Research Paper 43 | **2016**

ECONOMIC GROWTH AND AGRICULTURAL LAND CONVERSION UNDER UNCERTAIN PRODUCTIVITY IMPROVEMENTS IN AGRICULTURE

B. LANZ, S. DIETZ AND T. SWANSON

Economic growth and agricultural land conversion under uncertain productivity improvements in agriculture*

Bruno Lanz† Simon Dietz‡ Tim Swanson§

This version: May 2016

Abstract

We study how stochasticity in the evolution of agricultural productivity interacts with economic and population growth, and the associated demand for food. 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 contemporary population. In addition, sectors differ in that agriculture also 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 consumption and population trajectories.

Keywords: Economic growth; Stochastic control; Agricultural productivity; Endogenous innovations; Land conversion; Population dynamics; Food security.
JEL Classification numbers: O11, O13, O31, J11, C61, Q16, Q24.

---

*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 FOODSECURE. The authors alone are responsible for any omissions or deficiencies. Neither the FOODSECURE project and any of its partner organizations, nor any organization of the European Union or European Commission, are accountable for the content of the paper.

†Corresponding author. Graduate Institute of International and Development Studies, Department of Economics and Centre for International Environmental Studies, Eugène Rigot 2, 1202 Geneva, Switzerland; ETH Zurich, Chair for Integrative Risk Management and Economics; Massachusetts Institute of Technology, Joint Program on the Science and Policy of Global Change. e-mail: bruno.lanz@graduateinstitute.ch.

‡London School of Economics and Political Science, Grantham Research Institute on Climate Change and the Environment.

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

1 Introduction

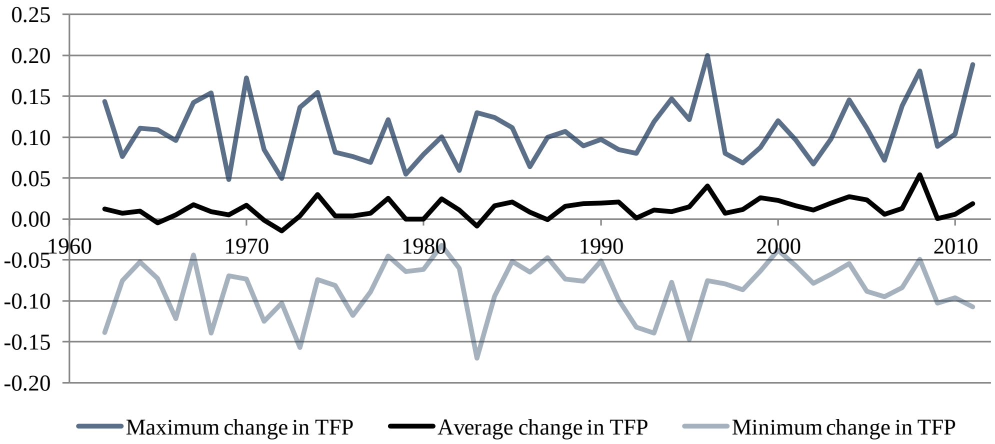
Global population has grown from around three billion in 1960 to seven billion in 2010, and over the same 50 years agricultural production has almost tripled, mostly on account of a sustained increase in agricultural productivity (Alexandratos and Bruinsma, 2012). Given projected growth in the population that will need to be fed – with global population expected to reach 10 billion before 2060 (Gerland et al., 2014) – further improvements to agricultural productivity will need to take place (Alston and Pardey, 2014). While these productivity improvements give an important role to innovation and technology adoption in agriculture, uncertainty and variability associated with agricultural output puts an increasing number of persons at risk of insufficient food supply.

Given the importance of the evolution of agricultural productivity for global development, in this paper our objective is to study how uncertainty about agricultural technology affects optimal allocation of resources at the macroeconomic level. As we illustrate in Figure 1, yearly growth of total factor productivity (TFP) in agriculture has been around one percent on average over the period 1960 to 2010, but there is ample variation in yearly growth rates both across regions and over time.[1] Specifically, maximum and minimum TFP growth suggest very large variability in the realization of productivity gains, with a range of -15 to +20 percent per year across regions.

