MIT JOINT PROGRAM
SCIENCE POLICY
GLOBAL CHANGE

Report 313
June 2017

Global economic growth and agricultural land conversion under uncertain productivity improvements in agriculture

Bruno Lanz, Simon Dietz and Tim Swanson

MIT Joint Program on the Science and Policy of Global Change combines cutting-edge scientific research with independent policy analysis to provide a solid foundation for the public and private decisions needed to mitigate and adapt to unavoidable global environmental changes. Being data-driven, the Joint Program uses extensive Earth system and economic data and models to produce quantitative analysis and predictions of the risks of climate change and the challenges of limiting human influence on the environment—essential knowledge for the international dialogue toward a global response to climate change.

To this end, the Joint Program brings together an interdisciplinary group from two established MIT research centers: the **Center for Global Change Science (CGCS)** and the **Center for Energy and Environmental Policy Research (CEEPR)**. These two centers—along with collaborators from the Marine Biology Laboratory (MBL) at Woods Hole and short- and long-term visitors—provide the united vision needed to solve global challenges.

At the heart of much of the program's work lies MIT's Integrated Global System Model. Through this integrated model, the program seeks to discover new interactions among natural and human climate system components; objectively assess uncertainty in economic and climate projections; critically and quantitatively analyze environmental management and policy proposals; understand complex connections among the many forces that will shape our future; and improve methods to model, monitor and verify greenhouse gas emissions and climatic impacts.

This reprint is intended to communicate research results and improve public understanding of global environment and energy challenges, thereby contributing to informed debate about climate change and the economic and social implications of policy alternatives.

—Ronald G. Prinn and John M. Reilly,
Joint Program Co-Directors

MIT Joint Program on the Science and Policy of Global Change

Massachusetts Institute of Technology
77 Massachusetts Ave., E19-411
Cambridge MA 02139-4307 (USA)

T (617) 253-7492 **F** (617) 253-9845
globalchange@mit.edu
http://globalchange.mit.edu/

Global economic growth and agricultural land conversion under uncertain productivity improvements in agriculture

Bruno Lanz[1], Simon Dietz[2] and Tim Swanson[3]

Abstract: We study how stochasticity in the evolution of agricultural productivity interacts with economic and population growth at the global level. We use a two-sector Schumpeterian model of growth, in which a manufacturing sector produces the traditional consumption good and an agricultural sector produces food to sustain contemporaneous population. Agriculture demands land as an input, itself treated as a scarce form of capital. In our model both population and sectoral technological progress are endogenously determined, and key technological parameters of the model are structurally estimated using 1960–2010 data on world GDP, population, cropland and technological progress. Introducing random shocks to the evolution of total factor productivity in agriculture, we show that uncertainty optimally requires more land to be converted into agricultural use as a hedge against production shortages, and that it significantly affects both optimal consumption and population trajectories.

1 Corresponding author. University of Neuchâtel, Department of Economics and Business; ETH Zurich, Chair for Integrative Risk Management and Economics; Massachusetts Institute of Technology, Joint Program on the Science and Policy of Global Change. Mail: A.-L. Breguel 2, CH-2000 Neuchâtel, Switzerland. Email: bruno.lanz@unine.ch.

2 London School of Economics and Political Science, Grantham Research Institute on Climate Change and the Environment, and Department of Geography and Environment, UK.

3 Graduate Institute of International and Development Studies, Department of Economics and Centre for International Environmental Studies, Switzerland.

1. Introduction

Between 1960 and 2010, the global population rose from about three to seven billion, more than it had increased in the previous two millennia (United Nations, 1999), while real global GDP per capita increased by a factor of about 2.5 (World Bank, 2016). With more people to feed and a positive relationship between income per capita and food consumption per capita (Subramanian and Deaton, 1996; Tilman *et al.*, 2011), aggregate food demand increased significantly. Over the same 50 years, however, agricultural production almost tripled, mostly on account of a sustained increase in agricultural productivity (Alexandratos and Bruinsma, 2012), with the result that food did not become more scarce, globally on aggregate (Alston and Pardey, 2014). Turning to the future, the global population is projected to continue expanding by several billion—likely reaching 10 billion before 2060 (United Nations, 2015)—and global GDP per capita might double by mid-century (Clarke *et al.*, 2014). Hence further improvements in agricultural productivity will need to take place, driven by innovation and technology adoption.

In this paper we study how uncertainty and variability in agricultural output affect the ability to feed a large, growing and increasingly rich global population. As we show in **Figure 1**, global average total factor productivity (TFP) growth in agriculture has been around one percent per year over the period 1960 to 2010, contributing greatly to meeting the increase in food demand. But it also shows that there has been large variation in growth rates across regions and over time, ranging from -17 to +20 percent per year.[1]

Weather variability is one cause of the stochasticity in the historical agricultural TFP series. As Auffhanuner and Schlenker (2014) observe in their review, the relationship between yields and weather, specifically temperature, is highly nonlinear and concave (also see Schlenker and Roberts, 2009). Consequently extreme heat over the growing season is a strong predictor of crop yields. Anthropogenic climate change is expected to change patterns of weather variability worldwide. The Intergovernmental Panel on Climate Change thinks that anthropogenic climate change is somewhere between "very likely" and "virtually certain" to result in more frequent incidences of extreme heat, depending on the definition and timescale, as well as increasing the frequency of other types of extreme weather, with varying, but generally lower, degrees of confidence (IPCC, 2013). In addition, structural models that do not incorporate weather variability nonetheless show that anthropogenic climate change is likely to reduce food supply and increase prices by way of gradual changes in average conditions (Nelson *et al.*, 2014a). Other emerging sources of variability in agricultural TFP have also been put forward, including the loss of genetic and species diversity in farming systems (Di Falco, 2012), and increasing homogeneity of global food supplies (Khoury *et al.*, 2014), making them potentially more vulnerable to covariate shocks.

Inspired by these risks, some long-standing and some only now emerging, in this paper we study the socially optimal global response to the risk of negative shocks to global agricultural productivity. To do so we employ a stochastic version of a quantitative, two-sector endogenous growth model of the global economy that was introduced in Lanz *et al.* (forthcoming). This provides an integrated framework to study the joint evolution of global population, sectoral technological progress, per-capita income, the demand for food, and agricultural land expansion (from a finite reserve of unconverted land). Specifically, the model distinguishes agriculture from other sectors of the economy (which produce a bundle of consumption goods) and treats both population and sectoral TFP as endogenous stock variables. The level of population in the model derives from preferences over fertility by a representative household (Barro and Becker, 1989), with fertility costs capturing two components. First, additional labor units demand food, and the level of per-capita food demand is proportional to income. In the model, food is produced by the agricultural sector, so that the evolution of agricultural productivity may act as a constraint on the evolution of population. A second fertility cost is the time needed to rear and educate children. Our model builds on the work of Galor and Weil (2000) by incorporating an increasing relationship between the level of technology in the economy and the cost of population increments. Technological progress raises education requirements and the demand for human capital, capturing the well-documented complementarity between technology and skills (Goldin and Katz, 1998).

Given the explicit representation of fertility decisions and the demand for food associated with population and income growth, the model is well-suited to study the role of technology as a driver of global economic development. In the model, sectoral technological progress is endogenously determined by the Schumpeterian R&D model of Aghion and Howitt (1992), in which TFP growth is a function of labor hired by R&D

1 Data on TFP growth are derived from Fuglie and Rada (2015) and FAO (2015). We use the growth accounting methodology of Fuglie and Rada (2015), which takes into account a broad set of inputs and aggregates TFP growth rates at the level of 27 macro regions. Compared to Fuglie and Rada (2015), who apply a Hodrick-Prescott filter to smooth year-on-year output fluctuations before calculating TFP, TFP growth rates reported in Figure 1 are based on raw (unsmoothed) output data from FAO (2015), with the purpose of highlighting variability of agricultural productivity growth.

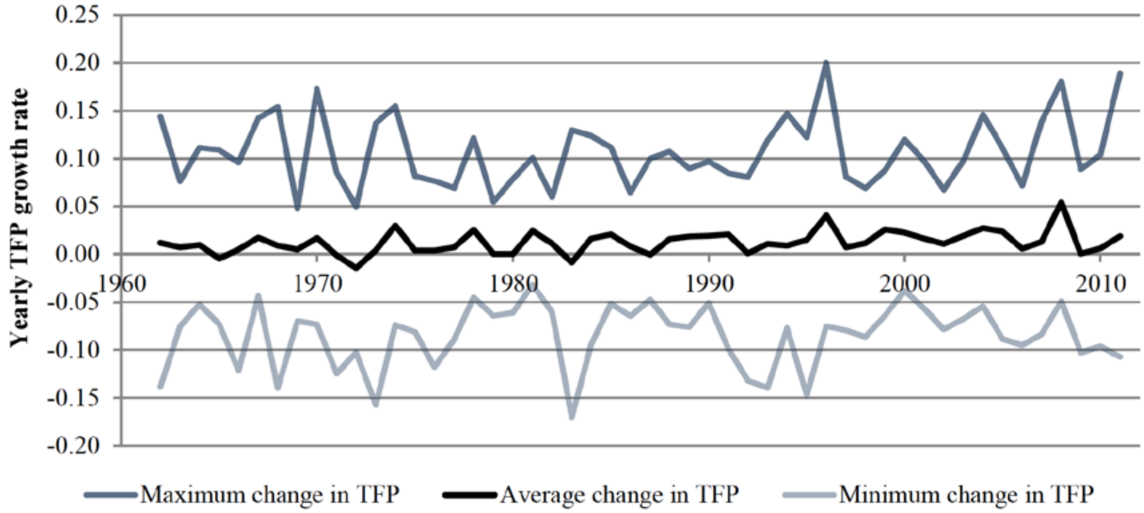


Figure 1. Total factor productivity growth in agriculture, 1960-2010

Plotted data on yearly TFP growth are derived from Fuglie and Rada (2015) and FAO (2015). Average change in TFP measures yearly growth rate of TFP averaged (without weights) across 27 macro regions defined in Fuglie and Rada (2015). Minimum and maximum yearly growth rates across regions are also reported. See footnote 1 for more details on the reported data.

firms. Thus, on the one hand technological progress in agriculture reduces the cost of producing food, and is an important driver of agricultural yields. In turn, agricultural technology improvements can alleviate Malthusian concerns about the finite land input. On the other hand, economy-wide technological progress implies a quantity-quality trade-off in fertility choices (through increasing education costs), and thus a slowdown of population growth (as per Galor and Weil, 2000). Taken together, technological progress is central to the development path generated by the model.

As discussed in detail in Lanz *et al.* (forthcoming), we use simulation methods to structurally estimate key parameters of the model, minimizing the distance between observed and simulated 1960–2010 trajectories for world GDP, population, TFP growth and agricultural land area. The estimated model closely replicates targeted data over the estimation period, and is also able to replicate untargeted moments, such as the share of agriculture in world GDP and the growth rate of agricultural yields.

In this article, we introduce uncertainty about the evolution of agricultural TFP in the coming years. Our objective is not to carry out an assessment of some specific uncertain event. Instead, our contribution is to provide an internally consistent picture of how uncertainty in the evolution of agricultural technology affects the socially optimal allocation of resources in a framework with endogenous land conversion, population, and R&D-based TFP growth. Our TFP shocks are therefore illustrative in nature, although they are calibrated to be within the same order of magnitude as shocks observed in the past. In the baseline, agricultural TFP growth starts at around one percent per year in 2010 and declines thereafter. This implies that agricultural yields increase linearly, which is consistent with extrapolating data on trend growth in yields from the past several decades, particularly for the main grain crops (e.g. Alston *et al.*, 2009; Godfray *et al.*, 2010). Given the structure of productivity shocks we consider, there is a 73 percent probability that this baseline situation prevails in 2030. If, on the other hand, negative productivity shocks occur, and realized shocks are permanent in the sense that they affect agricultural productivity in all subsequent periods, by 2030 there is a 24 percent probability that agricultural TFP is around 10 percent lower relative to its baseline value, a 3 percent probability that it is 15 percent lower, and a 0.1 percent probability that it is more than 20 percent lower.

In the model, the socially optimal response to uncertain agricultural productivity shocks occurs in a number of key dimensions. First, given a risk of lower agricultural productivity in the future, more labor can be allocated to R&D, so as to speed up technological progress. Second, when a negative shock occurs, more primary factors can be allocated to agricultural production, specifically labor, capital and land. Here, increasing agricultural land area involves a decision to deplete a finite reserve base, so there is an intertemporal trade-off involved. Third, changes in agricultural productivity affect population growth through food availability. In particular, depreciation of agricultural technology increases the relative cost of food, with a negative effect on fertility decisions, so that agricultural productivity shocks affect equilibrium trajectories in the long run. Finally, per-capita consumption also adjusts downwards, as more resources are allocated to the agricultural sector at the expense of manufacturing production.

Results from the model indicate that the risk of negative shocks to agricultural TFP induces a substantial reallocation of resources relative to the baseline. The planner allocates more resources to agricultural R&D, but we find that, once a negative shock has occurred, agricultural TFP does not catch up with its baseline path. Thus in our framework it is too expensive for the planner to simply compensate lost agricultural TFP with supplementary R&D expenditure. Rather the planner expands use of other primary inputs to agriculture. But, since there is an opportunity cost of labor and capital (which are also used to produce the manufactured good), the main response of the planner is to increase the area of agricultural land. In addition, as technology shocks make food more expensive to produce, a second major implication is that population declines relative to the baseline.

We carry out several extensions to the main analysis just described. First, we quantify how substitutability between land and other primary inputs to agriculture affects the finding that agricultural land is expanded. Our initial assumption is derived from the empirical work of Wilde (2013), which suggests an elasticity of substitution between land and other inputs of 0.6. We show that lower substitutability implies a significantly larger expansion of agricultural land in response to productivity shocks. Second, we shed light on the the role of per-capita income in the demand for food, by running a model in which food demand is simply proportional to population. This is equivalent to assuming a subsistence constraint, as considered by Strulik and Weisdorf (2008) for example, with zero income elasticity of food demand. Results suggest that agricultural land expansion is very similar, but the welfare cost of the productivity shocks is significantly larger. Finally, while our main set of runs is concerned with the occurrence of uncertain negative shocks to an otherwise increasing trend for agricultural productivity, the literature also raises the possibility of gradually stagnating and decreasing agricultural productivity (e.g. Alston *et al.*, 2009). We therefore use the model to study a scenario in which trend agricultural productivity growth gradually slows and eventually goes into reverse. The model again suggests an extension of cropland area in order to compensate productivity losses.

