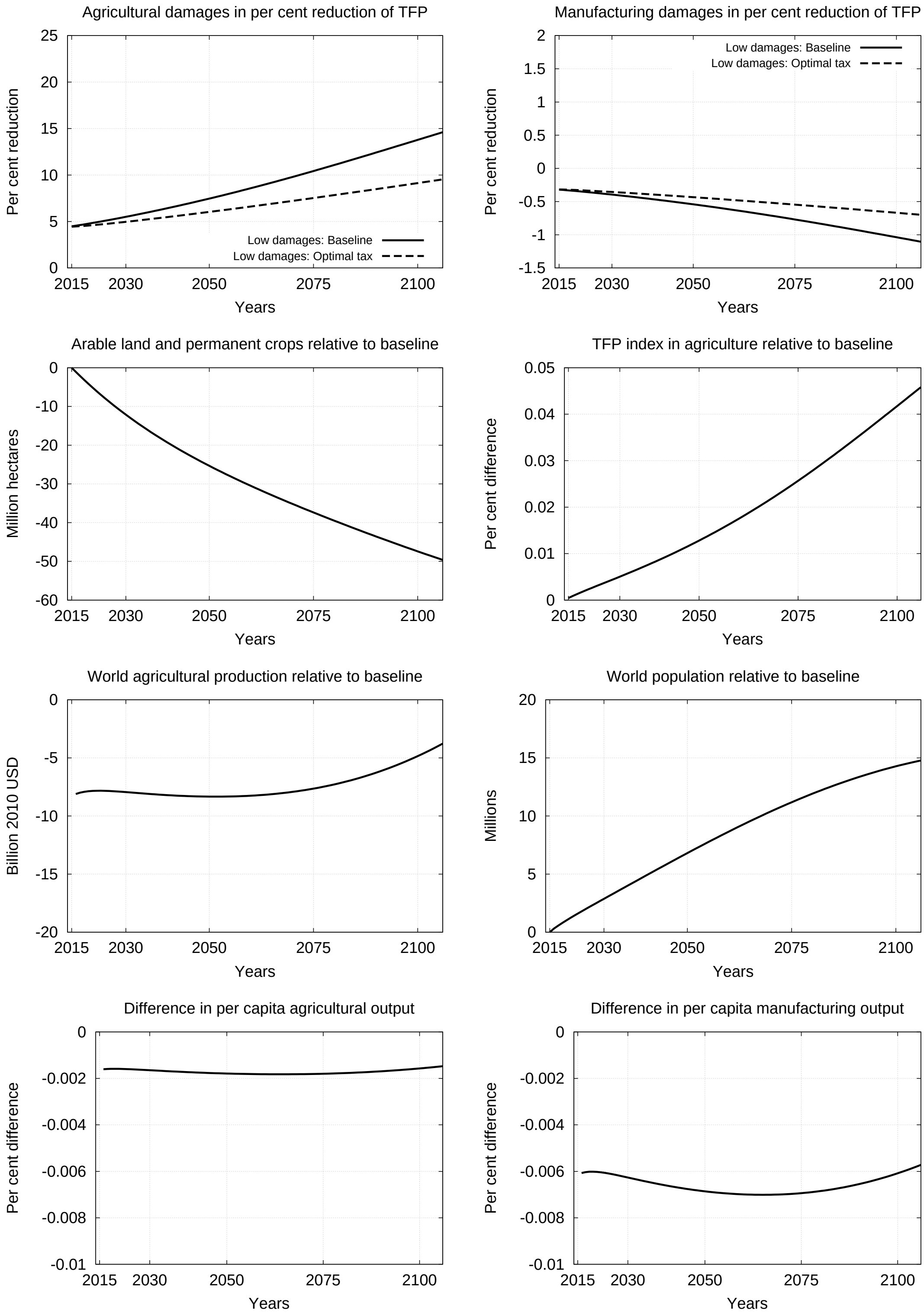




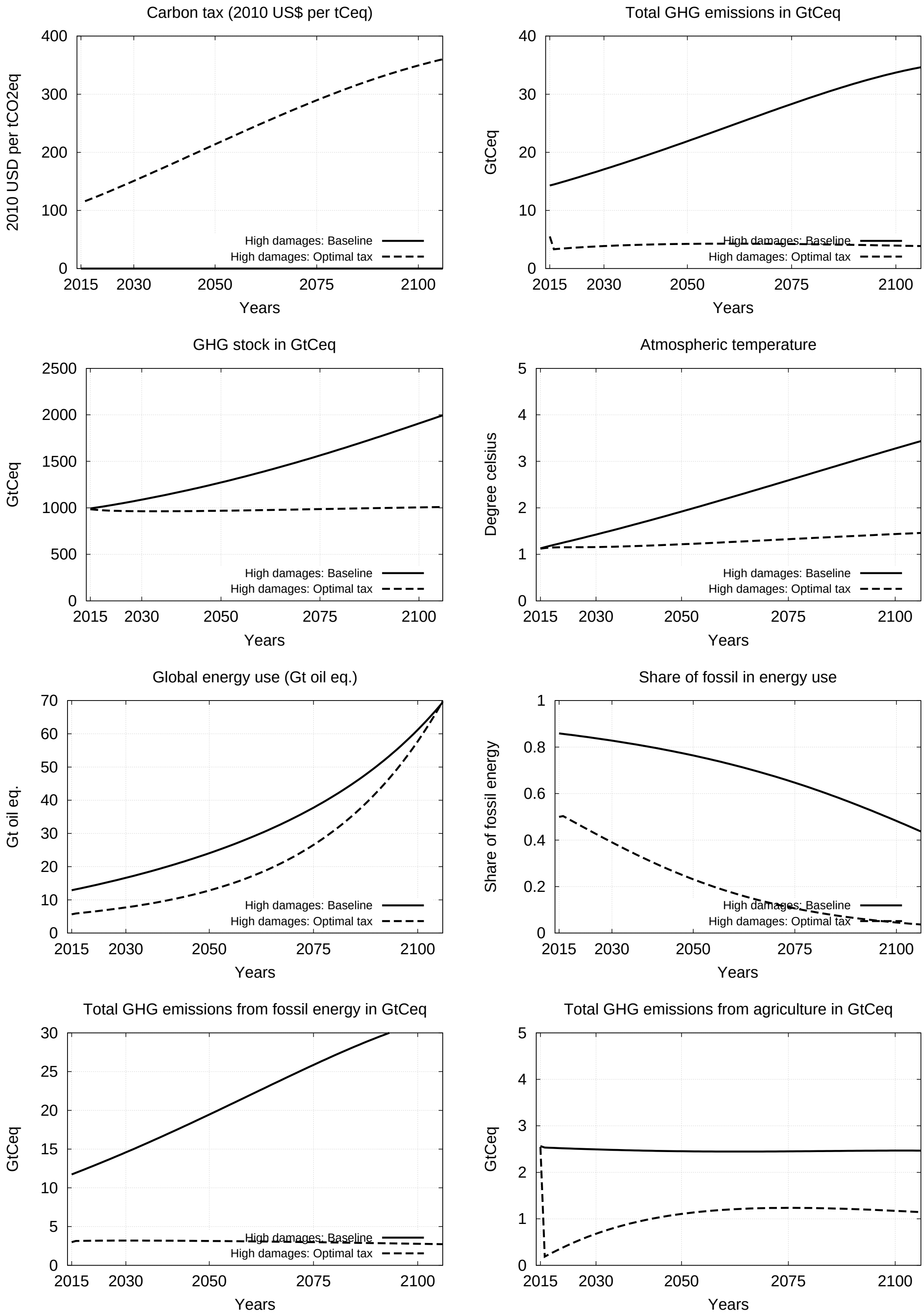


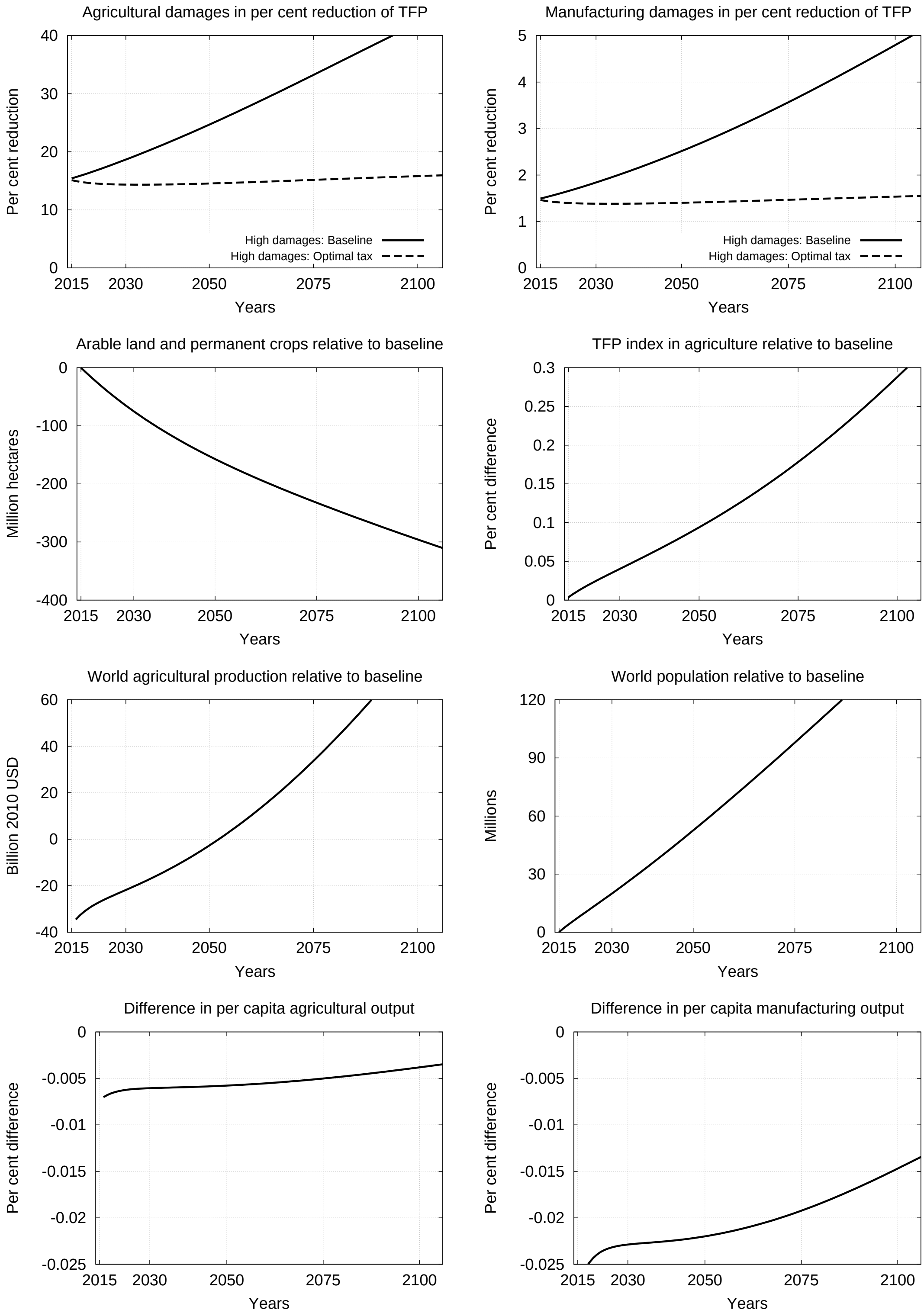




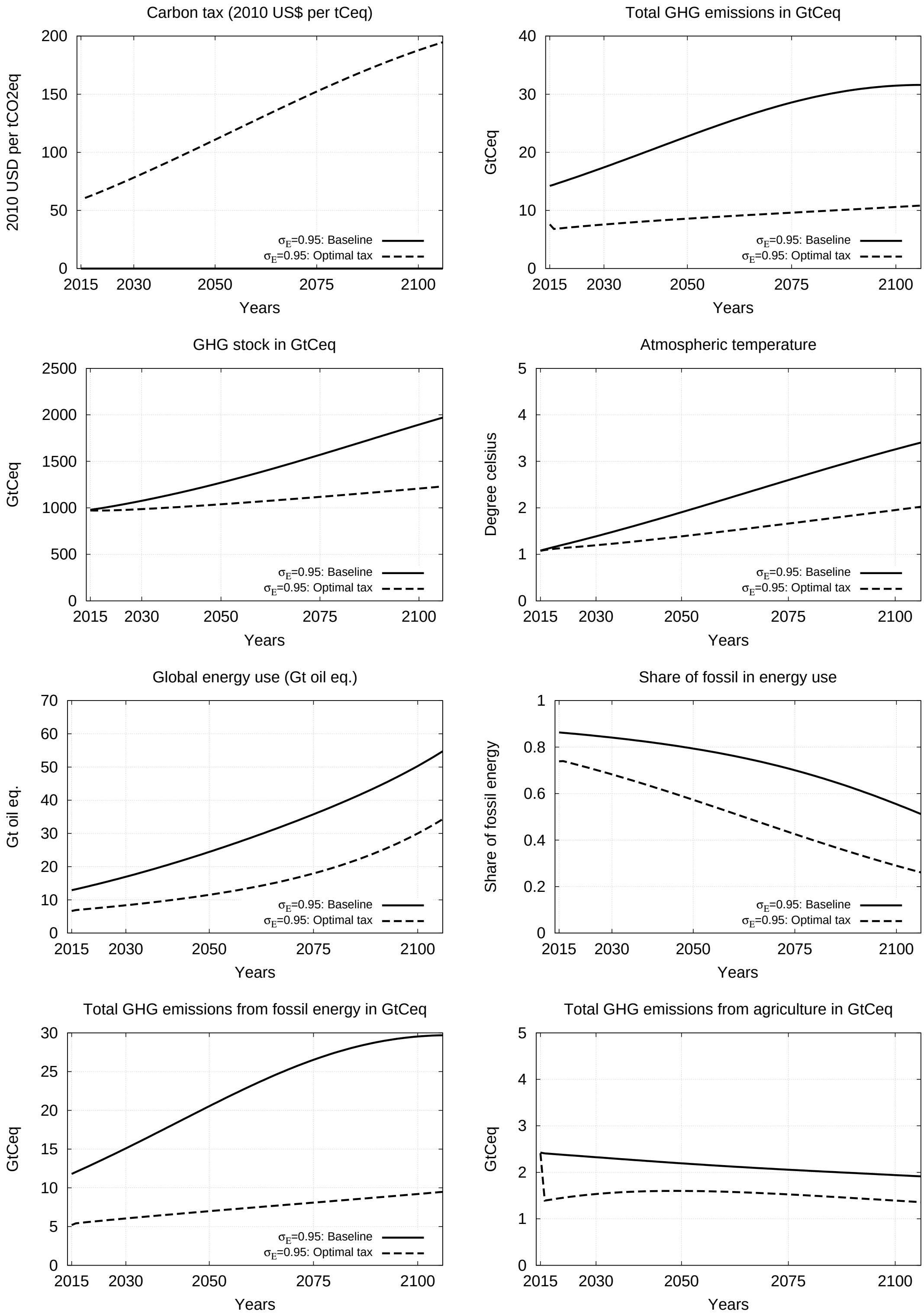

Agricultural damages in per cent reduction of TFP
Per cent reduction
Years
Low damages: Baseline
Low damages: Optimal tax
Manufacturing damages in per cent reduction of TFP
Per cent reduction
Years
Low damages: Baseline
Low damages: Optimal tax
Arable land and permanent crops relative to baseline
Million hectares
Years
TFP index in agriculture relative to baseline