In addition to the inherent variability of agricultural productivity, the evolution of future agricultural output may be affected by novel factors that have not been observed in the past fifty years. For example, a major source of uncertainty is future climate change, whose impacts on agriculture are difficult to evaluate. However, recent evidence suggests that agricultural productivity could deteriorate significantly, globally on aggregate (see e.g. Nelson et al., 2014). Another source of uncertainty stems from natural-resource and biological scarcities (e.g. Godfray et al., 2010; Tilman et al., 2011). An example of such risk involves an evolutionary argument, whereby the probability that pests and pathogens adapt to a given agricultural innovation in-

[1] Data on TFP growth are derived from Fuglie and Rada (2015) and FAO (2015), using 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. However, whereas Fuglie and Rada (2015) apply a Hodrick-Prescott filter to smooth year-on-year output fluctuations before calculating TFP, our focus is the variability of agricultural productivity, and TFP figures reported in Figure 1 are based on raw (unsmoothed) output data from FAO (2015).

Figure 1: Total factor productivity growth in agriculture, 1960–2010



Notes: 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.

creases with time(e.g. Evans, 1993; Scheffer, 1997). This may render particular agricultural technologies obsolete (such as making some classes of pesticide ineffective), and thus induce a drop in productivity (Weitzman, 2000; Goeschl and Swanson, 2003).[2]

To study the socially optimal response to agricultural productivity shocks, we employ a stochastic version of a quantitative two-sector endogenous growth model of the global economy first introduced in Lanz et al. (2016). 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 in the economy (producing 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 key components. First, additional labor units demand food, and the level of per-capita food demand is proportional to income, reflecting empirical evidence on diet changes as affluence rises (e.g. Subramanian and Deaton, 1996; Thomas and Strauss, 1997). In the model, food is produced

[2] As we discuss in Lanz et al. (2014), this sort of risk may be related to the scale of modern agriculture, although in the present work we focus on a more general *exogenous* source of uncertainty.

by the agricultural sector, so that the evolution of agricultural productivity may act as a constraint to the evolution of population. A second component of fertility costs is the time needed to rear and educate children. Our model builds on the work of Galor and Weil (2000), and we posit an increasing relationship between the level of technology in the economy and the cost of population increments. In this context, technological progress raises the demand for human capital and education requirements, 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 our model, technological progress in each sector is endogenous, and we use the Schumpeterian R&D model of Aghion and Howitt (1992), in which TFP growth is a function of labor hired by R&D firms. Thus, on the one hand, technological progress in agriculture reduces the cost of producing food, and is a key driver of agricultural yields (agricultural output per unit of area). In turn, agricultural technology improvements can alleviate Malthusian concerns associated with the finiteness of the 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. (2016), 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 paper, we introduce introduce uncertainty in the evolution of agricultural TFP from 2010 onwards. 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, with a growth rate of 1.2 percent per year in 2010, and reaches 0.9 percent per year in 2030.[3] Given

[3] Linear increase in agricultural yields is consistent with existing literature; see for example Alston et al. (2009) and Godfray et al. (2010).

the structure of productivity shocks we consider, there is a 73 percent probability that this baseline situation prevails by 2030. If 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 reduced by around 15 percent, and a small (0.1 percent) probability that it is reduced by more than 20 percent.[4]

In the model, the socially optimal response to uncertain agricultural productivity shocks occurs in a number of important dimensions. First, given the possibility of lower productivity in the future, allocating more labor to R&D can speed up the pace of agricultural productivity growth. Second, when a 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 the supply of food and thus population growth. In particular, population will be negatively affected by depreciation of agricultural technology, so that shocks will thus affect equilibrium trajectories over the long run. Finally, per-capita consumption is also expected to decline, as more resources need to be allocated to the agricultural sector at the expense of manufacturing production.

Our results indicate that variability in agricultural TFP induces a substantial reallocation of resources relative to baseline trajectories. Specifically, 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 supplemental 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 for the production of 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.