The remainder of the article is organized as follows. In Section 2, we discuss how our work relates to a number of strands of the literature. Section 3 provides an overview of the model and estimation procedure, and then describes how we introduce stochasticity in agricultural productivity. Section 4 reports our main simulation results. Section 5 discusses implications of these results and sensitivity analysis. We close with some concluding comments in Section 6.

2. Relation to the Literature

Our work is related to at least two distinctive strands of literature that consider interactions between economic growth, food production and population development. First, our article is related to the seminal work of Galor and Weil (2000) and Jones (2001), which is aimed at fundamental understanding of the joint evolution of economic growth and population over the long run, and to Hansen and Prescott (2002), Strulik and Weisdorf (2008), Vollrath (2011), Sharp *et al.* (2012) and Strulik and Weisdorf (2014), who also consider the role of agriculture and land in growth. Related work by Bretschger (2013) and Peretto and Valente (2015) studies natural resource scarcity in a general, growth-theoretic setting. While our approach shares these theoretical underpinnings, it is distinctive in that key parameters of our quantitative model are structurally estimated, so that our model closely replicates observed trajectories over the past fifty years. In turn this allows us to investigate quantitatively the implications of stylized uncertainty about future technological progress.

Second, our work is related to the literature on structural modeling of global agriculture, land use and food trade, which is used to estimate the impact of future climate change. Many of these models are brought together in the Agricultural Model Intercomparison and Improvement Project (AgMIP) (see in particular Nelson and Shively, 2014, and other papers in the same volume), which suggests that climate change could reduce global crop yields significantly and result in an increase of global cropland area. The models used to derive these results feature high-resolution sectoral and regional representations of agriculture and land use, which allows investigations into specific crops, regional impacts and trade. On the other hand, the evolution of key drivers determining global impacts (such as population, the demand for food, and agricultural yields) is exogenous to the simulations. By contrast, the model we formulate endogenizes global aggregate population, per-capita income, and technology, which allows us to study how these variables jointly respond to uncertainty about future agricultural productivity growth. Our work also differs in how uncertainty about agricultural productivity is implemented. In structural modeling of climate impacts, different scenarios are used to introduce gradual changes in long-run average conditions, changes that are precisely calibrated on the outputs of climate and crop models. Our scenarios focus instead on short-run (but persistent) productivity shocks, which are calibrated to an order of magnitude on variability in past agricultural TFP, but are more illustrative in spirit.

A paper in this line of research that is particularly close in spirit to our work is Cai *et al.* (2014), as they use a dynamic-stochastic partial equilibrium model of global land use to study the risk of an irreversible reduction in agricultural productivity. They show that, by 2100, this risk increases the demand for cropland globally, at the expense of valuable biodiversity and ecosystem services. Our work shares the purpose of Cai *et al.* (2014), but is otherwise complementary: while their work considers more finely partitioned land uses,[2] ours emphasizes the role of endogenous technological progress through R&D activities, and also allows population to respond to changes in agricultural productivity through endogenous fertility.

As we consider responses to agricultural productivity shocks, our work also relates to an extensive microeconometric literature that studies variability in agricultural productivity. In this area, one line of research exploits exogenous variations in rainfall to quantity the impact of TFP variations on outcomes in the agricultural sector (see notably Jayachandran, 2006; Di Falco and Chavas, 2008). Close to our main topic of interest, Auffhanuner *et al.* (2006) have shown that rainfall variability affects the choice of cropland area under cultivation *at the farm level.*[3] As Auffhammer and Schlenker (2014) note, one limitation of these reduced-form studies is that long-run effects and feedback mechanisms (e.g. general equilibrium) are difficult to identify from the data. From this perspective, our structural empirical model provides novel perspectives on these issues, accounting for a number of macro-level interrelationships between endogenous outcomes, and quantifying how these jointly respond to negative agricultural supply shocks.

It is also important to stress that our aggregate global representation has its limitations, and abstracts from a number of dimensions that have been discussed in the literature. First, by construction, our model cannot inform spatial aspects of development, which include international markets for agricultural commodities, and trade. In particular, because the world as a whole is modeled as one region, factors are mobile in our framework, and openness to trade is only implicit. Our model is, however, consistent with a multiregional model with trade in which the expansion of agricultural land is incentivized through changes in international commodity prices. For example, a negative agricultural supply shock in a given region may not have an impact on population or agricultural land area in that particular region, but if the shock is large enough to have macro-level repercussions (as we do assume in our work), it will cause an increase in world agricultural prices. This would in turn affect outcomes in price-sensitive regions (typically developing regions), including fertility choices and agricultural land expansion.[4] This is consistent with Burgess and Donaldson (2010) and Costinot *et al.* (2016) for example, who emphasize the role of interregional price signals in the allocation of resources, as well as the literature that uses detailed numerical trade models of agricultural production, mentioned above.

Second, our model does not capture more complex institutional dimensions of growth and food production that have been discussed elsewhere in the literature. One example is related to political dynamics at work in the presence of agricultural output variability. Using data from Sub-Saharan Africa, Bruckner and Ciccone (2011) suggest that negative agricultural supply shocks may provide a window of opportunity for improved democracy. In turn, improved democracy would be expected to have a positive impact on economic growth (Acemoglu *et al.*, 2017). In our model, while negative shocks do lead to faster TFP growth, the channel through which TFP increases (labor-intensive R&D) is inconsistent with an institutional view of growth. Similarly, an extensive literature studies how local scarcities induce conflict and migration (see e.g. Prieur and Schumacher, 2016, for an overview); the associated welfare costs are only implicit in our highly aggregated representation of the world. Therefore, while our empirical framework brings together several well-established strands of economic research to provide novel insights into the impacts of negative agricultural productivity shocks, its limitations ought to be kept in mind.

3. The Model

This section first summarizes the key components of the model. Second, we present the simulation-based structural estimation procedure. Third, we explain how we introduce stochastic shocks to the evolution of agricultural productivity.[5]

2 More specifically, Cai *et al.* (2014) consider the allocation of land to commercially managed forests (with many different stock variables capluring different forest vintages) and to biofuel crops. Forest products and energy are consumed by households. Non-converted 'natural' land generates ecosystem services, which are also valued by households.

3 See also Schlenker and Roberts (2009) and Fezzi and Bateman (2015) on the role of temperature variability.

4 Note that our model accounts for the fact That remaining reserve lands are likely to be less productive, compared to land already under cultivation. We come back to this below.

5 As noted above, Lanz *et al.* (forthcoming) provides a comprehensive motivation for the structure of the model, analytical results on the evolution of population and land, discussion of the selection and estimation of the parameters, as well as ensuing baseline projection s from 2010 onwards. Extensive sensitivity analysis is also reported, showing that the baseline projections are robust to a number of changes to the structure of the model, which comes from the fact That we estimate the model over a relatively long horizon. The GAMS code for the model, replicating the baseline runs reported here, is available on Bruno Lanz's website.

3.1 The Economy

3.1.1 Manufacturing production and agriculture

A manufacturing sector produces the traditional consumption bundle in one-sector models, with aggregate output $Y_{t,nm}$ at time t given by:

$$Y_{t,mn} = A_{t,mn} K_{t,mn}^{\vartheta} L_{t,mn}^{1-\vartheta} \quad (1)$$

where $A_{t,mn}$ is TFP in manufacturing, $K_{t,mn}$ is capital and $L_{t,mn}$ is the workforce.[6] The share of capital is set to 0.3, which is consistent with Gollin (2002), for example.

Agricultural output $Y_{t,ag}$ is given by a flexible nested constant elasticity of substitution (CES) function (see Kawagoe *et al.*, 1986; Ashraf *et al.*, 2008), in which the lower nest is Cobb-Douglas in capital and labor, and the upper nest trades off the capital-labor composite with the land input X_t:

$$Y_{t,ag} = A_{t,ag} \left[(1-\theta_X) \left(K_{t,ag}^{\theta_K} L_{t,ag}^{1-\theta_K} \right)^{\frac{\sigma-1}{\sigma}} + \theta_X X_t^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \quad (2)$$

where σ determines substitution possibilities between the capital-labor composite and land. Following empirical evidence reported in Wilde (2013), representing long-term substitution possibilities between land and other factors in agriculture, we set $\sigma = 0.6$. We further set the share parameters $\theta_X = 0.25$ and $\theta_K = 0.3$ based on data from Hertel *et al.* (2012).

3.1.2 Innovations and technological progress

The evolution of sectoral TFP is given by (in the absence of negative productivity shocks, discussed below):

$$A_{t+1,j} = A_{t,j} \cdot (1 + \rho_{t,j} S), \quad j \in \{mn, ag\} \quad (3)$$

where j is an index for sectors (here mn is manufacturing and ag is agriculture), $S = 0.05$ is the maximum aggregate growth rate of TFP each period (based on Fuglie, 2012), and $\rho_{t,j} \in [0,1]$ measures the arrival rate of innovations, i.e. how much of the maximum growth rate is achieved each period. TFP growth in the model, which is driven by $\rho_{t,j}$, is a function of labor allocated to sectoral R&D:

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

where $L_{t,Aj}$ is labor employed in R&D for sector j, λ_j is a productivity parameter (normalized to 1 to ensure that TFP growth is bounded between 0 and S) and $\mu_j \in (0,1)$ is an elasticity. The parameters μ_{mn} and μ_{ag} are structurally estimated and capture the extent of decreasing returns to labor in R&D (e.g. duplication of ideas among researchers; Jones and Williams, 2000).

Expressions (3) and (4) represent a discrete-time version of the original model by Aghion and Howitt (1992), in which the arrival of innovations is modeled as a continuous-time Poisson process.[7] One key departure from Aghion and Howitt (1992), however, is that the growth rate of TFP is a function of the share of labor allocated to R&D. This representation, which is also discussed in Jones (1995a) and Chu *et al.* (2013), is consistent with microfoundations of more recent product-line representations of technological progress (e.g. Dinopoulos and Thompson, 1998; Peretto, 1998; Young, 1998), in which individual workers are hired by R&D firms and entry of new firms is allowed (Dinopoulos and Thompson, 1999). One feature of such representations, and therefore of ours, is the absence of the population scale effect, in other words a positive equilibrium relationship between the size of the population and technological progress.[8] Indeed, over time the entry of new firms dilutes R&D inputs and neutralizes the scale effect, and in equilibrium *aggregate* TFP growth is proportional to the share of labor in R&D (see Lainez and Peretto, 2006).

3.1.3 Population dynamics

Population in the model represents the stock of effective labor units N_t and evolves according to the standard motion equation:

$$N_{t+1} = N_t(1 + n_t - \delta_N), \quad N_0 \text{ given}, \quad (4)$$

where $1 / \delta_N$ captures the expected working lifetime, which is set to 45 years (hence $\delta_N = 0.022$), and increments to the labor force $n_t N_t$ are a function of labor $L_{t,N}$ allocated to rearing and educating children:

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

In this setting, $1 / \overline{\chi}_t$ is a measure of the time (or opportunity) cost of effective labor units, and a significant component of this cost is education. As mentioned earlier, empirical evidence suggests a complementarity between human capital and technology (e.g. Goldin and Katz, 1998), and we specify the cost of children as an increas-

6 Note that under the assumption That technology is Hicks-neutral, the Cobb-Douglas functional form is consistent with long-term empirical evidence reported in Antras (2004).

7 We implicitly make use of the law of large number to integrate out random arrival of innovation over discrete time intervals.

8 Note that Boserup (1965) and Kremer (1993) use the population scale effect to explain the sharp increase of productivity growth following stagnation in the pre-industrial era, and it is also present in unified growth theory models by Galor and Weil (2000) and Jones (2001) among others. Empirical evidence from more recent history, however, is at odds with the scale effect (e.g. Jones, 1995b; Lainez and Perelto, 2006). The fact that it is absent from our model is important, because population is endogenous, so that accumulating population could be exploited to artificially increase long-run growth.

ing function of the economy-wide level of technology:

$$\overline{X}_t = \chi L_{t,N}^{\zeta-1} / A_t^{\omega}$$

where $\chi > 0$ is a productivity parameter, $\zeta \in (0,1)$ is an elasticity representing scarce factors required in child rearing, A_t is an output-weighted average of sectoral TFP, and $\omega > 0$ measures how the cost of children increases with the level of technology. The parameters determining the evolution of the cost of increments to the labor force (χ, ζ and ω) are estimated as described below.

We show analytically in Lanz *et al.* (forthcoming) that this representation of the cost of children is consistent with the more comprehensive model of Galor and Weil (2000), in which education decisions are explicit and the relationship between technology and human capital arises endogenously. More specifically, in our model the accumulation of human capital is implicit, as it is functionally related to the contemporaneous level of technology. Like in Galor and Weil (2000), however, technological progress raises the cost of children by inducing higher educational requirements, and is therefore an important driver of the demographic transition. In other words, the positive relationship between technology and the cost of effective labor units implies that, over time, the 'quality' of children (measured by their level of education) required to keep up with technology is favored over the quantity of children, leading to a decline of fertility and population growth.

In addition to the opportunity cost of time, there is an additional cost to population increments through the requirement that sufficient food must be produced. Formally, we follow Strulik and Weisdorf (2008) and make agricultural output a necessary condition to sustain the contemporaneous level of population (see also Vollrath, 2011; Sharp *et al.*, 2012, for similar approaches):

$$Y_t^{ag} = N_t \overline{f}_t \qquad (5)$$

where $\overline{f}_t$ is per-capita demand for food. In order to include empirical evidence about the income elasticity of food demand, we further specify

$$\overline{f} = \xi \cdot \left(\frac{Y_{t,mn}}{N_t}\right)^{\kappa}$$

with income elasticity of food demand $\kappa = 0.25$ reflecting estimates reported in Thomas and Strauss (1997) and Beatty and LaFrance (2005). We further calibrate the parameter $\xi = 0.4$ so that aggregate food demand in 1960 is about 15 percent of world GDP (as per data reported in Echevarria, 1997).