Per cent difference
Years
World agricultural production relative to baseline
Billion 2010 USD
Years
World population relative to baseline
Millions
Years
Difference in per capita agricultural output
Per cent difference
Years
Difference in per capita manufacturing output
Per cent difference
Years

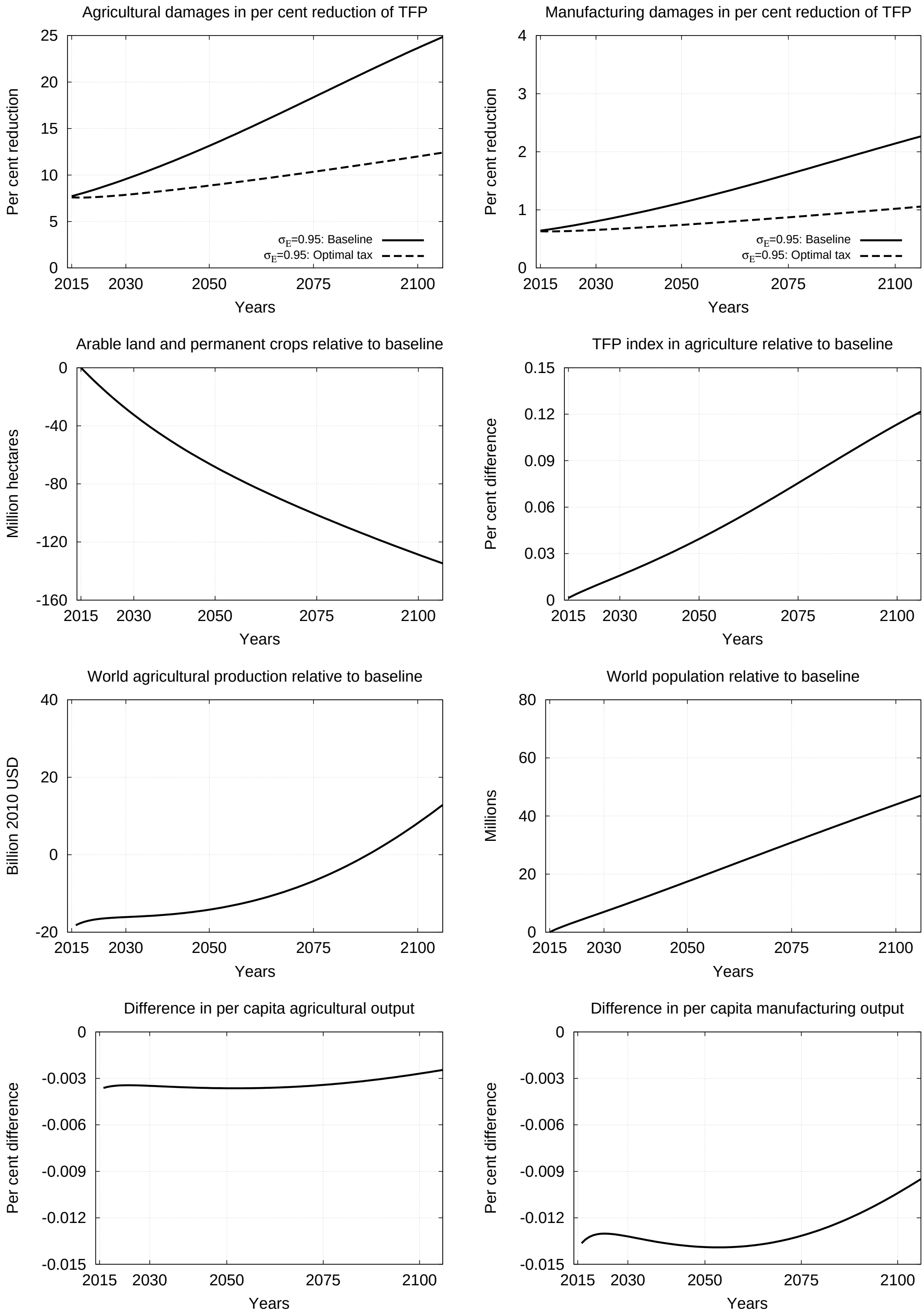
Appendix E.4 High damages




Agricultural damages in per cent reduction of TFP
Per cent reduction
High damages: Baseline
High damages: Optimal tax
Years
Manufacturing damages in per cent reduction of TFP
Per cent reduction
High damages: Baseline
High damages: Optimal tax
Years
Arable land and permanent crops relative to baseline
Million hectares
Years
TFP index in agriculture relative to baseline
Per cent difference
Years
World agricultural production relative to baseline
Billion 2010 USD
Years
World population relative to baseline
Millions
Years
Difference in per capita agricultural output
Per cent difference
Years
Difference in per capita manufacturing output
Per cent difference
Years