Our work is related to at least two streams of literature that consider interactions between

[4] Note that our objective is *not* to carry out an assessment of some specific uncertain event that would affect agricultural productivity. 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.

economic growth, food production and population development. First, our paper is related to the seminal work of Galor and Weil (2000) and Jones (2001), who study the joint evolution of economic growth and population over the long run, and to Hansen and Prescott (2002), Strulik and Weisdorf (2008), Vollrath (2011) and Sharp et al. (2012), who also consider the role of land and agriculture. In this context, Bretschger (2013) and Peretto and Valente (2015) consider the related issue of natural resource scarcity, and Strulik and Weisdorf (2014) study quantitatively the linkages between technology, agriculture and population. However, none of these growth papers attempt to introduce uncertainty about future technological progress. Another important difference is that key parameters of our quantitative model are structurally estimated, so that our model closely replicates observed trajectories over the past fifty years.

Second, our work contributes to the growing literature that provides evidence on the impact of future climate change on agriculture and food production. For example, the large-scale model comparison exercise carried out under the AgMIP project (see notably Nelson and Shively, 2014, and other papers in this volume) suggests that climate change is expected to reduce global yields by 17 percent on average by 2050, although an adaptive, economic response would reduce this negative impact to 11 percent (e.g. by switching crops). See the summary results reported in Nelson et al. (2014). This is associated with an increase of crop area by 11 percent on average relative to the baseline. Whereas models used to derived these results feature high-resolution sectoral and regional representations, they treat the evolution of other drivers (such as the demand for food and agricultural yields) as exogenous. Instead, our contribution considers the globally aggregated evolution of population, per capita income, and technology as endogenous outcomes, which allows us to study how these variables jointly respond to uncertainty about future agricultural productivity growth.

Another paper that is 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 the risk increases the demand for cropland globally by 2100, 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,[5] ours emphasizes the role of endogenous technological progress through R&D activities, and also allows population to respond to changes in agricultural productivity.

The remainder of the paper is organized as follows. Section 2 provides an overview of the model, estimation procedure, and then describes how we introduce stochasticity in the outcomes of agricultural R&D. Section 3 reports our results, and we provide a discussion in Section 4. We close with some concluding comments in Section 5.

2 The model

This section first summarizes the key components of the growth model. Second, we present the simulation-based structural estimation procedure. Third, we explain how we introduce stochastic shocks to the evolution of agricultural productivity.[6]

2.1 The economy

2.1.1 Manufacturing production and agriculture

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

$$Y_{t,mn} \;=\; A_{t,mn}K_{t,mn}^{\vartheta}L_{t,mn}^{1-\vartheta}\,, \tag{1}$$

where $A_{t,mn}$ is TFP in manufacturing, $K_{t,mn}$ is capital and $L_{t,mn}$ is the workforce.[7] 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)

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

[6] As noted above, Lanz et al. (2016) 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 projections 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 from Bruno Lanz's website.

[7] Note that under the assumption that technology is Hicks-neutral, the Cobb-Douglas functional form is consistent with long-term empirical evidence reported in Antràs (2004).

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:

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

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).

2.1.2 Innovations and technological progress

In the absence of productivity shocks, which are discussed in Section 2.3, the evolution of sectoral TFP is given by:

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

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,A_j} 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.[8] 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 population and technological progress.[9] 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 Laincz and Peretto, 2006).

2.1.3 Population dynamics

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

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

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 sug-

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

[9] 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; Laincz and Peretto, 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.

gests a complementarity between human capital and technology (e.g. Goldin and Katz, 1998), and we specify the cost of children as an increasing function of the economy-wide level of technology:

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

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. (2016) that this representation of the cost of children is consistent with the more comprehensive model by 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):

$$Y_t^{ag} = N_t \overline{f}_t, \tag{5}$$

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).

2.1.4 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 $L_{t,X}$. In our model, land is therefore treated as a scarce form of capital, and we write the motion equation for agricultural land as:

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

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 the cost associated with bringing marginal plots into production is higher.

2.1.5 Households preferences and savings

In the tradition of Barro and Becker (1989), household preferences are defined over own consumption of a (composite) manufacturing 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. (2016), it is straightforward to express preferences 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 $\eta = 0.01$ so that the household's objective is akin to the standard Classical Utilitarian welfare function. Intuitively, it implies that altruism towards surviving members of the dynasty remains almost constant as the number of survivors increases.