3.1.4 Agricultural land conversion

Land is a necessary input to agriculture, and agricultural land X_t has to be converted from a fixed stock of natural land reserves ($\overline{X}$) by applying labor $L_{t,x}$.[9] In our model, land is therefore treated as a scarce form of capital, and we write the motion equation for agricultural land as:

$$X_{t+1} = X_t(1-\delta_X) + \psi \cdot L_{t,X}^{\varepsilon}, \quad X_0 \text{ given}, \quad X_t \leq \overline{X}, \qquad (6)$$

where the parameters $\psi > 0$ and $\varepsilon \in (0,1)$ are structurally estimated. Through equation (6), we allow converted land to revert back to its natural state over a fifty-year time frame (i.e. $\delta_X = 0.02$). Note also that an important implication of (6) is that, as labor is subject to decreasing returns in land-conversion activities, the marginal cost of land conversion increases with X_t. Intuitively, this captures the fact that the most productive plots are converted first, whereas additional land might be less amenable to exploit for agricultural production. An implication is that the cost associated with bringing marginal plots into production because of uncertainty is higher than the cost of converting land earlier in the development process.

3.1.5 Households preferences and savings

In the tradition of Barro and Becker (1989), household preferences are defined over own consumption of a (composite) manufactured good, denoted c_t, the level of fertility n_t and the utility that surviving members of the family will enjoy in the next period $U_{i,t+1}$. Given survival probability $1 - \delta_N$, and simplifying assumptions that (i) children are identical and (ii) parents value their own utility in period $t+1$ the same as their children's (see Jones and Schoonbroodt, 2010), the utility function of a representative household is defined recursively as:

$$U_t = \frac{c_t^{1-\gamma} - 1}{1-\gamma} + \beta[(1-\delta_N) + n_t]^{1-\eta} U_{t+1}$$

where $\gamma = 2$ reflects an intertemporal elasticity of substitution of 0.5 (e.g. Guvenen, 2006), $\beta = 0.99$ is the discount factor and η is an elasticity determining how the utility of parents changes with the number of surviving members of the household. As we show in Lanz *et al.* (forthcoming), it is straightforward to express preferenc-

9 Note that aside from the space needed to grow the food, the model does not quantify the demand for space by agents in the model, such as industrial use to produce manufactured goods, or residential use to accommodate the growing population. While this sort of land-use competition is certainly important at a local level, we abstract from that to focus on an aggregate global representation of development rnrhe numerical problem is formulated in GAMS and solved with KNITRO (Byrd *et al.*, 1999, 2006), a specialized software programme for constrained non-linear programs. Note that this solution method can only approximate the solution to the infinite horizon problem, as finite computer memory cannot accommodate an objective with an infinite number of terms and an infinite number of constraints. However, for $\beta < 1$ only a finite number of terms matter for the solution, and we truncate the problem to the first $T = 200$ periods without quantitatively relevant effects for our results.

es from the perspective of the dynastic household head, yielding the following dynastic utility function:

$$U_0 = \sum_{t=0}^{\infty} \beta^t N_t^{1-\eta} \frac{c_t^{1-\gamma} - 1}{1-\gamma} \tag{7}$$

and we set $\eta = 0.01$. This implies that altruism towards surviving members of the dynasty remains almost constant as the number of survivors increases. It makes the household's objective close to the standard Classical Utilitarian welfare function.

As in the multi-sector growth model of Ngai and Pissarides (2007), manufacturing output can either be consumed or invested into a stock of physical capital:

$$Y_{t,mn} = N_t c_t + I_t \tag{8}$$

where $N_t c_t$ and I_t measure aggregate consumption and investment respectively. The motion equation for capital is given by:

$$K_{t+1} = K_t(1-\delta_K) + I_t\,, \quad K_0 \text{ given}\,, \tag{9}$$

where $\delta_K = 0.1$ is the yearly rate of capital depreciation (Schündeln, 2013).

3.2 Structural estimation of the model

A schematic representation of the model is provided in **Figure 2**. We formulate the model as a social-planner problem, selecting paths for investment I_t, and allocating labor $L_{t,j}$ and capital $K_{t,j}$ across activities in order to maximize intertemporal welfare (7) subject to technological constraints (1), (2), (3), (4), (5) (6), (8), (9) and feasibility conditions for capital and labor:

$$K_t = K_{t,mn} + K_{t,ag}\,,$$
$$N_t = L_{t,mn} + L_{t,ag} + L_{t,A_{mn}} + L_{t,A_{ag}} + L_{t,N} + L_{t,X}$$

The constrained non-linear optimization problem associated with the planner's program is solved numerically by searching for a local optimum of the objective function (the discounted sum of utility) subject to the requirement of maintaining feasibility as defined by the constraints of the problem.[10]

We apply simulation methods to structurally estimate parameters determining the cost of fertility (χ, ζ, ω), labor productivity in R&D ($\mu^{mn,ag}$) and labor productivity in land conversion (ψ, ε).

In practice, we first calibrate the initial value of the state variables to match 1960 data, so that the model is initialized in the first year of the estimation period. For

10 The numerical problem is formulated in GAMS and solved with KNITRO (Byrd *et al.*, 1999, 2006), a specialized software programme for constrained non-linear programs. Note that this solution method can only approximate the solution to the infinite horizon problem, as finite computer memory cannot accommodate an objective with an infinite number of terms and an infinite number of constraints. However, for $\beta < 1$ only a finite number of terms matter for the solution, and we truncate the problem to the first $T = 200$ periods without quantitatively relevant effects for our results.

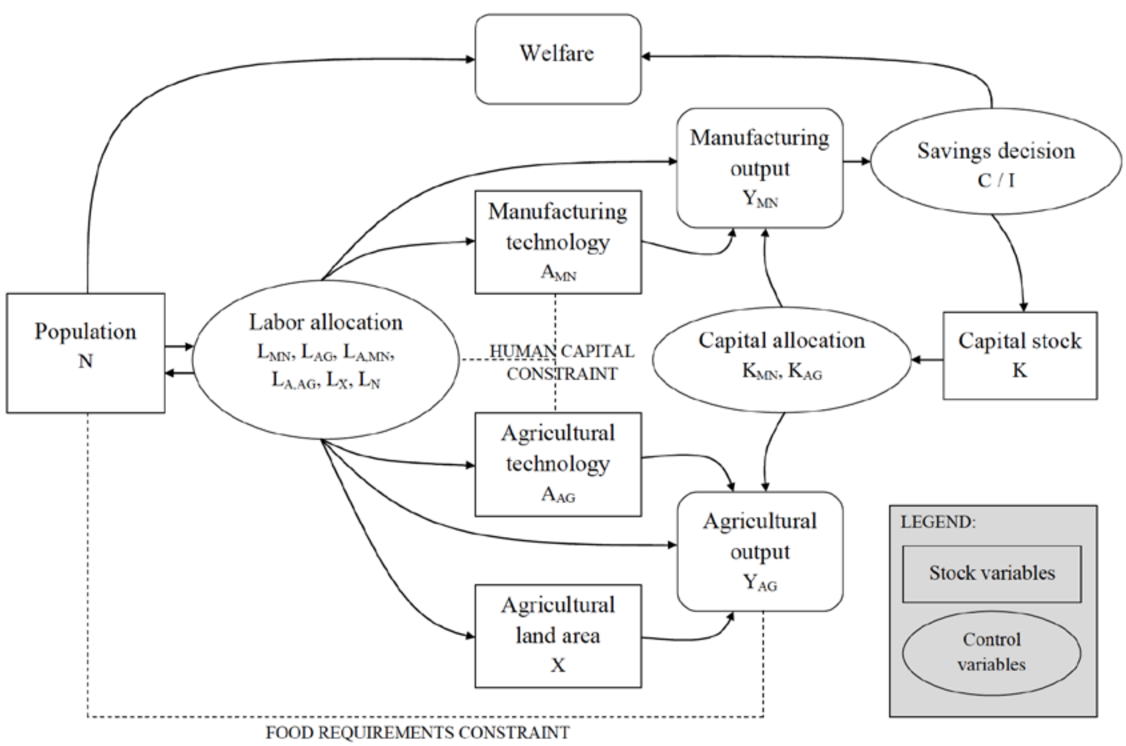


Figure 2. Schematic representation of the model

each parameter to be estimated from the data, we define bounds for possible values (0.1 and 0.9 for elasticities and 0.03 and 0.3 for labor productivity parameters) and simulate the model for a randomly drawn set of 10,000 vectors of parameters. We then formulate a minimum distance criterion, which compares observed 1960–2010 time series for world GDP (Maddison, 1995; Bolt and van Zanden, 2013), population (United Nations, 1999, 2013), cropland area (Goldewijk, 2001; Alexandratos and Bruinsma, 2012) and sectoral TFP (Martin and Mitra, 2001; Fuglie, 2012) with trajectories simulated from the model.[11] In the model these data correspond to $Y_{t,mn} + Y_{t,ag}$, N_t, X_t, $A_{t,mn}$ and $A_{t,ag}$ respectively. Thus, formally, for each vector of parameters and associated model solution, we compute:

$$\sum_k \left[\sum_\tau (Z^*_{k,\tau} - Z_{k,\tau})^2 / \sum_\tau Z_{k,\tau} \right] \quad (10)$$

where $Z_{k,\tau}$ denotes the observed quantity k at time τ and $Z^*_{k,\tau}$ is the corresponding value simulated by the model. By gradually refining the bounds of each parameter, we converge to a vector of parameters that minimizes objective (10). We find that the model closely fits the targeted data; the resulting vector of estimates and fitted trajectories over the estimation period are reported and briefly discussed in the Appendix (see also Lanz *et al.*, forthcoming, for an extensive discussion of the estimation results).

At this stage it is important to note that the social planner representation is mainly used as a tool to make structural estimation of the model tractable: we rationalize the data "as if" it had been generated by a social planner. Thus market imperfections prevailing over the estimation period will be reflected in the parameters that we estimate from observed trajectories, and will thus be reflected in the baseline simulations of the model (i.e. using the model to extrapolate the behavior of the system observed over the past fifty years).[12] But given the estimated technological parameters, simulations with the model *away from the baseline* will reflect a socially optimal allocation of resources.

3.3 Introducing stochastic shocks to agricultural productivity

In the basic formulation of the model, which is used for estimating the parameters over the period 1960–2010, the evolution of sectoral TFP is deterministic and depends on the share of labor employed in sectoral R&D activities. We now study the evolution of the system beyond 2010, and introduce stochasticity in how agricultural TFP evolves over time. Specifically, it is assumed that technological progress in agriculture is subject to stochastic shocks of size $\epsilon > 0$ that occur with probability p. Conversely with probability 1 - p there is no shock to agricultural productivity (hence $\epsilon = 0$) and the evolution of TFP occurs as per the deterministic specification described above. Both p and ϵ are assumed to be known by the planner, thus the situation is one of pure risk.[13]

Formally, equation (3) describing the evolution of agricultural productivity is augmented with a non-negative term, which represents the possibility that agricultural TFP may not follow the functional trajectory we have postulated:

$$\tilde{A}_{t+1,ag,s} = \tilde{A}_{t,ag,s} \cdot (1 + \rho_{t,ag,s} S - \epsilon_{t+1,s}) \quad (11)$$

where $\epsilon_{t+1,s}$ captures the specific realization of the shock in state of the world s, and we index all variables by s to capture the fact that they are conditional on a specific sequence of $\epsilon_{t,s}$ over time. A stochastic shock affects outcomes in period $t+1$, while the planner only observes the outcome after allocating resources in period t. We further assume that the planner is an expected utility maximizer, weighting welfare in the different states of the world by its respective probability. The ensuing objective function is then:

$$W = \sum_s p_s \sum_{t=0}^{\infty} \beta^t N_{t,s}^{1-\eta} \frac{c_{t,s}^{1-\gamma} - 1}{1-\gamma} \quad (12)$$

with $\sum_s p_s = 1$.[14]

Even though this stochastic structure is quite simple, the number of possible states of the world in each period grows at 2^t.

In turn, because the model is formulated as a non-linear optimization problem, this implies that the number

11 Note that TFP growth estimates are subject to significant uncertainty, and we conservatively assume that it declines from 1.5 percent between 1960 and 1980 to 1.2 percent between 1980 and 2000, and then stays at 1 percent over the last decade.

12 Because there are externalities in the model, most notably in R&D activities (see Romer, 1994, for example) the optimum determined by the social planner solution will differ from a decentralized allocation. Thus if we were able to estimate the parameters using a decentralized solution method, a different set of estimates would be required to match observed trajectories over the estimation period. As shown by Tournemaine and Luangaram (2012) in the context of similar model (without land), however, quantitalive differences between centralized and decentralized solutions are likely to be small.

13 We note that the probability of negative shocks and their size might be a function of agricultural activities. In a companion paper (Lanz *et al.*, 2016), we discuss how the scale of modern agriculture may affect such negative feedback effect, focusing on the expected impact of negative shock s over time rather than on stochastic occurrences. In the present paper, however, we focus on a more general *exogenous* source of uncertainty, in which the probability and size of shocks is fixed.

14 Note that this formulation implies the standard assumption that markets are complete, both over time and across states of the world.

of variables that needs to be computed over the whole horizon increases exponentially.[15] Given that the dimensionality of the decision problem grows with the set of possible states of the world, we make two further simplifications. First, we solve the model from 2010 onwards using two-year time steps (instead of yearly time steps). This significantly reduces the number of variables that needs to be computed, without significantly affecting the resulting trajectories.[16] Second, we consider shocks in only three time periods, which is sufficient to illustrate the mechanisms at work.

The shock we consider is a 10 percent probability that agricultural production declines by 5 percent each year over two years. This is in the range implied by Figure 1, and is also broadly consistent with changes in productivity discussed in Nelson *et al.* (2014b) and Cai *et al.* (2014). Hence, starting the simulation in 2010, we assume that the first realization of the shock may occur after 2016 allocation decisions have been made, so that effects are felt in 2018. In the bad state of the world, which occurs with a probability of 10%, agricultural TFP is $(1 - 0.05)^2 \cong 0.9$ of that prevailing in the good state of the world. In expected value terms, the shock is thus roughly equivalent to a one percent decrease in TFP over two years. The same shock can then occur in 2018, with effects felt in 2020, and in 2020, with effects felt in 2022.