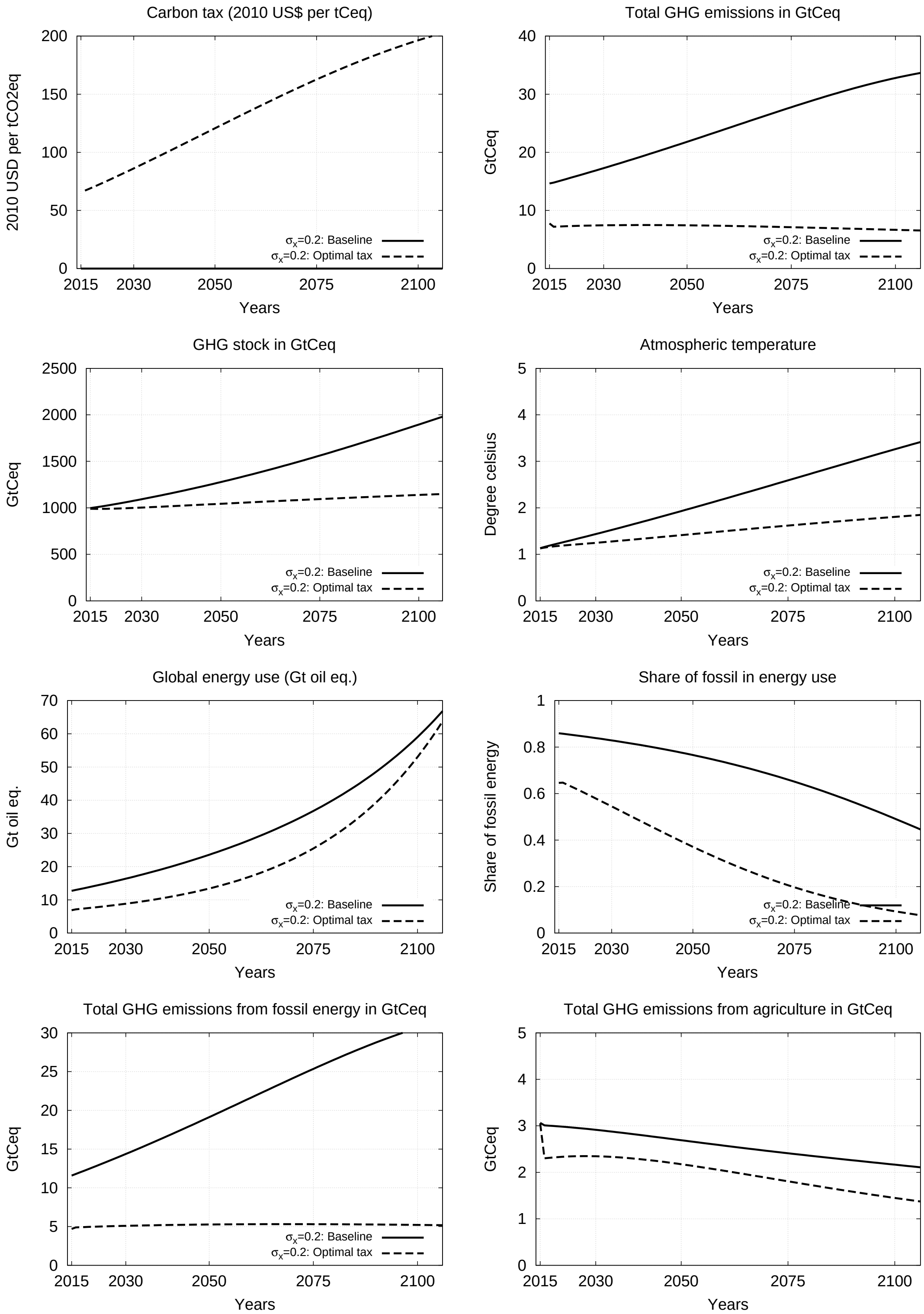
Appendix E.5 Low substitutability of clean and dirty energy intermediates