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:

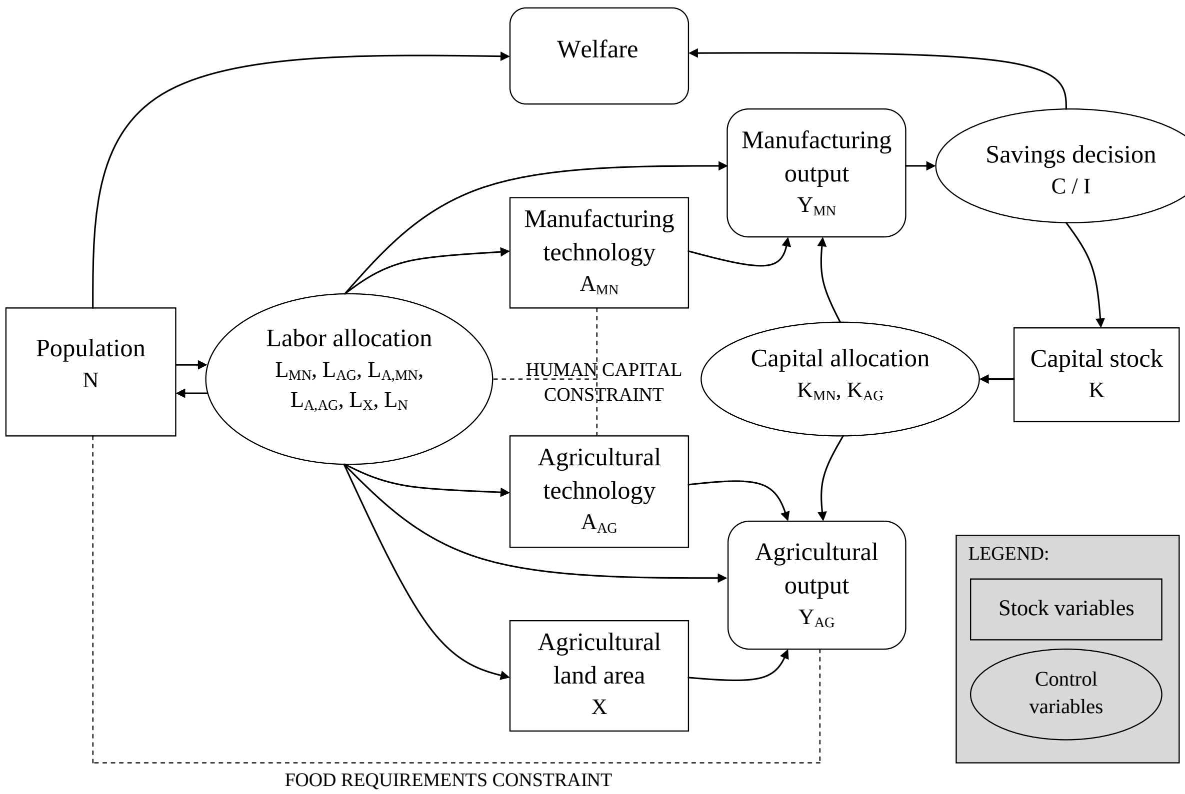
$$K_{t+1} \; = \; K_t(1-\delta_K) + I_t \, , \quad K_0 \text{ given} \, , \tag{9}$$

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

2.2 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

Figure 2: Schematic representation of the model



constraints (1), (2), (3), (4), (5) (6), (8), (9) and feasibility conditions for capital and labor:

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

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

[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.

(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 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), crop land 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 this data corresponds 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:

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

where $Z_{k,\tau}$ denotes the observed quantity k at time τ and $Z^*_{k,\tau}$ is the corresponding value simulated from the model. By gradually refining the bounds defined for 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., 2016, 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

[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 from 1980 to 2000, and then stays at 1 percent over the last decade.

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.

2.3 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.

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:

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

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:

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

[12] Because there are externalities in the model, most notably in R&D activities (see Romer, 1994, for example) the social optimum determined by the social planer 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, quantitative differences between centralized and decentralized solutions are likely to be small.

with $\sum_s p_s = 1$.[13]

Even though this stochastic structure is quite simple, the number of possible states of the world in each period grows with 2^t. In turn, because the model is formulated as a non-linear optimization problem, this implies that the number of variables that needs to be computed over the whole horizon increases exponentially.[14] 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.[15] 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. (2014) and Cai et al. (2014), as we further discuss below. 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

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

[14] 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.