To summarize, we initialize the model in 2010, and negative TFP shocks can occur in 2016, 2018 and 2020, with effects being felt in subsequent periods. After 2022, no more shocks occur and the problem becomes deterministic (conditional on the state of the world in which the planner happens to be). Of course, the results would remain qualitatively similar if we were to consider the reoccurrence of shocks beyond 2020, so that it is relatively easy to see how our results would generalize.

15 More specifically, as the planner faces a dynamic problem, optimal decisions in each time period are conditional on the history of shocks (i.e. where he is in the exponentially-growing uncertainty tree), and the planner maximizes the expected utility of his decisions over the remaining event tree. Thus states of the world sharing a common parent node will share decision variables until the subsequent realization of the productivity shock, and diverge thereafter, so that computational requirements increase.

16 Increasing the time-steps to evaluate the choice of the controls implies some small differences in optimal paths relative to the solution using one-year time steps. Another approach would be to formulate the problem recursively and solve it with dynamic programming methods. This approach is, however, subject to dimensionality restrictions in terms of the number of state variables that can be included.

4. Results: Optimal Control and Simulations

This section provides the main results from solving the stochastic control problem. First, we describe the particular agricultural productivity scenarios that we focus on. Second, we report implied trajectories for agricultural technology, agricultural land, population and welfare.

4.1 Scenario Description

To evaluate the socially optimal response to agricultural productivity risk, we contrast trajectories resulting from four different situations. First, we consider a case in which no shocks to agricultural TFP will occur, and the planner knows this for sure. This represents our baseline, as reported in Lanz *et al.* (forthcoming). Values for selected variables are reported in **Table 1**. World population starts at just below 7 billion in 2010 and grows to 8.5 billion by 2030, a 20 percent increase. At the same time, cropland area increases by 70 million hectares, or 5 percent. These figures are broadly consistent with the latest population projections of the United Nations (2015) and with land-use projections by FAO, reported in Alexandratos and Bruinsma (2012), and Ag-MIP, reported in Schmitz *et al.* (2014). The growth rate of agricultural TFP starts at 0.9 percent per year in 2010 and declines over time, which is rather conservative compared with the assumptions used in Alexandratos and Bruinsma (2012). Importantly, these figures represent projections from the fitted model and are thus informed by the evolution of agricultural TFP from 1960 to 2010, as the estimated model essentially projects forward the pace of development that has been observed in recent history.

The second situation we consider is also deterministic. We assume that shocks occur in 2016, 2018 and 2020. We label this scenario '2016-2018-2020.' In the period just following each of the three shocks, agricultural TFP is exogenously brought down by 10 percent, although the planner anticipates each shock and can reallocate resources relative to the baseline.

Table 1. Deterministic 'no shocks' scenario: Baseline values for selected variables

Year	World Population *billion*	Cropland Area *billion hectares*	Yearly Agricultural TFP Growth Rate	Per-capita Consumption *thousand intl. dollars*
2010	6.95	1.62	0.0094	4.29
2020	7.73	1.66	0.0086	4.88
2030	8.47	1.69	0.0078	5.46

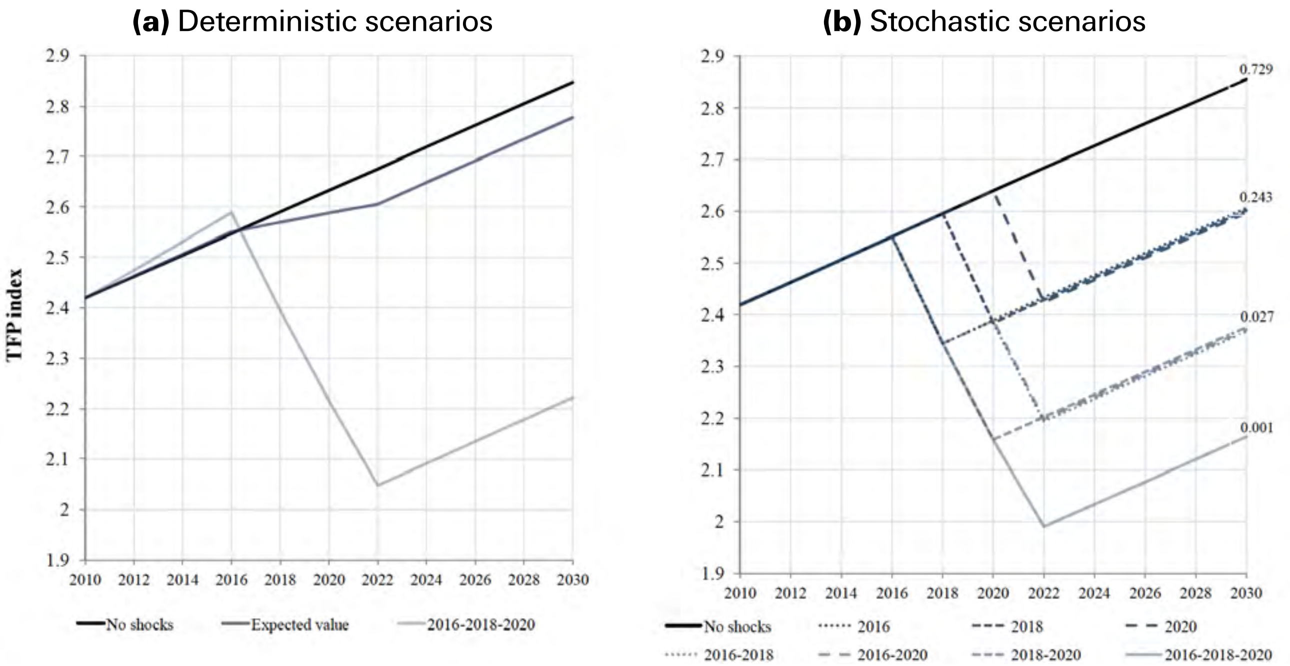


Figure 3. Agricultural TFP under alternative scenarios

In the third scenario, labeled 'expected value', the planner allocates resources taking into account the expected value of the TFP reduction. In other words, he takes into account the risk of a 10 percent reduction in TFP each decision period, but weights that reduction by the associated probability of 10 percent. Thus, agricultural TFP growth in each decision period is exogenously brought down by around one percentage point. This scenario amounts to analyzing the allocation decisions of a risk-neutral planner, and where the realization of the shock happens to be exactly the expected value of the shock.

Finally, we compute trajectories that maximize expected utility. In this situation, the planner is risk-averse (relative risk aversion is set to $\gamma = 2$). He takes into account the risk that agricultural TFP may decline, and what this entails for social welfare. A key point is that allocation decisions are contingent on the realized state of the world. In other words, after each decision period in which the risk is realized, the decision tree branches out, and the planner makes allocation decisions contingent on being in a particular node in the uncertainty tree. By construction, there are then $2^3 = 8$ possible states of the world in 2030, and thus the same number of stochastic scenarios for an expected-utility maximizing planner (we label each stochastic scenario according to the years in which TFP shocks are realized).

4.2 Agricultural Technology Paths

Figure 3 shows the paths for agricultural TFP under alternative scenarios. Starting with the deterministic scenarios, which are displayed in panel (a), agricultural TFP grows linearly at around one percent per year (and falling slightly) under the best-case 'no shocks' scenario. Under the deterministic 'expected value' path, TFP grows at a lower pace from 2016 to 2020, reflecting the expected value of the negative shocks. But before 2016 TFP grows ever so slightly quicker in the 'expected value' scenario, because the planner knows that small negative shocks will occur from 2016 to 2020 and makes provisions for them (see below). This anticipatory effect, as well as the subsequent shock to productivity, is more clearly apparent in the worst-case '2016-2018-2020' scenario. Differences across deterministic scenarios are further illustrated in **Figure 4**, panel (a), which reports paths for agricultural TFP relative to the 'no shocks' scenario. It shows that, by 2022, agricultural TFP on the 'expected value' path is around three percent lower than on the 'no shocks' path, and in the '2016-2018-2020' scenario TFP it is more than 20 percent lower.

Turning to the stochastic scenarios, reported in panel (b) of Figures 3 and 4, we distinguish four different groups of possible realizations according to the number of shocks that occur over time (in Figure 3 we also report the posterior probability distribution for each scenario). First, under the stochastic 'no shocks' scenario there is no shock occurring in either 2016, 2018 or 2020, a state of the world with posterior probability of around 0.73. However, unlike the deterministic 'no shocks' scenario, the planner prepares for the possibility of negative TFP shocks, and accordingly TFP is slightly higher. By contrast, in stochastic scenario '2016-2018-2020 ' a negative shock occurs in all three periods. This scenario has a

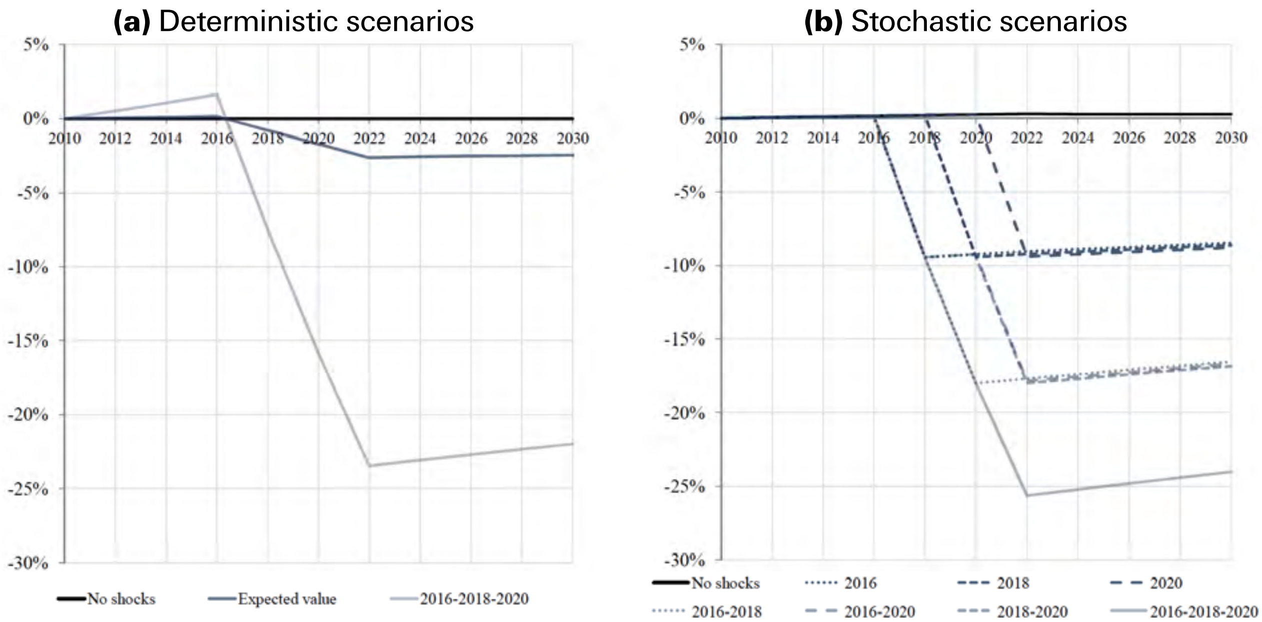


Figure 4. Agricultural TPF relative to the deterministic 'no shocks' scenario

posterior probability of 0.001. Before the first shock, the planner does not know for sure whether the world will end up in a good state, or in a bad, shock state. Because of the consequent need to hedge, agricultural TFP is not significantly different from that in the deterministic 'no shocks' scenario. However, after 2020 agricultural TFP in stochastic scenario '2016-2018-2020' is significantly lower than in the deterministic '2016-2018-2020 ' scenario, because the planner did not fully anticipate that he would end up in the worst outcome possible.

The last two groups of stochastic scenarios include those where either one or two negative TFP shocks occur. In scenarios '2016', '2018' and '2020', only one TFP shock occurs in each of these respective years, so that by 2022 agricultural TFP is roughly 10 percent lower than under the deterministic 'no shocks' scenario. The posterior probability associated with this group of scenarios is around 0.24. Under scenarios '2016-2018,' '2016-2020' and '2018-2020' there are two shocks occurring, so that by 2020 agricultural TFP is roughly 20 percent lower relative to the deterministic 'no shocks' scenario. The posterior probability is around 0.03. Note that, in both groups of scenarios, TFP growth after 2020 is slightly more rapid than under the 'no shocks' scenarios, as more resources are allocated to R&D. However, catching up lost productivity gains is very slow.

4.3 Optimal Global Land Use

Implications for global cropland of alternative paths for agricultural TFP are displayed in **Figure 5**. We report the differences in cropland area relative to the deterministic 'no shocks' scenario (in million hectares). Recall that, in the deterministic 'no shocks' scenario, cropland area increases by 70 million hectares between 2010 and 2030 (see Table 1).

An important feature of Figure 5 is that, if the planner knows for sure that TFP will decline in the future (panel a), optimal cropland area immediately diverges from the 'no shocks' scenario, with significantly more land being converted from natural land reserves. By 2030, an additional 70 million hectares are converted in the deterministic '2016-2018-2020' scenario, which corresponds with a doubling of the pace at which land is converted in the 'no shocks' scenario. Why is so much extra land brought into agricultural use? The answer is that the planner prefers to substitute towards land to maintain the level of food production, because other production factors have to be taken away from the manufacturing and R&D sectors, with a consequent large opportunity cost. The deterministic 'expected value' path only features a slightly larger stock of cropland than in the 'no shocks' scenario. Indeed, over 20 years only an additional 7 million hectares are converted.