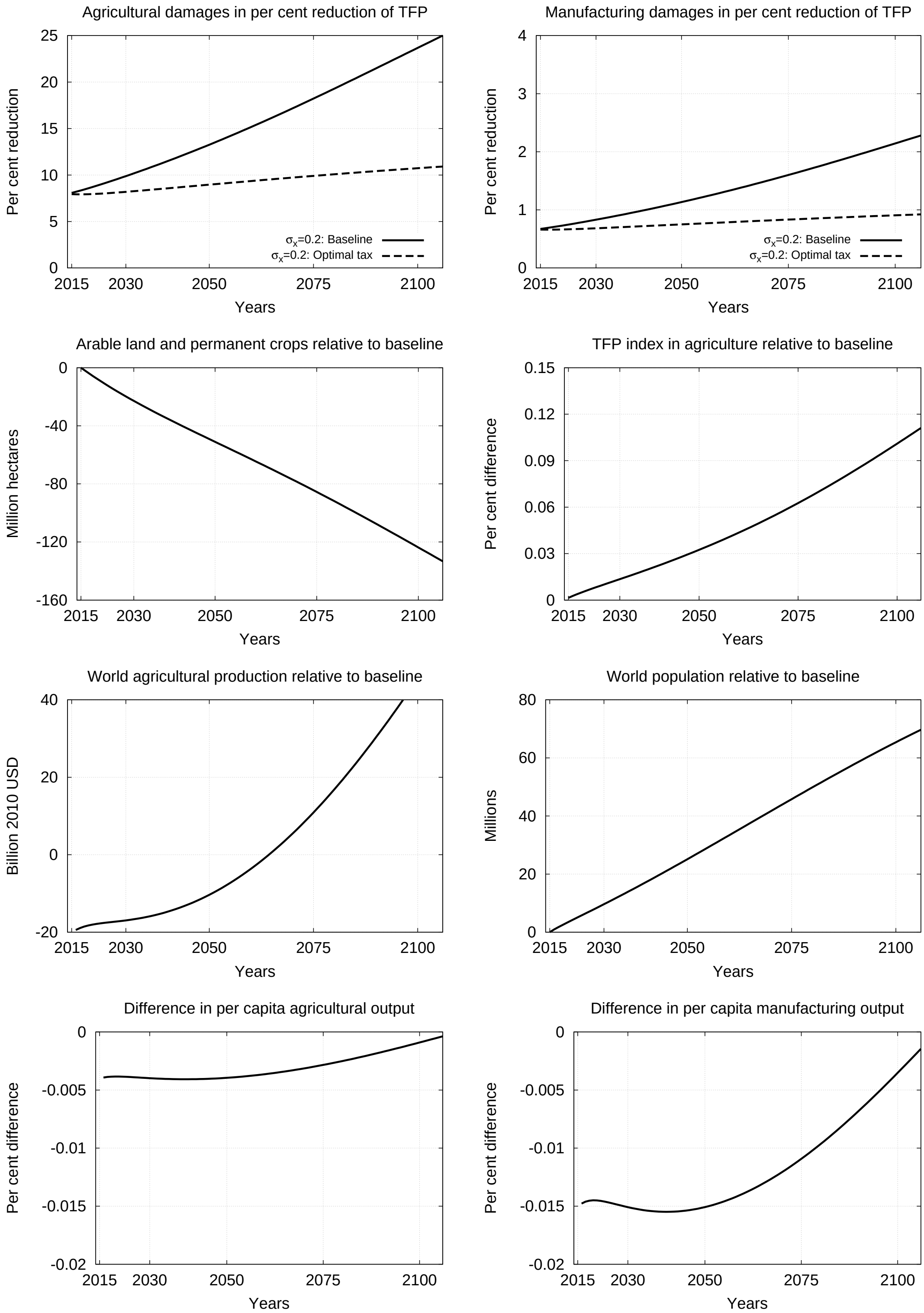




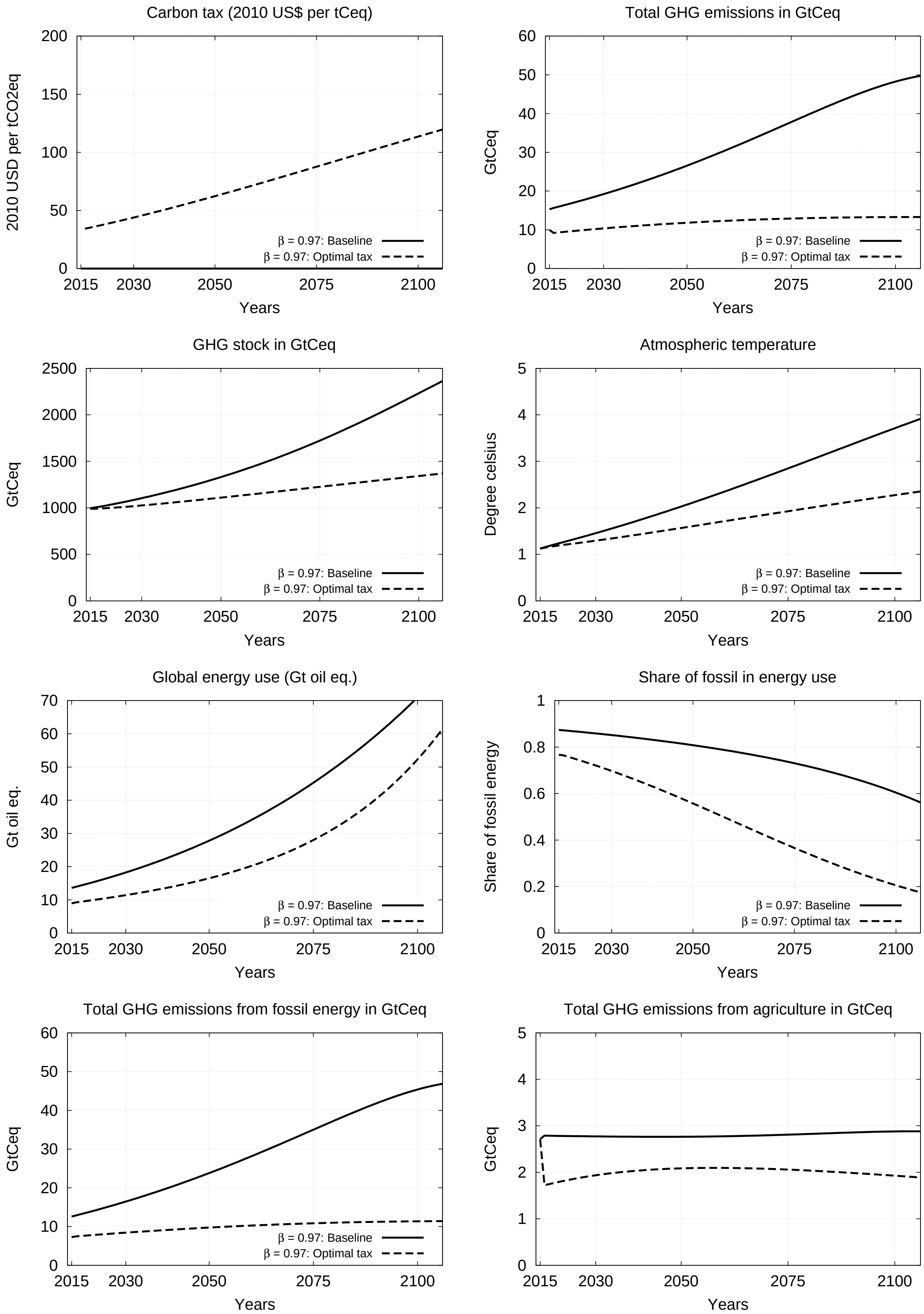
Agricultural damages in per cent reduction of TFP
Per cent reduction
σE=0.95: Baseline
σE=0.95: Optimal tax
Manufacturing damages in per cent reduction of TFP
Per cent reduction
σE=0.95: Baseline
σE=0.95: Optimal tax
Arable land and permanent crops relative to baseline
Million hectares
TFP index in agriculture relative to baseline
Per cent difference
World agricultural production relative to baseline
Billion 2010 USD
World population relative to baseline
Millions
Difference in per capita agricultural output
Per cent difference
Difference in per capita manufacturing output
Per cent difference
Years
2015
2030
2050
2075
2100

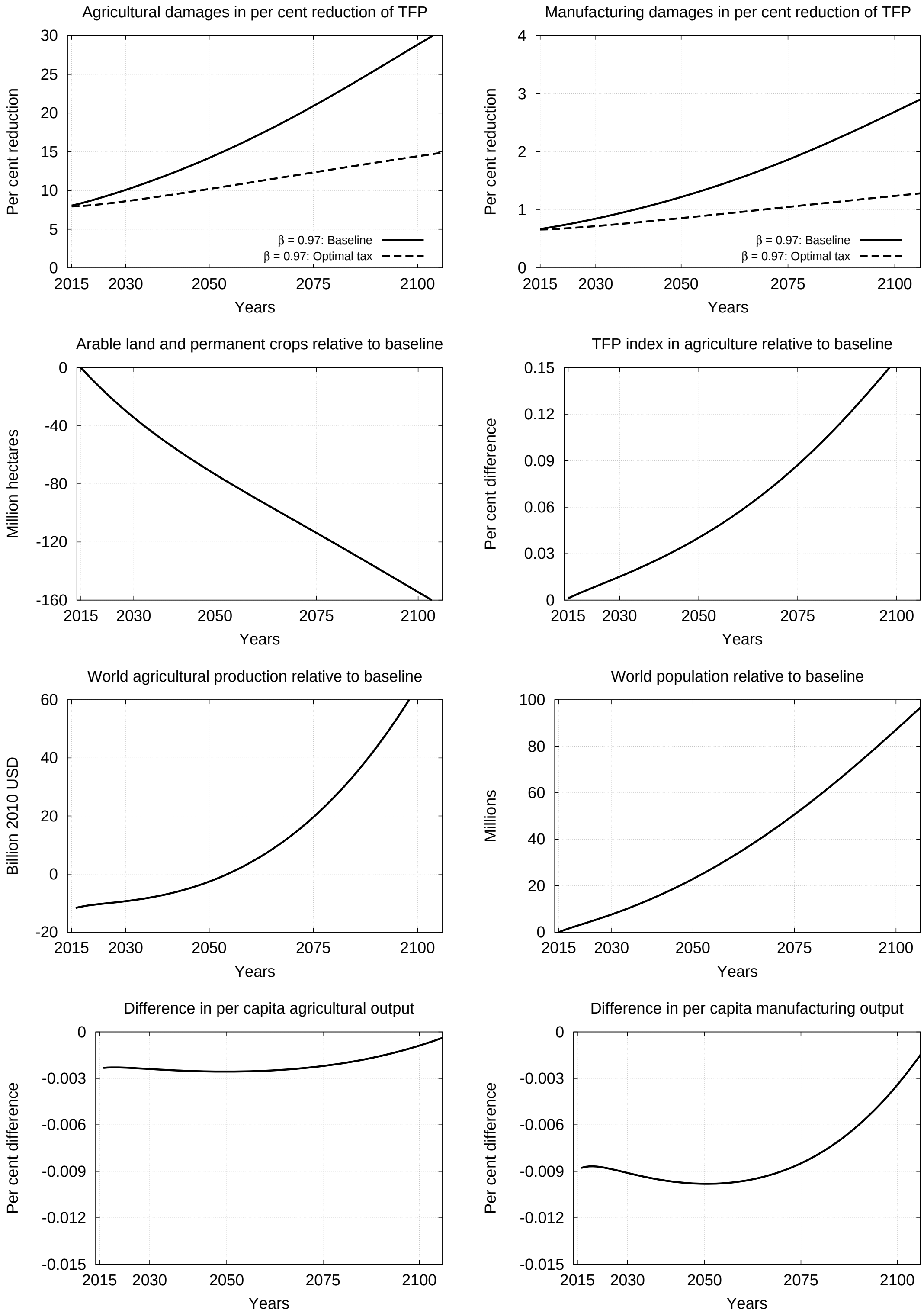
Appendix E.6 Low substitutability of land in agriculture