[15] 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.

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

	2010	2020	2030
World population (billion)	6.95	7.73	8.47
Cropland area (billion hectares)	1.62	1.66	1.69
Yearly agricultural TFP growth rate	0.0094	0.0086	0.0078
Per-capita consumption (thousand intl. dollars)	4.29	4.88	5.46

to consider the reoccurence of shocks beyond 2020, so that it is relatively easy to see how our results would generalize.

3 Results: Optimal control and simulations

3.1 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. (2016). 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, crop land area increases by 70 million hectares, or 5 percent. These figures are broadly consistent with the latest population projections of the United Nations (2013) and with land-use projections by FAO, reported in Alexandratos and Bruinsma (2012). 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.

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, in each decision period, agricultural TFP growth is exogenously brought down by around one percent. 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).

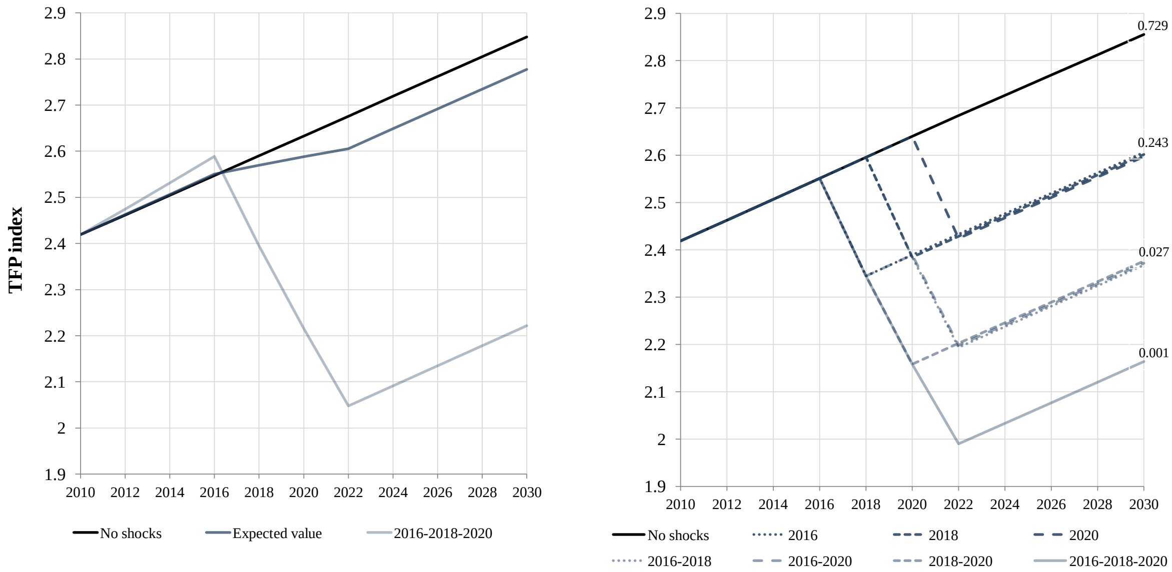
3.2 Agricultural technology paths

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 at around one percent per year until 2030 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 is more than 20 percent lower.

Turning to the stochastic scenarios, reported in panel (b) of Figures 3 and 4, we distinguish