Turning to the stochastic scenarios, reported in panel (b), we observe that they all feature a larger stock of land relative to the 'no shocks' scenario. However the stock of land in stochastic scenario '2016-2018-2020' (in which three negative shocks occur) is significantly lower than that in the corresponding deterministic '2016-2018-2020' scenario. Again, the planner must always hedge against an uncertain future in the stochastic scenarios, but whenever a negative TFP shock occurs there is an immediate increase in the amount of agricultural land

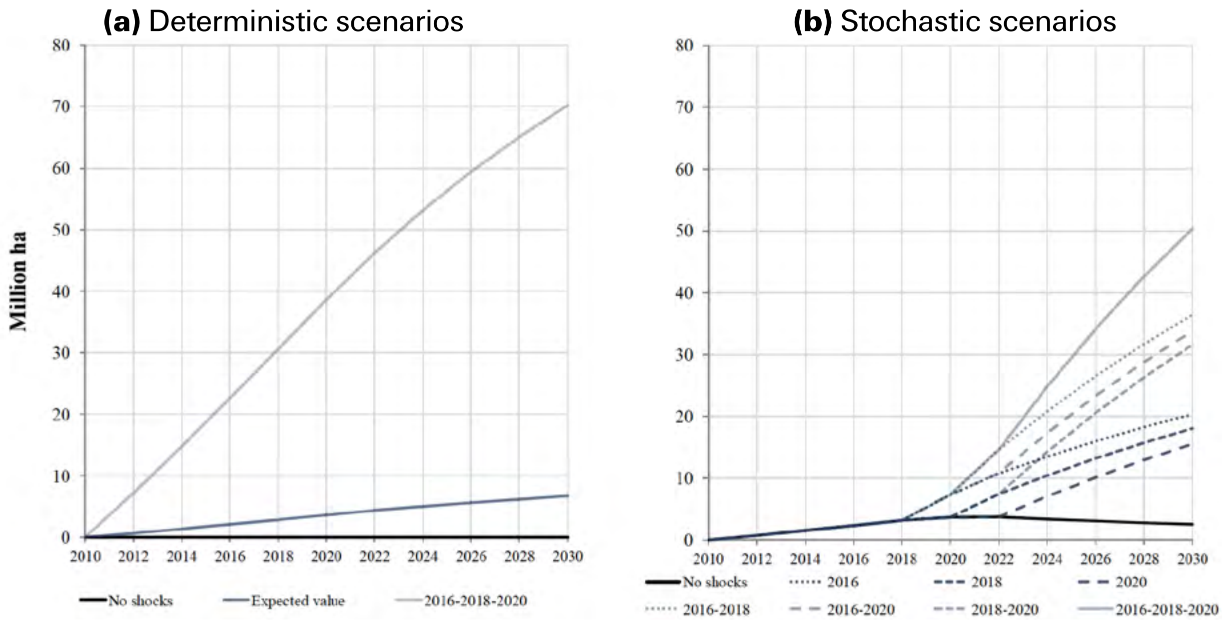


Figure 5. Global cropland area relative to the deterministic 'no shocks' scenario

brought into the system, in order to compensate for lower agricultural TFP

4.4 Welfare Analysis: Population and Per-capita Consumption

We now turn to the welfare implications of uncertainty about agricultural TFP, focusing on population dynamics and per-capita consumption of the manufacturing product. Recall that these are the two variables entering the objective function of the social planner (see equation 7).

Results for global population paths, relative to the deterministic 'no shocks' scenario, are reported in **Figure 6**. As expected, a reduction in agricultural TFP has a negative impact on population. This follows from the fact that agricultural productivity growth declines, and the relative cost of food production increases, so the planner optimally chooses to reduce fertility on account of the higher cost of feeding the population. The effect is again most striking in the deterministic '2016-2018-2020' scenario, where the accumulation of population is significantly slower compared to the 'no shocks' scenario: by 2030, population is 170 million lower. This is substantial, given it is caused by a reduction of agricultural TFP of 25 percent below the deterministic 'no shocks' reference scenario over a window of 6 years.

The impact of a reduction of agricultural TFP on population is long lasting, as differences between paths in which a negative shock occurs and the deterministic 'no shocks' scenario are hysteretic, that is they remain in the long run. In particular, we observe that stochastic scenarios with the same number of shocks (on the one hand '2016', '2018' and '2020', and on the other hand '2016-2018', '2016-2020' and '2018-2020') converge to the same loss of global population relative to the deterministic 'no shocks' scenario.

Per-capita consumption of the manufacturing good relative to the deterministic 'no shocks' scenario is reported in **Figure 7**. We find that differences in per-capita consumption between the deterministic best and worst cases (panel a) fluctuate at around one percent. This captures the fact that, in our model, the two consumption goods are complements, so that more expensive agricultural products also reduce the demand for other consumption goods. In other words, in the face of a certain or uncertain shock to agricultural TFP in the future, the planner reduces consumption of both goods in order to smooth consumption over time, and allocates manufacturing output towards increasing the stock of capital.

In stochastic scenarios, reported in panel b, per-capita consumption fluctuates significantly. In stochastic scenario 'no shocks', per-capita consumption is initially lower than it is in the deterministic 'no shocks' scenario, although after the first shock the stochastic 'no shocks' scenario reaches almost 0.5 percentage points higher than the deterministic 'no shocks' scenario. This reflects the extra consumption afforded by the hedging behavior once the planner knows that the anticipated shock will not occur. However, when a negative shock occurs, there is a sharp decline in per-capita consumption of around 1.5 percent relative to the deterministic 'no shocks' scenario. In the worst-case stochastic scenario '2016-2018-2020' where three shocks occur, the drop in per-capita consumption is much larger than the corresponding deterministic '2016-2018-2020' scenario.

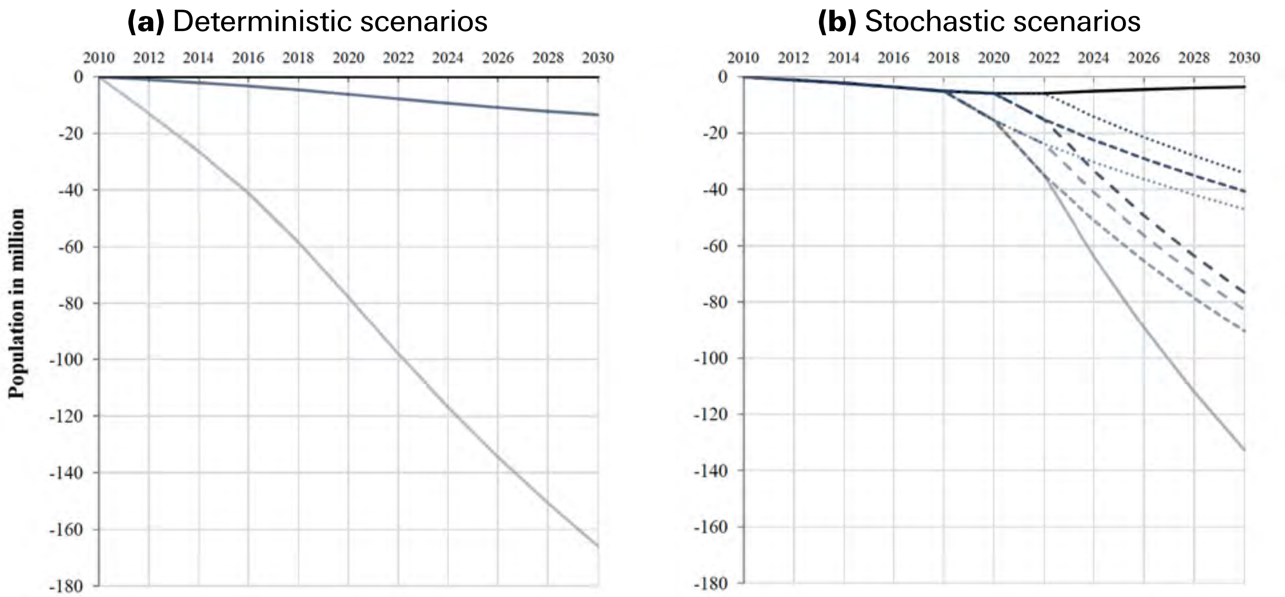


Figure 6.

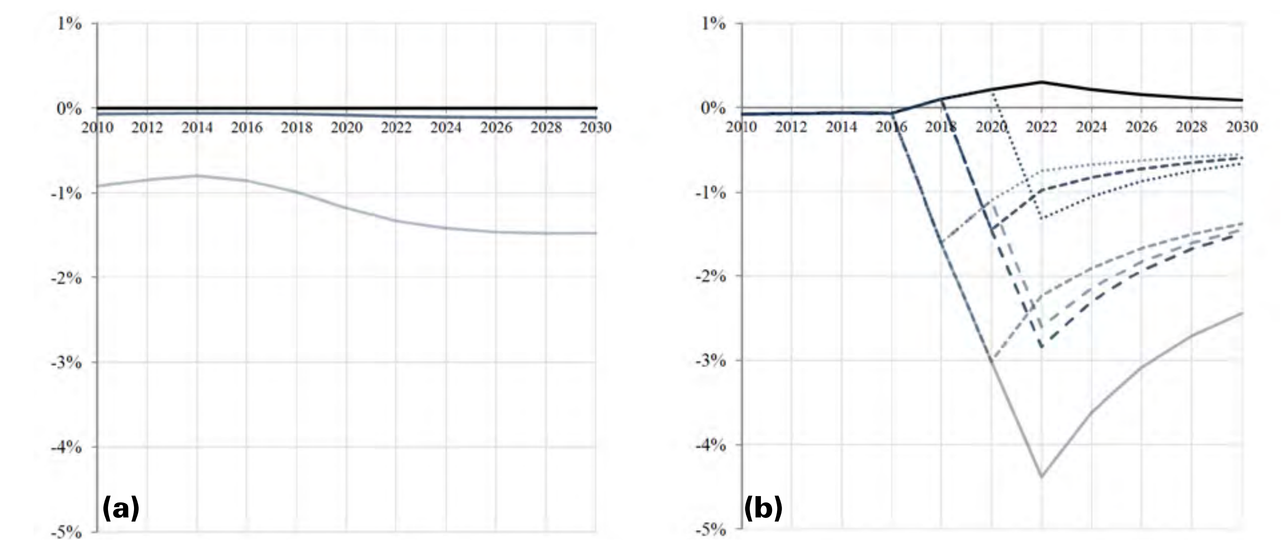
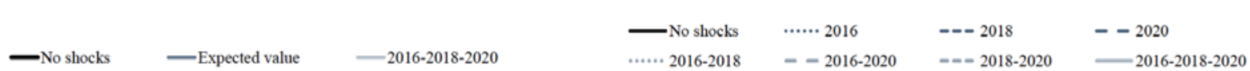


Figure 7.



5. Discussion and Sensitivity Analysis

Overall, our results suggest that uncertainty about the future evolution of agricultural TFP has major implications for growth, population and land use. In scenarios where one shock occurs, agricultural TFP is around 10 percent lower than in the deterministic 'no shocks' trajectory (which we shall henceforth refer to as the 'baseline', for convenience). Given baseline growth of agricultural TFP of about one percent per year, this would correspond roughly to a ten-year hiatus in technological progress. Given our assumptions, the probability that the planner faces such a state of the world is around 25 percent. By 2030, our model indicates that a shock in 2016, 2018 or 2020 would trigger cropland expansion of approximately 20 million hectares, which would be in addition to the 70 million hectares conversion occurring in the baseline, while the optimal population would be around 40 million lower than in the baseline. If two shocks occur, so that agricultural TFP is around 17 percent lower than the baseline, more than 30 million hectares of additional cropland are created. At the same time, global population is 80 million lower.

While these figures may appear to be small relative to the current cropland area and population, they are, from a policy perspective, quite large. From 1990 to 2010, about

100 million hectares of land were brought into cropping. In this period, there has been growing concern about the value of the lost natural land and associated ecosystem services (e.g. Millennium Ecosystem Assessment, 2005). Most of the land conversion has been and will be taking place in developing countries, where a large share of valuable biodiversity remains, whereas in developed countries we observe a decline in cropland area (Alexandratos and Bruinsma, 2012). In addition, as strategies to mitigate climate change, in the future we may see increasing land used for the production of biofuels, or for afforestation, instead of for food production. The scale of our results is thus important from the perspective of global conservation and rural land-use policy. Second, while the 'loss' of population is small relative to observed population growth and that expected to take place in the near future, it is substantial, as it represents the *optimal* fertility response to lower agricultural productivity. Put another way, a non-optimal fertility response by a large number of households maximizing their own private objectives could generate a food-security problem at the aggregate level.

In the following, we assess the sensitivity of our results with respect to three key assumptions we have made. First, we consider the role of substitutability between land and the capital-labor composite in agriculture. Second, we discuss how the income elasticity of food demand affects our results.[17] Finally, we study the implications of a scenario in which trend agricultural productivity growth declines to zero and then becomes negative.

5.1 Lower Land Substitutability ($\sigma = 0.2$)

A key determinant of the demand for agricultural land is the parameter σ (see equation 2), which measures the elasticity of substitution between land and a capital-labor composite. The baseline value for σ in our model is 0.6. This estimate is derived from Wilde (2013), who uses data from pre-industrial England to measure long-run substitution possibilities between land and other inputs. There is, however, some uncertainty about the external validity of this estimate when it comes to the present model and in particular the present context, where we use the model not to project into the very long run (as we do in Lanz *et al.* (forthcoming)), but rather to focus on the period from 2010 to 2030 and study deviations from the baseline trajectories. Other applied modeling work typically uses lower elasticities of substitution. The example we consider here is taken from Hertel *et al.* (2012), who suggest a value of 0.2.

17 For these two sets of simulations, we re-estimate the model to remain on the same trajectory over the estimation period 1960-2010. This ensures that the results are comparable with those reported above (see Lanz *et al.*, forthcoming, for a complete description of the re-estimation of the parameters).

Figure 8 reports results, with $\sigma = 0.2$, for agricultural land area under both deterministic scenarios (panel a) and stochastic scenarios (panel b). **Figure 9** reports the corresponding results for consumption per capita.

Panel (a) of Figure 8 shows that, under the deterministic scenarios, global cropland expands in a qualitatively similar fashion when substitutability of land is lower, but the size of the expansion is significantly greater. Relative to the deterministic 'no shocks' scenario, an additional 110 million hectares is brought under cultivation globally by 2030 in the worst-case '2016-2018-2020' scenario. Recall that when $\sigma = 0.6$ the equivalent difference between scenarios was about 70 million hectares, so reducing the substitutability of land results in an additional 40 million hectares of cropland. Panel (b) shows that, under the stochastic scenarios, the area of additional cropland (relative to the deterministic 'no shocks' scenario) is roughly doubled when $\sigma = 0.2$. For example, the increment rises from 50 to 100 million additional hectares of cropland by 2030 in the stochastic '2016-2018-2020' scenario.

Figure 9 shows that, despite the greater expansion of cropland that is triggered when the substitutability of land is lower, the planner makes a substantial reduction in consumption of the manufactured good in order to cope with the shocks to agricultural TFP and the associated increase in the cost of producing food. According to panel (a), in the deterministic '2016-2018-2020' scenario, consumption per capita is 9 percent lower than in the deterministic 'no shocks' scenario by 2030. Panel (b) also shows large reductions in optimal consumption per capita under the various stochastic shock scenarios. In the worst-case stochastic '2016-2018-2020' scenario, consumption per capita falls by as much as 17 percent relative to the deterministic 'no shocks' scenario in 2022, before recovering to about 13 percent lower in 2030. Hence a key consequence of a lower substitutability of land in agriculture is a higher welfare cost of agricultural TFP shocks.