Agricultural damages in per cent reduction of TFP
Per cent reduction
σx=0.2: Baseline
σx=0.2: Optimal tax
Years
Manufacturing damages in per cent reduction of TFP
Per cent reduction
σx=0.2: Baseline
σx=0.2: Optimal tax
Years
Arable land and permanent crops relative to baseline
Million hectares
Years
TFP index in agriculture relative to baseline
Per cent difference
Years
World agricultural production relative to baseline
Billion 2010 USD
Years
World population relative to baseline
Millions
Years
Difference in per capita agricultural output
Per cent difference
Years
Difference in per capita manufacturing output
Per cent difference
Years

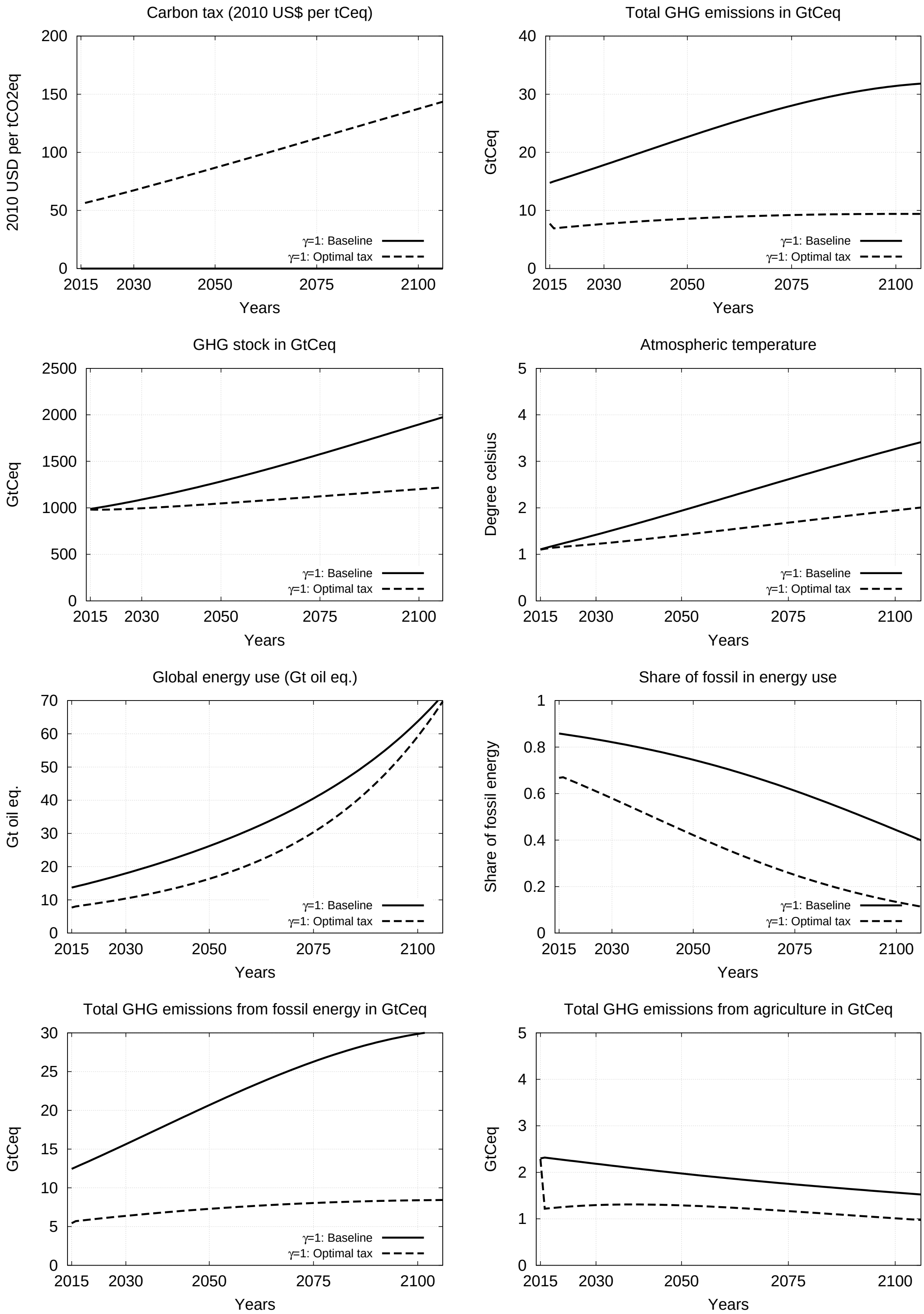
Appendix E.7 High discount rate

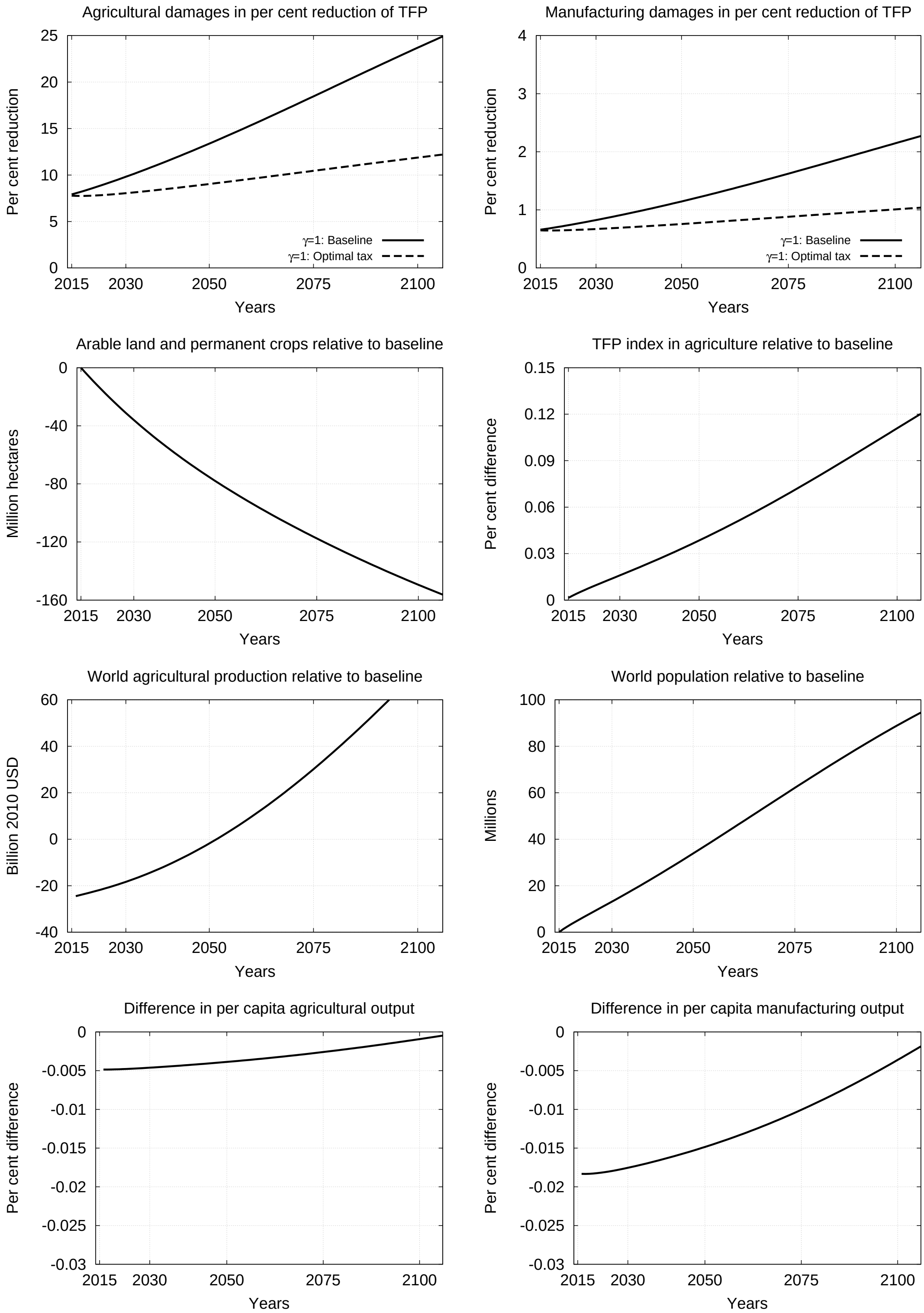




Agricultural damages in per cent reduction of TFP
Per cent reduction
30
25
20
15
10
5
0
β = 0.97: Baseline
β = 0.97: Optimal tax
2015
2030
2050
2075
2100
Years
Manufacturing damages in per cent reduction of TFP