Figure 3: Agricultural TFP under alternative scenarios

(a) Deterministic scenarios (b) Stochastic scenarios

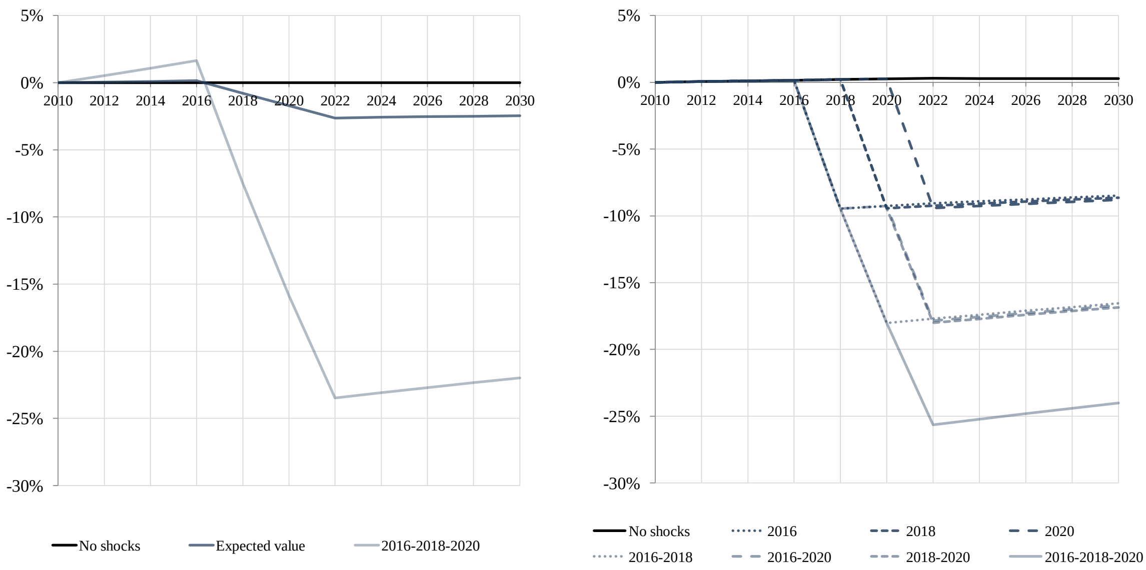


four different groups of possible realizations according to the number of shocks that occur over time (in Figure 3 we report the posterior probability distribution for each groups of outcomes). First, under the stochastic 'no shocks' scenario there is no shock occurring in either 2016, 2018 or 2020, 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 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 of 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

Figure 4: Agricultural TFP relative to the deterministic ‘no shocks’ scenario

(a) Deterministic scenarios (b) Stochastic scenarios



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.

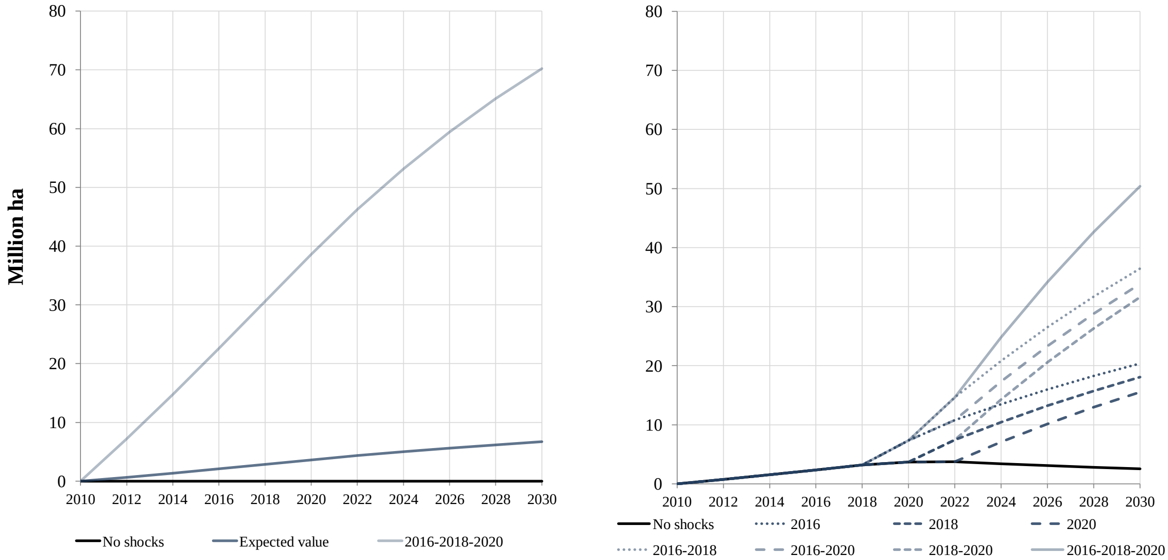
3.3 Optimal global land use

Implications of alternative paths for agricultural TFP in terms of global cropland 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 in 2030 relative to 2010 (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

Figure 5: Global cropland area relative to the deterministic ‘no shocks’ scenario