5.2 Subsistence Food Demand ($\kappa = 0$)

In our main model specification, food demand is proportional to the level of population and is also an increasing (but concave) function of per-capita income (here per-capita output from the manufacturing sector). This is shown in equation (5), where the parameter κ measures the income elasticity of food demand. By making a link between manufacturing and agricultural output, the parameter $\kappa > 0$ creates complementarity, so that negative shocks to agricultural productivity will have a direct negative impact on production in the manufacturing sector. As an alternative, in this section we consider a case in which food demand is solely proportional to population ($\kappa = 0$), which is equivalent to a case in which food demand represents a physiological requirement. In this

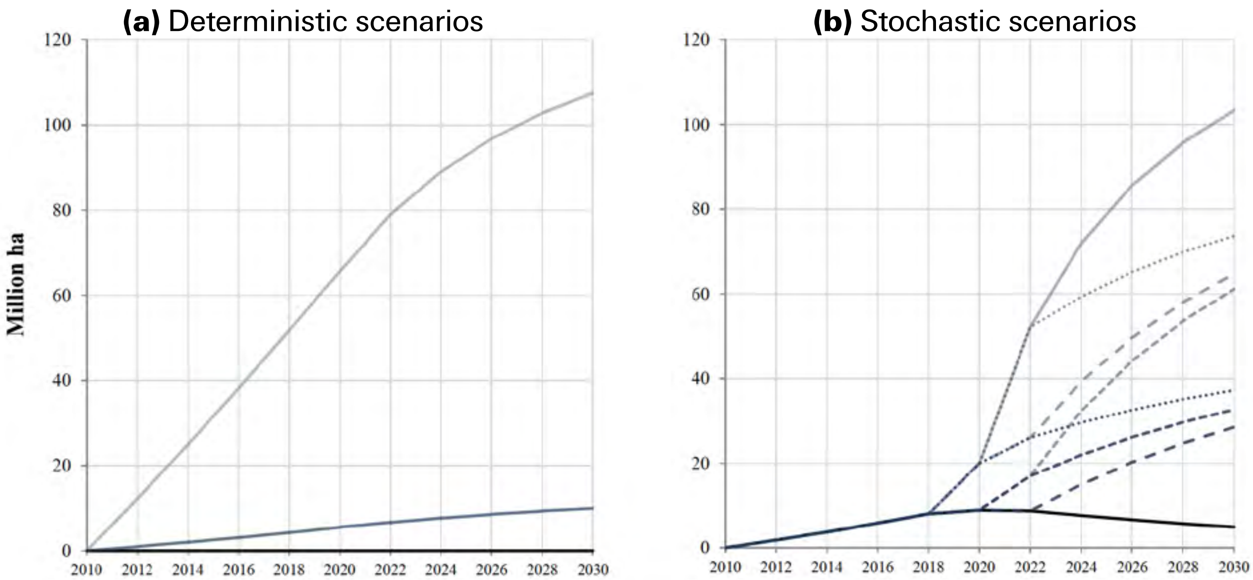


Figure 8.

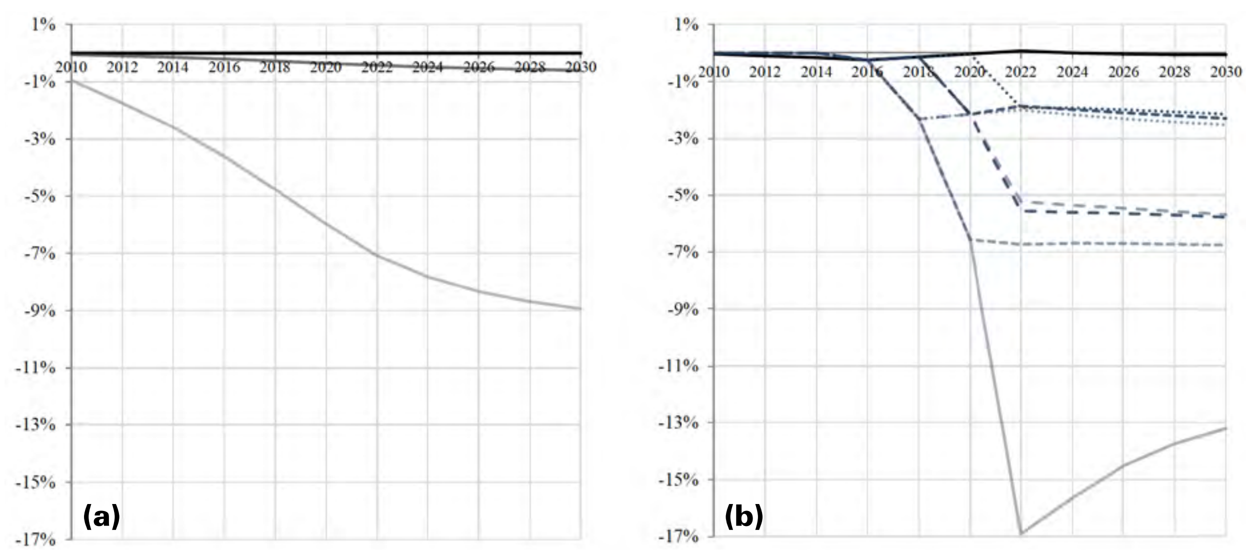


Figure 9.

framework, which is also studied in Strulik and Weisdorf (2008), Vollrath (2011) and Sharp *et al.* (2012), food production is directly proportional to population and hence implicitly directly enters into the objective of the planner.

Figure 10 reports results for $\kappa = 0$. As usual, panel (a) includes the deterministic scenarios and panel (b) the stochastic scenarios. **Figures 11 and 12** report corresponding results for population and consumption per capita respectively.

Figure 10 shows that optimal cropland area is fairly insensitive to changing the income elasticity of food demand. Cropland expansion in all scenarios, deterministic and stochastic, is only slightly lower relative to the comparable trajectories reported in Figure 5. However, Figure 12 shows that, when the income elasticity of food demand is zero, the trajectory for optimal consumption per capita differs significantly from that derived with $\kappa = 0.25$ (cf. Figure 7). In particular, when $\kappa = 0$ and the planner faces a negative shock to agriculture, the decline in per-capita consumption relative to the 'no shock' scenario is initially small, but then increases with time. Ultimately, therefore, the decline in per-capita consumption is more pronounced when $\kappa = 0$ than when $\kappa = 0.25$.

There are two main drivers of these differences. First, as expected, when the demand for food is not driven by

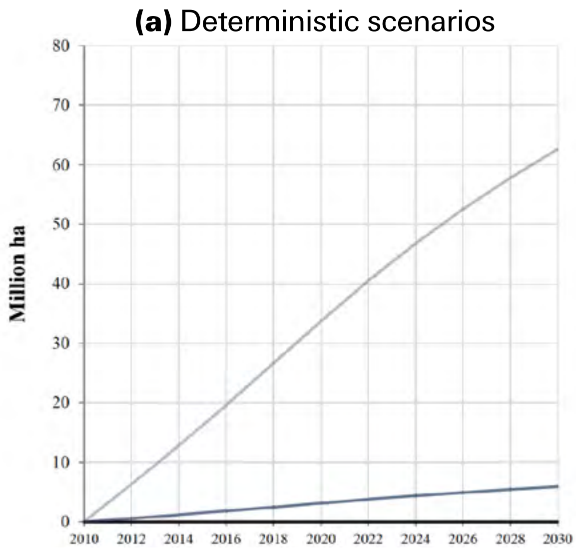


Figure 10.

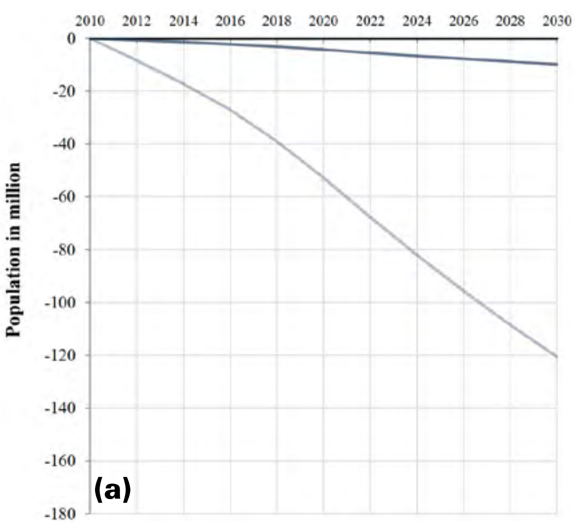


Figure 11.

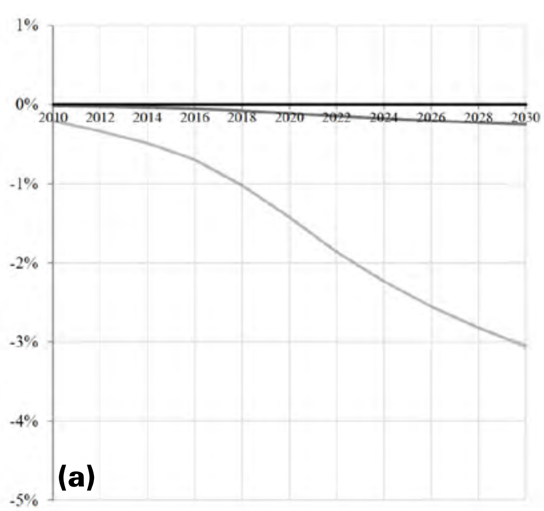
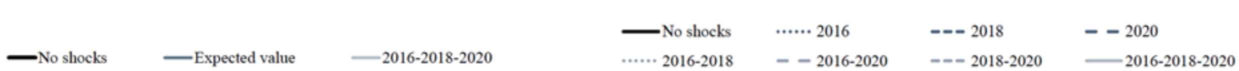


Figure 12.



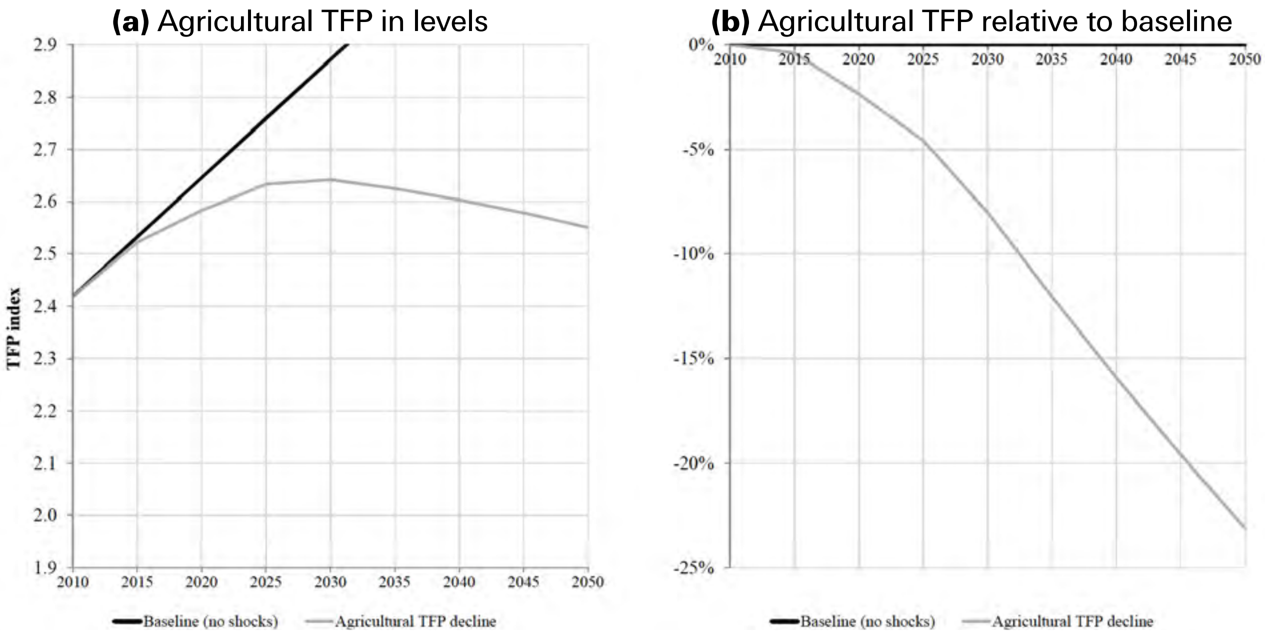


Figure 13.

income ($\kappa = 0$), *aggregate* consumption declines in response to an agricultural productivity shock, but not as much as when $\kappa = 0.25$. This is because $\kappa > 0$ implies some degree of complementarity between manufacturing and food consumption. Second, as we show in Figure 11, since $\kappa > 0$ implies that more weight is given to sustaining population, the decline in population following a shock is significantly smaller than when $\kappa = 0$. As the stock of population grows larger over time, this in turn implies that the decline in per-capita consumption is larger.

Thus, in sum, when food consumption reflects a subsistence constraint, the planner favors a large population over per-capita consumption, reflecting a preference over quantity rather than quality.

5.3 Negative Agricultural Productivity Growth

Our last extension to the model considers the possibility of a secular decline in the growth trend, rather than sudden and persistent shocks to a trend of otherwise growing agricultural TFP. This possibility has been raised by Alston *et al.* (2009) for example. Specifically, we consider a trajectory for agricultural TFP in which growth is around 1 percent from 2010 to 2015 (which is the same as our main specification), declines to 0.5 percent during the period 2015 to 2025, then drops to around zero and smoothly declines thereafter (at the same pace as in the main specification). The resulting trend is plotted in **Figure 13**, alongside agricultural TFP growth in our main specification. To make alternative specifications readily comparable, we constrain R&D-based TFP growth (and its associated labor requirements) to remain on its baseline trajectory, so agricultural R&D cannot compensate for this secular decline. In other words, the planner cannot add more labor to agricultural R&D so as to speed up technological progress in that sector. Therefore, since the planner cannot affect productivity growth, other adjustments are needed to compensate.