Per cent reduction
4
3
2
1
0
β = 0.97: Baseline
β = 0.97: Optimal tax
2015
2030
2050
2075
2100
Years
Arable land and permanent crops relative to baseline
Million hectares
0
-40
-80
-120
-160
2015
2030
2050
2075
2100
Years
TFP index in agriculture relative to baseline
Per cent difference
0.15
0.12
0.09
0.06
0.03
0
2015
2030
2050
2075
2100
Years
World agricultural production relative to baseline
Billion 2010 USD
60
40
20
0
-20
2015
2030
2050
2075
2100
Years
World population relative to baseline
Millions
100
80
60
40
20
0
2015
2030
2050
2075
2100
Years
Difference in per capita agricultural output
Per cent difference
0
-0.003
-0.006
-0.009
-0.012
-0.015
2015
2030
2050
2075
2100
Years
Difference in per capita manufacturing output
Per cent difference
0
-0.003
-0.006
-0.009
-0.012
-0.015
2015
2030
2050
2075
2100
Years

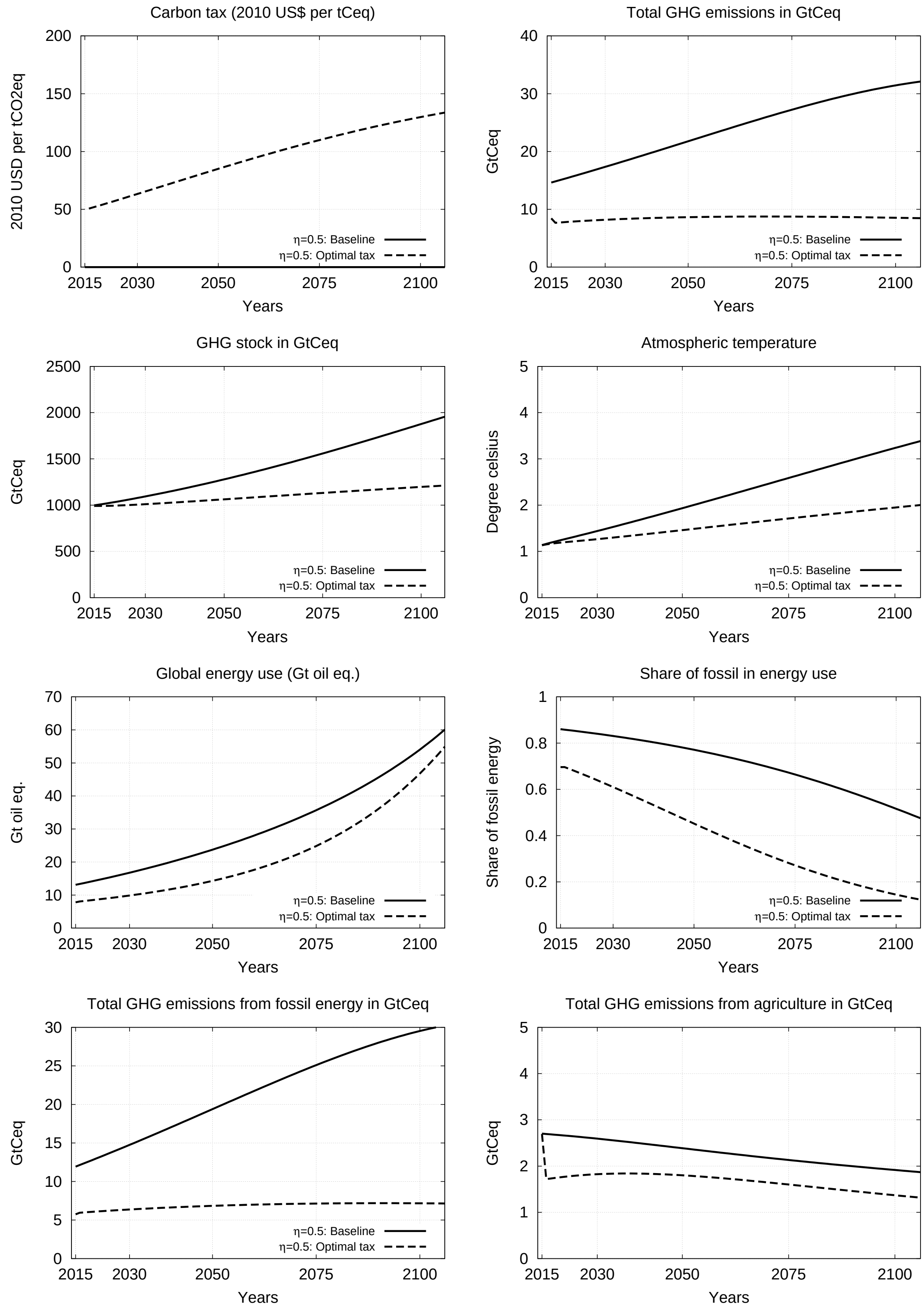
Appendix E.8 Low elasticity of marginal utility with respect to consumption