(a) Deterministic scenarios (b) Stochastic scenarios



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

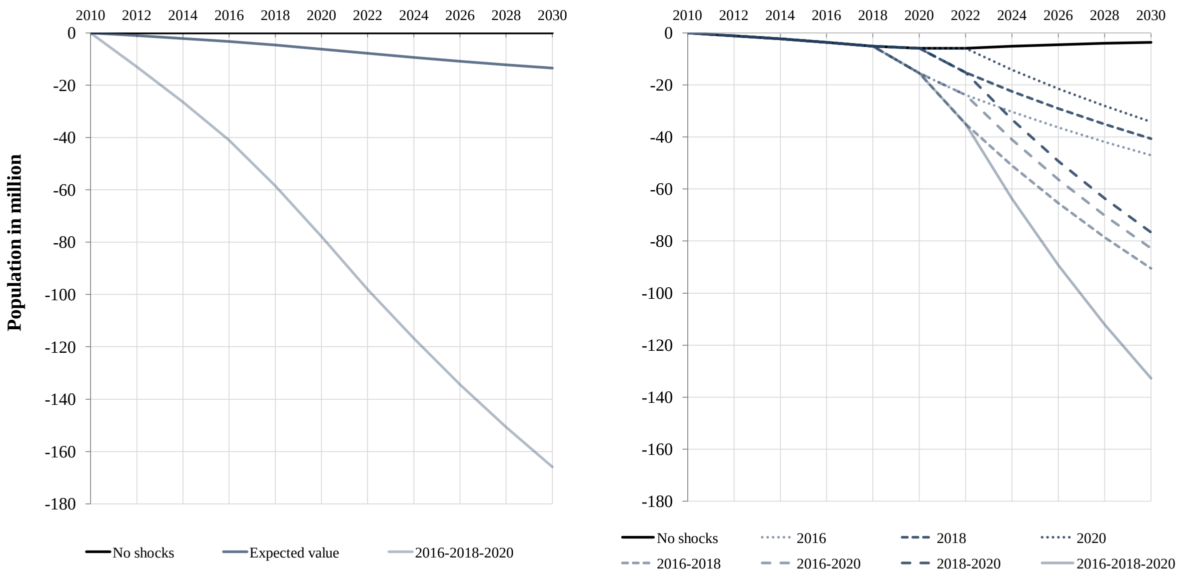
3.4 Welfare analysis: Population and per-capita consumption

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

Figure 6: Global population relative to the deterministic 'no shocks' scenario

(a) Deterministic scenarios

(b) Stochastic scenarios



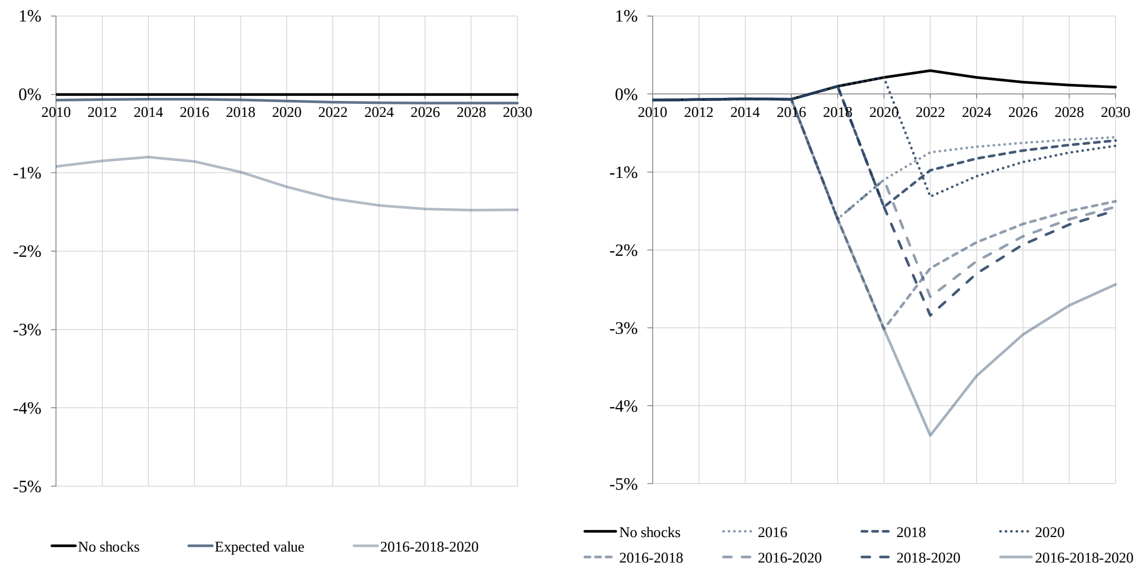
these are the two variables entering the objective function of the social planner (see equation 7).