Results for agricultural land and per-capita consumption are reported in **Figure 14**. Global cropland is expanded gradually but significantly relative to the main deterministic 'no shocks' specification, with more than 200 million hectares of additional land brought under cultivation by 2050. When added to cropland expansion under the deterministic 'no shocks' scenario, this amounts to a total expansion of about 320 million hectares by 2050. As a sense-check, the median projection of the AgMIP models is for global cropland to expand by about 175 million hectares by 2050 in a reference scenario without climate change, but the range of uncertainty (i.e. the inter-model range) extends from about -100 million hectares to more than 400 million hectares (Schmitz *et al.*, 2014).

The right panel of Figure 14 shows that consumption per capita is initially higher under the scenario of agricultural TFP decline, which may appear puzzling at first. But this increase is due to the fact that, with an unexpected change in the trajectory for agricultural TFP growth, the saving rate is too high, and the planner i1runediately starts to consume more than he initially intended to. However, despite a short-term increase in per-capita consumption, over the longer run the difference erodes and after 2030 it is lower, falling to about 2.7 percent below the deterministic 'no shocks' scenario by 2050. This result confirms the view that a decline in agricultural TFP

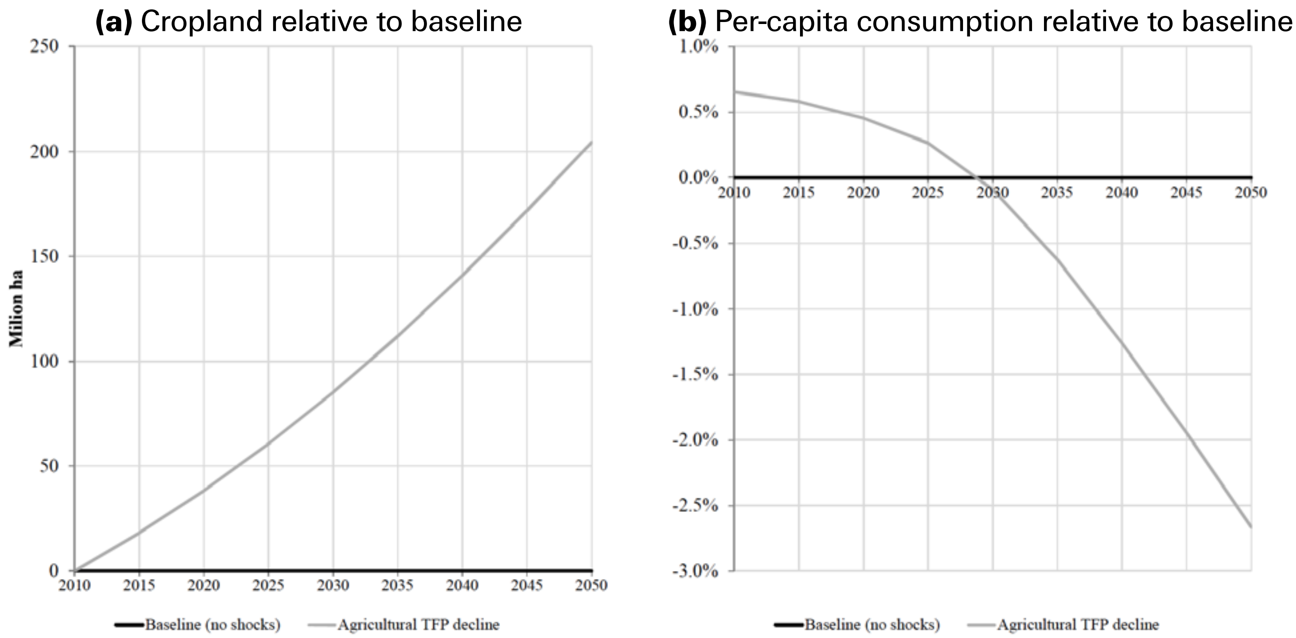


Figure 14.

growth in the near future has large and long-lasting macroeconomic consequences in terms of living-standards.

6. Conclusion

The development of agricultural technology is a key determinant of the ability to sustain enough food production in a world with growing population and per-capita income. Yet assessing uncertainties about its future evolution is difficult because of the wide ranging implications it will have. In this article we have taken a dynamic-stochastic view of the problem, focusing on the macroeconomic consequences at the global level, where both technological progress and population are endogenous.

The main contribution of our work is to quantify implications of technological uncertainty, showing that it implies significantly more land conversion to sustain agricultural production. Because our model combines a set of carefully selected theoretical blocks with an empirically-driven approach to the selection of parameters determining the quantitative response of the model, it suggests a number of hypothesis that could be tested empirically in future work. One of these is to focus on closed economies (presumably in the past) and quantify the change in agricultural land area following a negative agricultural shock. Another related empirical endeavor suggested by our work is related to substitutability of land in agriculture. We have shown that our results are significantly affected by assumptions about this quantity, and further evidence along the lines suggested by Wilde (2013) is warranted.

Our work further shows that population is significantly affected by variability in agricultural TFP. The scale of the population impacts with our baseline assumptions goes into the tens of millions, eventually even more than that. We emphasize that, in our model, this effect goes through lower fertility, as negative agricultural productivity shocks increase the relative cost of food. In other words, our model captures a socially optimal adjustment of population that is based on a constant mortality assumption. It is nevertheless indicative of a large food security issue, as in the real world smooth forward looking adjustments are unlikely.

We close by highlighting that our global view of the problem hides distributional issues. Most famines and environmental degradation occur at the local level, and in particular in developing countries. Agricultural TFP shocks may disproportionately affect low-income countries. Similarly, since land conversion will most likely occur in developing countries, technological uncertainty may exacerbate further land conversion and biodiversity losses there.

Acknowledgements

We thank David Laborde, Guy Meunier, Pietro Peretto, John Reilly, David Simpson, Simone Valente and Marty Weitzman, as well as seminar participants at ETH Zürich, INRA-ALISS and MIT for comments and discussions. Excellent research assistance was provided by Ozgun Haznedar. The research leading to these results has received funding from the European Union's Seventh Framework Programme FP7/2007-2011 under Grant Agreement Number 290693 FOOD-SECURE. The authors alone are responsible for any omissions or deficiencies. Neither the FOOD-SECURE project and any of its partner organizations, nor any organization of the European Union or European Commission, are accountable for the content of the article.

7. References

Acemoglu, D., S. Naidu, P. Restrepo & J. Robinson (2017): Democracy does cause growth. *Journal of Political Economy,* forthcoming.

Aghion, P. & P. Howitt (1992): A model of growth through creative destruction. *Econometrica,* 60(2): 323–351.

Alexandratos, N. & J. Bruinsma (2012): World agriculture towards 2030/2050, The 2012 revision. ESA Working Paper No. 12-03.

Alston, J.M., J.M. Beddow & P.G. Pardey (2009): Agricultural research, productivity, and food prices in the long run. *Science,* 325: 1209–1210.

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

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

Ashraf, Q.H., A. Lester & D. Weil (2008): When does improving health raise GDP? In D. Acemoglu, K. Rogoff & M. Woodford eds. *NBER Macroeconomics Annual:* 157–204: University of Chicago Press.

Auffuammer, M., V. Ramanathan & J. Vincent (2006): Integrated model shows that athmospheric brown clouds and greenhouse gases have reduced rice harvests in India. *Proceedings of the National Academy of Sciences,* 103(52): 19668–19672.

Auffuammer, M. & W. Schlenker (2014): Empirical studies on agricultural impacts and adaptation. *Energy Economics,* 46: 555–561.

Barro, R.J. & G.S. Becker (1989): Fertility choice in a model of economic growth. *Econometrica,* 57: 481–501.

Beatty, T.K.M. & J.T. LaFrance (2005): United States demand for food and nutrition in the twentieth century. *American Journal of Agricultural Economics,* 87(5): 1159–1166.

Bolt, J. & J.L. van Zanden (2013): The first update of the maddison project; re-estimating growth before 1820. Maddison Project Working Paper 4.

Boserup, E. (1965) *The Conditions of Agricultural Progress:* Chicago, IL: Aldine Publishing Company.

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

Bruckner, M. & A. Ciccone (2011): Rain and the democratic window of opportunity. *Econometrica,* 79(3): 923–947.

Burgess, R. & D. Donaldson (2010): Can openness mitigate the effects of weather shocks? evidence from India's famine era. *American Economic Review,* 100(2): 449–453.

Byrd, R., M.E. Hribar & J. Nocedal (1999): An interior point method for large scale nonlinear programming. *SIAM Journal on Optimization,* 9(4): 877–900.

Byrd, R.H., J. Nocedal & R.A. Waltz (2006): KNITRO: An integrated package for nonlinear optimization. In G. di Pillo & M. Roma eds. *Large-Scale Nonlinear Optimization:* Springer-Verlag, pp. 35–59.

Cai, Y., J. Steinbuks, J. Elliott & T. Hertel (2014): The effect of climate and technological uncertainty in crop yields on the optimal path of global land use. World Bank Policy Research Working Paper 7009.

Chu, A., G. Cozzi & C.-H. Liao (2013): Endogenous fertility and human capital in a Schumpeterian growth model. *Journal of Population Economics,* 26: 181–202.

Clarke, L., K. Jiang, K. Akimoto *et al.* (2014): Asessing transformation pathways. In O. Edenhofer, R. Pichs-Madruga, Y. Sokona *et al.* eds. *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change,* Cambridge, UK and New York, NY, USA: Cambridge University Press.

Costinot, A., D. Donaldson & C. Smith (2016): Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world. *Journal of Political Economy,* 124(1): 205–248.

Di Falco, S. (2012): On the value of agricultural biodiversity. *Annu. Rev. Resow: Econ.,* 4(1): 207–223.

Di Falco, S. & J.-P. Chavas (2008): Rainfall shocks, resilience, and the effects of crop biodiversity on agroecosystem productivity. *Land Economics,* 84(1): 83–96.

Dinopoulos, E. & P. Thompson (1998): Schumpeterian growth without scale effects. *Journal of Economic Growth,* 3: 313–335.

Dinopoulos, E. & P. Thompson (1999): Scale effects in Schumpeterian models of economic growth. *Journal of Evolutionary Economics,* 9: 157–185.

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

FAO (2015): FAOSTAT Database. Food and Agriculture Organization of the United Nations, Rome (http://faostat3.fao.org/home/E, accessed 20 January 2016).

Fezzi, C. and L Bateman (2015): Aggregation bias and non-linear effects in Ricardian models of climate change. *Journal of the Association of Environmental and Resource Economists,* 2: 57–92.

Fuglie, K.O. (2012): Productivity growth and technology capital in the global agricultural economy. In K.O. Fuglie, S.L. Wang & V.E. Ball eds. *Productivity Growth in Agriculture: An International Perspective:* Wallingford, U.K.: CAB International, pp. 335–368.

Fuglie, K. & N. Rada (2015): Agricultural total factor productivity growth indices for geographic regions, 1961–2012. United States Department of Agriculture, Economic Research Service, Washington, DC (http://www.ers.usda.gov/data-products/international-agricultural-productivity/documentation-and-methods.aspx, accessed 20 January 2016).

Galor, O. & D.N. Weil (2000): Population, technology, and growth: From Malthusian stagnation to the demographic transition and beyond. *American Economic Review,* 90(4): 806–828.

Godfray, H.C.J., J.R. Beddington, L R. Crute, L. Haddad, D. Lawrence, J.F. Muir, J. Pretty, S. Robinson, S.M. Thomas & C. Toulmin (2010): Food security: The challenge of feeding 9 billion people. *Science,* 327: 812–818.

Goldewijk, K. (2001): Estimating global land use change over the past 300 years: The hyde database. *Global Biogeochemical Cycles,* 15(2): 417–433.

Goldin, C. & L. Katz (1998): The origins of technology-skill complementarity. *Quarterly Journal of Economics,* 113: 693–732.

Gollin, D. (2002): Getting income shares right. *Journal of Political Economy,* 110(2): 458–474.

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

Hansen, G.D. & E.C. Prescott (2002): Malthus to Solow. *American Economic Review,* 92(4): 1204–1217.

Hertel, T., M. Tsigas & B. Narayanan (2012): Chapter 12.a: Primary factor shares. In B. Narayanan, A. Aguiar & R. McDougall eds. *Global Trade, Assistance, and Production: The GTAP 8 Data Base:* Center for Global Trade Analysis, Purdue University.

IPCC (2013): Working Group I Contribution to the IPCC Fifth Assessment Report: Summary for Policymakers. In *Climate Change 2013: The Physical Science Basis:* IPCC.

Jayachandran, S. (2006): Selling labor low: Wage responses to productivity shocks in developing countries. *Journal of Political Economy,* 114(3): 538–575.

Jones, C.I. (1995a): R&D-based mmodel of economic growth. *The Journal of Political Economy,* 103(4): 759–784.

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

Jones, C.I. (2001): Was an industrial revolution inevitable? Economic growth over the very long run. *The B.E. Journal of Macroeconomics,* 1(2): 1–45.

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

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

Kawagoe, T., K. Otsuka & Y. Hayami (1986): Induced bias of technical change in agriculture: The United States and Japan, 1880–1980. *Journal of Political Economy,* 94(3): 523–544.

Khoury, C.K., A.D. Bjorkman, H. Dempewolf, J. Ramirez-Villegas, L. Guarino, A. Jarvis, L.H. Rieseberg & P.C. Strulik (2014): Increasing homogeneity in global food supplies and the implications for food security. *Proceedings of the National Academy of Sciences,* p. 201313490, March.

Kremer, M. (1993): Population growth and technological change: One milion B.C. to 1990. *Quarterly Journal of Economics,* 108(30): 681–716.

Lainez, C.A. & P.F. Peretto (2006): Scale effects in endogenous growth theory: an error of aggregation not specification. *Journal of Economic Growth,* 11: 263–288.

Lanz, B., S. Dietz & T. Swanson (2016): The expansion of modern agriculture and global biodiversity decline: An integrated assessment. Grantham Research Institute Working Paper 167.

Lanz, B., S. Dietz & T. Swanson (forthcoming): Global population growth, technology, and land conversion: A quantitative growth theoretic perspective. *International Economic Review.*

Maddison, A. (1995): Monitoring the world economy 1820–1992. Paris: Organization for Economic Cooperation and Development.

Martin, W. & D. Mitra (2001): Productivity growth and convergence in agriculture versus manufacturing. *Economic Development and Cultural Change,* 49(2): 403–422.