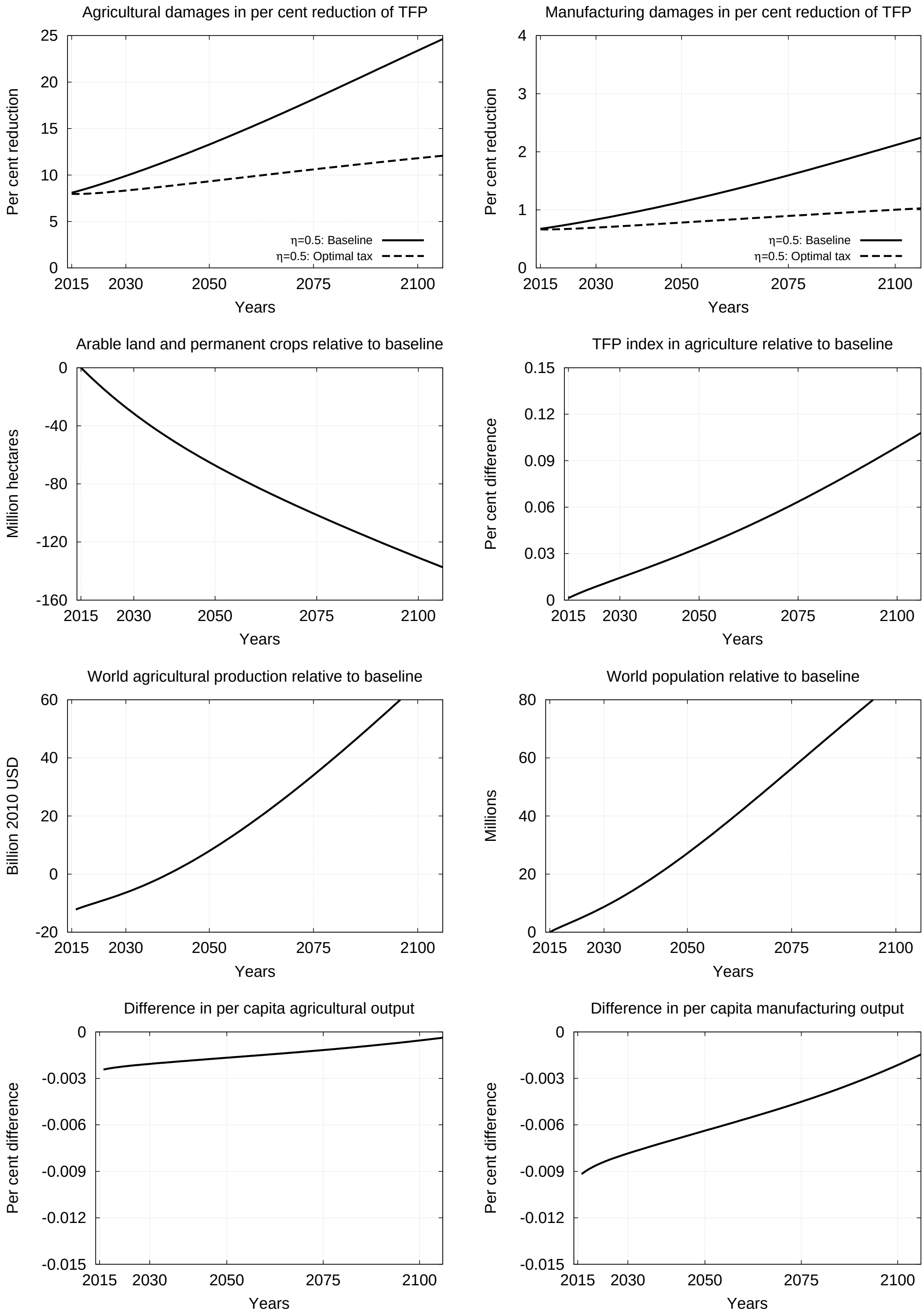




Agricultural damages in per cent reduction of TFP
Per cent reduction
0
5
10
15
20
25
2015
2030
2050
2075
2100
Years
γ=1: Baseline
γ=1: Optimal tax
Manufacturing damages in per cent reduction of TFP
Per cent reduction
0
1
2
3
4
2015
2030
2050
2075
2100
Years
γ=1: Baseline
γ=1: Optimal tax
Arable land and permanent crops relative to baseline
Million hectares
0
-40
-80
-120
-160
2015
2030
2050
2075
2100
Years
TFP index in agriculture relative to baseline
Per cent difference
0
0.03
0.06
0.09
0.12
0.15
2015
2030
2050
2075
2100
Years
World agricultural production relative to baseline
Billion 2010 USD
-40
-20
0
20
40
60
2015
2030
2050
2075
2100
Years
World population relative to baseline
Millions
0
20
40
60
80
100
2015
2030
2050
2075
2100
Years
Difference in per capita agricultural output
Per cent difference
0
-0.005
-0.01
-0.015
-0.02
-0.025
-0.03
2015
2030
2050
2075
2100
Years
Difference in per capita manufacturing output
Per cent difference
0
-0.005
-0.01
-0.015
-0.02
-0.025
-0.03
2015
2030
2050
2075
2100
Years

Appendix E.9 High elasticity of marginal utility with respect to fertility




Agricultural damages in per cent reduction of TFP
Per cent reduction
η=0.5: Baseline
η=0.5: Optimal tax
Years
Manufacturing damages in per cent reduction of TFP
Per cent reduction
η=0.5: Baseline
η=0.5: Optimal tax
Years
Arable land and permanent crops relative to baseline
Million hectares
Years
TFP index in agriculture relative to baseline
Per cent difference
Years
World agricultural production relative to baseline
Billion 2010 USD
Years
World population relative to baseline
Millions
Years
Difference in per capita agricultural output
Per cent difference
Years
Difference in per capita manufacturing output
Per cent difference
Years