Millennium Ecosystem Assessment (2005): *Ecosystems and Human Well-Being: Synthesis,* Washington, DC: Island Press. Nelson, G.C., D. Mensbrugghe, H. Ahammad, E. Blanc, K. Calvin, T. Hasegawa, P. Havlik, E. Heyhoe, P. Kyle, H. Lotze-Campen *et al.* (2014a): Agriculture and climate change in global scenarios: why don't the models agree? *Agricultural Economics,* 45(1): 85–101.

Nelson, G.C., H. Valin, R.D. Sands, P. Havlk, H. Ahammad, D. Deryng, J. Elliott, S. Fujimori, T. Hasegawa, E. Heyhoe, P. Kyle, M. Von Lampe, H. Lotze-Campen, D. Mason dCroz, H. van Meijl, D. van der Mensbrugghe, C. Mller, A. Popp, R. Robertson, S. Robinson, E. Schmid, C. Schmitz, A. Tabeau & D. Willenbockel (2014b): Climate change effects on agriculture: Economic responses to biophysical shocks. *Proceedings of the National Academy of Sciences,* 111(9): 3274–3279.

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

Ngai, L.R. & C.A. Pissarides (2007): Structural change in a multisector model of growth. *American Economic Review,* 97(1): 429–443.

Peretto, P.F. (1998): Technological change and population growth. *Journal of Economic Growth,* 3: 283–311.

Peretto, P. & S. Valente (2015): Growth on a finite planet: Resources, technology and population in the long run. *Journal of Economic Growth,* 20: 305–331. Working Papers 11-12, Duke University, Department of Economics.

Prieur, F. & I. Schumacher (2016): The role of conflict for optimal climate and immigration policy. TSE working paper.

Romer, P.M. (1994): The origins of endogenous growth. *The Journal of Economic Perspectives,* 8(1): 3–22.

Schlenker, W. & M. Roberts (2009): Estimating the impact of climate change on crop yields: The importance of nonlinear temperature effects. *Proceedings of the National Academy of Sciences,* 106(37): 15594–15598.

Schmitz, C., H. van Meijl, P. Kyle, G.C. Nelson, S. Fujimori, A. Gurgel, P. Havlik, E. Heyhoe, C., M. d'Croz, A. Popp *et al.* (2014): Land-use change trajectories up to 2050: insights from a global agro-economic model comparison. *Agricultural Economics,* 45(1): 69–84.

Schündeln, M. (2013): Appreciating depreciation: Physical capital depreciation in a developing country. *Empirical Economics,* 44: 1277–1290.

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

Strulik, H. & J. Weisdorf (2008): Population, food, and knowledge: A simple unified growth theory. *Journal of Economic Growth,* 13: 195–216.

Strulik, H. & J. Weisdorf (2014): How child costs and survival shaped the industrial revolution and the demographic transition: A theoretical inquiry. *Macroeconomic Dynamics,* 18: 114–144.

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

Thomas, D. & J. Strauss (1997): Health and wages: evidence on men and women in urban brazil. *Journal of Econometrics,* 77(1): 159–185.

Tilman, D., C. Balzer, J. Hill & B.L. Befort (2011): Global food demand and the sustainable intensification of agriculture. *Proceedings of the National Academy of Sciences,* 108(50): 20260–20264.

Tournemaine, F. & P. Luangaram (2012): R&D, human capital, fertility and growth. *Journal of Poulation Economics,* 25: 923–953.

United Nations (1999): *The world at six billion.* New York: Population Division, Department of Economic and Social Affairs, United Nations Secretariat.

United Nations (2013): World population prospects: The 2012 revision. Department of Economic and Social Affairs, Population Division, New York.

United Nations (2015): *World population prospects: the 2015 revision, DVD edition:* United Nations, Department of Economic and Social Affairs, Population Division.

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

Wilde, J. (2013): How substitutable are fixed factors in production? evidence from pre-industrial england. Working paper 0113, University of South Florida, Department of Economics.

World Bank (2016): *World development indicators:* Washington, D.C.: The World Bank.

Young, A. (1998): Growth without scale effects. *Journal of Political Economy,* 106: 41–63.

Appendix: Estimated parameters and model fit

The vector of parameters that minimizes equation (10) is reported in **Table A1**, and the resulting trajectories are reported in **Figure A1**, comparing observations over the period from 1960 to 2010 with simulations from the estimated model. As evident from the figures, the estimated model provides a very good fit to recent history, and the relative squared error (10) across all variables is 3.52 percent. The size of the error is mainly driven by the error on output (3.3 percent), followed by land (0.1 percent) and population (0.03 percent). Figure Al also reports the growth rate of population, which is not directly targeted by the estimation procedure, showing that the simulated trajectory closely fits the observed dynamics of population growth.

Table A1.

Parameter	Description	Estimates
μ_{mn}	Elasticity of labor in manufacturing R&D	0.581
μ_{ag}	Elasticity of labor in agricultural R&D	0.537
χ	Labor productivity parameter in child rearing	0.153
ζ	Elasticity of labor in child rearing	0.427
ω	Elasticity of labor productivity in child rearing w.r.t. technology	0.089
ψ	Labor productivity in land conversion	0.079
ε	Elasticity of labor in land conversion	0.251

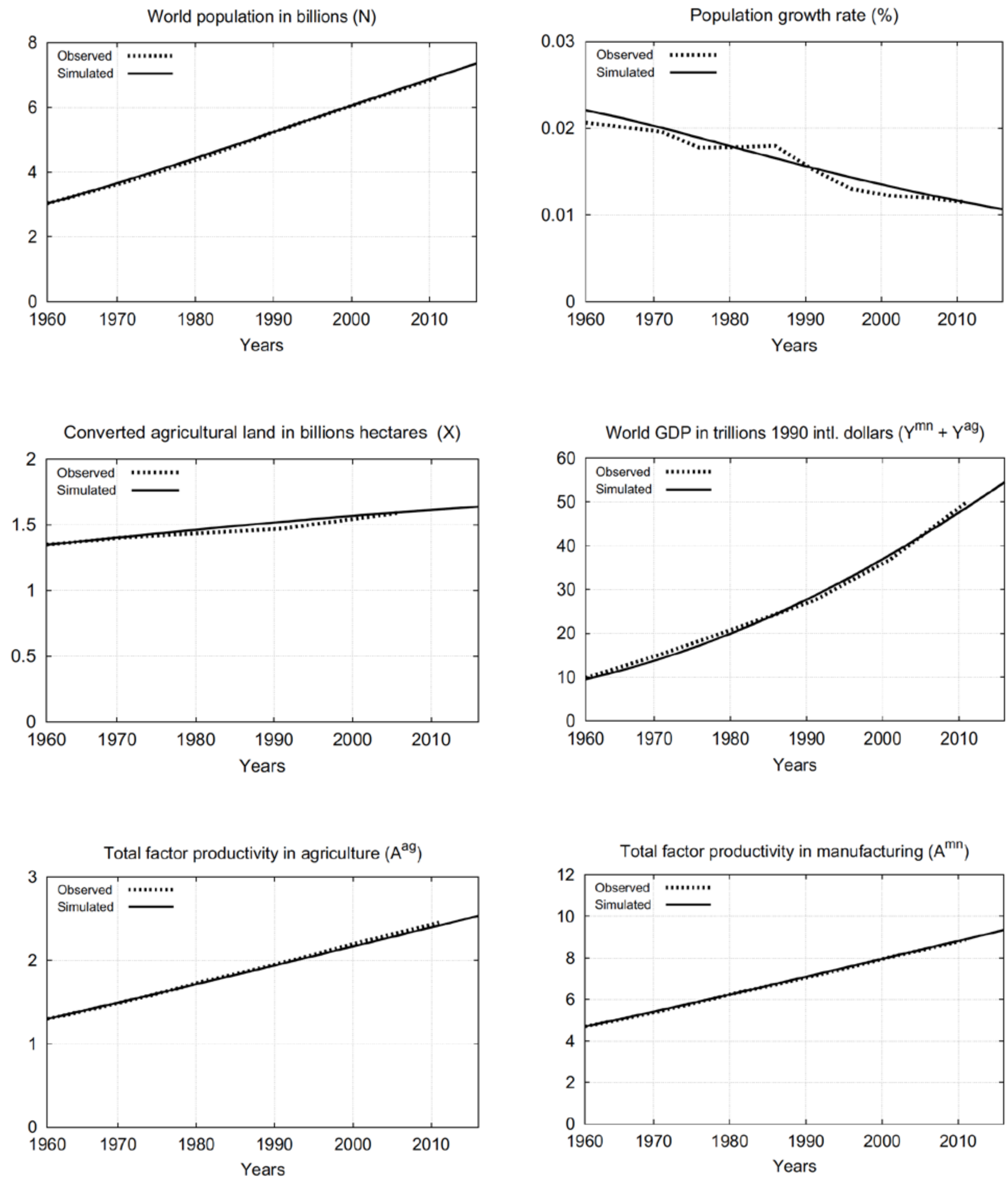


Figure A1. Estimation of the model 1960–2010 (source: Lanz *et al.*, forthcoming)

Joint Program Report Series - Recent Articles

For limited quantities, Joint Program Reports are available free of charge. Contact the Joint Program Office to order.
Complete list: http://globalchange.mit.edu/publications

313. **Global economic growth and agricultural land conversion under uncertain productivity improvements in agriculture.** *Lanz et al., Jun 2017*

312. **Can Tariffs be Used to Enforce Paris Climate Commitments?** *Winchester, Jun 2017*

311. **A Review of and Perspectives on Global Change Modeling for Northern Eurasia.** *Monier et al., May 2017*

310. **The Future of Coal in China.** *Zhang et al., Apr 2017*

309. **Climate Stabilization at 2°C and Net Zero Carbon Emissions.** *Sokolov et al., Mar 2017*

308. **Transparency in the Paris Agreement.** *Jacoby et al., Feb 2017*

307. **Economic Projection with Non-homothetic Preferences: The Performance and Application of a CDE Demand System.** *Chen, Dec 2016*

306. **A Drought Indicator based on Ecosystem Responses to Water Availability: The Normalized Ecosystem Drought Index.** *Chang et al., Nov 2016*

305. **Is Current Irrigation Sustainable in the United States? An Integrated Assessment of Climate Change Impact on Water Resources and Irrigated Crop Yields.** *Blanc et al., Nov 2016*

304. **The Impact of Oil Prices on Bioenergy, Emissions and Land Use.** *Winchester & Ledvina, Oct 2016*

303. **Scaling Compliance with Coverage? Firm-level Performance in China's Industrial Energy Conservation Program.** *Karplus et al., Oct 2016*

302. **21st Century Changes in U.S. Heavy Precipitation Frequency Based on Resolved Atmospheric Patterns.** *Gao et al., Oct 2016*

301. **Combining Price and Quantity Controls under Partitioned Environmental Regulation.** *Abrell & Rausch, Jul 2016*

300. **The Impact of Water Scarcity on Food, Bioenergy and Deforestation.** *Winchester et al., Jul 2016*

299. **The Impact of Coordinated Policies on Air Pollution Emissions from Road Transportation in China.** *Kishimoto et al., Jun 2016*

298. **Modeling Regional Carbon Dioxide Flux over California using the WRF-ACASA Coupled Model.** *Xu et al., Jun 2016*

297. **Electricity Investments under Technology Cost Uncertainty and Stochastic Technological Learning.** *Morris et al., May 2016*

296. **Statistical Emulators of Maize, Rice, Soybean and Wheat Yields from Global Gridded Crop Models.** *Blanc, May 2016*

295. **Are Land-use Emissions Scalable with Increasing Corn Ethanol Mandates in the United States?** *Ejaz et al., Apr 2016*

294. **The Future of Natural Gas in China: Effects of Pricing Reform and Climate Policy.** *Zhang & Paltsev, Mar 2016*

293. **Uncertainty in Future Agro-Climate Projections in the United States and Benefits of Greenhouse Gas Mitigation.** *Monier et al., Mar 2016*

292. **Costs of Climate Mitigation Policies.** *Chen et al., Mar 2016*

291. **Scenarios of Global Change: Integrated Assessment of Climate Impacts.** *Paltsev et al., Feb 2016*

290. **Modeling Uncertainty in Climate Change: A Multi-Model Comparison.** *Gillingham et al., Dec 2015*

289. **The Impact of Climate Policy on Carbon Capture and Storage Deployment in China.** *Zhang et al., Dec 2015*

288. **The Influence of Gas-to-Liquids and Natural Gas Production Technology Penetration on the Crude Oil-Natural Gas Price Relationship.** *Ramberg et al., Dec 2015*

287. **Impact of Canopy Representations on Regional Modeling of Evapotranspiration using the WRF-ACASA Coupled Model.** *Xu et al., Dec 2015*

286. **Launching a New Climate Regime.** *Jacoby & Chen, Nov 2015*

285. **US Major Crops' Uncertain Climate Change Risks and Greenhouse Gas Mitigation Benefits.** *Sue Wing et al., Oct 2015*

284. **Capturing Natural Resource Dynamics in Top-Down Energy-Economic Equilibrium Models.** *Zhang et al., Oct 2015*

283. **Global population growth, technology, and Malthusian constraints: A quantitative growth theoretic perspective.** *Lanz et al., Oct 2015*

282. **Natural Gas Pricing Reform in China: Getting Closer to a Market System?** *Paltsev & Zhang, Jul 2015*

281. **Impacts of CO_2 Mandates for New Cars in the European Union.** *Paltsev et al., May 2015*

280. **Water Body Temperature Model for Assessing Climate Change Impacts on Thermal Cooling.** *Strzepek et al., May 2015*

279. **Emulating maize yields from global gridded crop models using statistical estimates.** *Blanc & Sultan, Mar 2015*

278. **The MIT EPPA6 Model: Economic Growth, Energy Use, and Food Consumption.** *Chen et al., Mar 2015*

277. **Renewables Intermittency: Operational Limits and Implications for Long-Term Energy System Models.** *Delarue & Morris, Mar 2015*

MIT Joint Program on the Science and Policy of Global Change

Massachusetts Institute of Technology
77 Massachusetts Ave., E19-411
Cambridge MA 02139-4307 (USA)

T (617) 253-7492 **F** (617) 253-9845
globalchange@mit.edu
http://globalchange.mit.edu/