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 only caused by a reduction of agricultural TFP of 25 percent 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.

Figure 7: Per-capita consumption relative to the deterministic ‘no shocks’ scenario

(a) Deterministic scenarios (b) Stochastic scenarios



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 under the deterministic ‘no shocks’ scenario, although after the first shock the stochastic ‘no shocks’ scenario reaches almost 0.5 percentage point higher than the deterministic ‘no shocks’ scenario. When a negative shock occurs, however, there is a sharp decline in per-capita consumption of around 1.5 percent relative to the deterministic ‘no shocks’ scenario. In turn, in the worst 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.

4 Discussion

As expected, our results suggest that uncertainty about the future evolution of agricultural TFP has major implications for growth and land use. In our first group of scenarios, agricultural TFP is around 10 percent lower as compared to our baseline trajectory. If the growth rate of agricultural TFP is one percent per year, this corresponds 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 it would correspond to approximately 20 million hectares of crop land in addition to the 70 million hectares conversion occurring in the baseline, and a population around 40 million lower than in the baseline. If two shocks occur, so that agricultural TFP is around 17 percent lower relative to the baseline, more than 30 million hectares of cropland are converted. At the same time, 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 were converted into cropland. In this period, there has been growing concern about the value of the lost natural land and associated ecosystem services. 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 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.

How do our results compare with those of Cai et al. (2014)? First, it is useful to provide some more details of their work. They formulate a partial equilibrium model of land allocation calibrated to 2005 data and solved up to 2100. Households are fully forward-looking and value different products from land, namely food, energy goods (including biofuels), timber production and ecosystem services. As in our model, preferences are non-homothetic, so that as agents become wealthier their consumption of food grows less rapidly than that of other products. Agricultural yields (measured in tons per hectares) are assumed to grow linearly, so that the growth rate declines over time, which is similar to our model (see Lanz et al., 2016). Furthermore, their baseline paths for population and land, when compared up to 2030, are very similar to ours. In 2030, they report a world population of 8.2 billion and cropland area around 1.7 billion hectare.

They then introduce a risk of an irreversible shift to a bad state of the world (or "tipping point"). The hazard rate associated with the bad state of the world is assumed to be 0.34 percent in each period, so that by 2025 the probability that the bad scenario occurs is around 10 percent. In the pessimistic state of the world, agricultural yield is around 10 percent lower relative to that prevailing in the optimistic state. This broadly corresponds to our scenario 2, in which one negative productivity shock occurs by 2022.

In their framework, however, agricultural productivity shocks do not affect population, and the main adjustment is the allocation of land across different usages. In particular, if the 10 percent probability of a 10 percent productivity shock materializes in 2025, crop land increases by 5 million hectares by 2030 relative to the baseline. This is significantly lower than in our model (see scenario 2 in Figure 5). The main explanation for this difference lies in the fact that, in Cai et al. (2014), consumers also value alternative uses of land, notably through ecosystem services associated with unconverted land. Furthermore, consumers can also substitute away from food production if it becomes relatively more expensive. By contrast, our model is a general equilibrium framework, and agriculture competes with manufacturing over other primary factors. An implication is that land will appear more attractive relative to other factors of production as a way to maintain agricultural production. Thus, in this sense, the planner in our model will be more likely to convert land in order to sustain food production.

5 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 paper 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. This result has direct implications for conservation policies. Importantly, our model does not account for welfare effects associated with preserving non-converted land. In our view, calibrating the demand function for biodiversity services is inherently difficult. However, we recognize that it may become an important component in the allocation of land, especially in the future as the population grows richer and biodiversity becomes scarcer. In this sense, our results thus represent a business-as-usual path, where there is no policy intervention aiming to internalize the value of biodiversity.

Our work further shows that population is significantly affected by variability in agricultural TFP. Lower fertility on account of higher food prices may be interpreted as higher mortality, since the planner cares about the final level of population.

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.

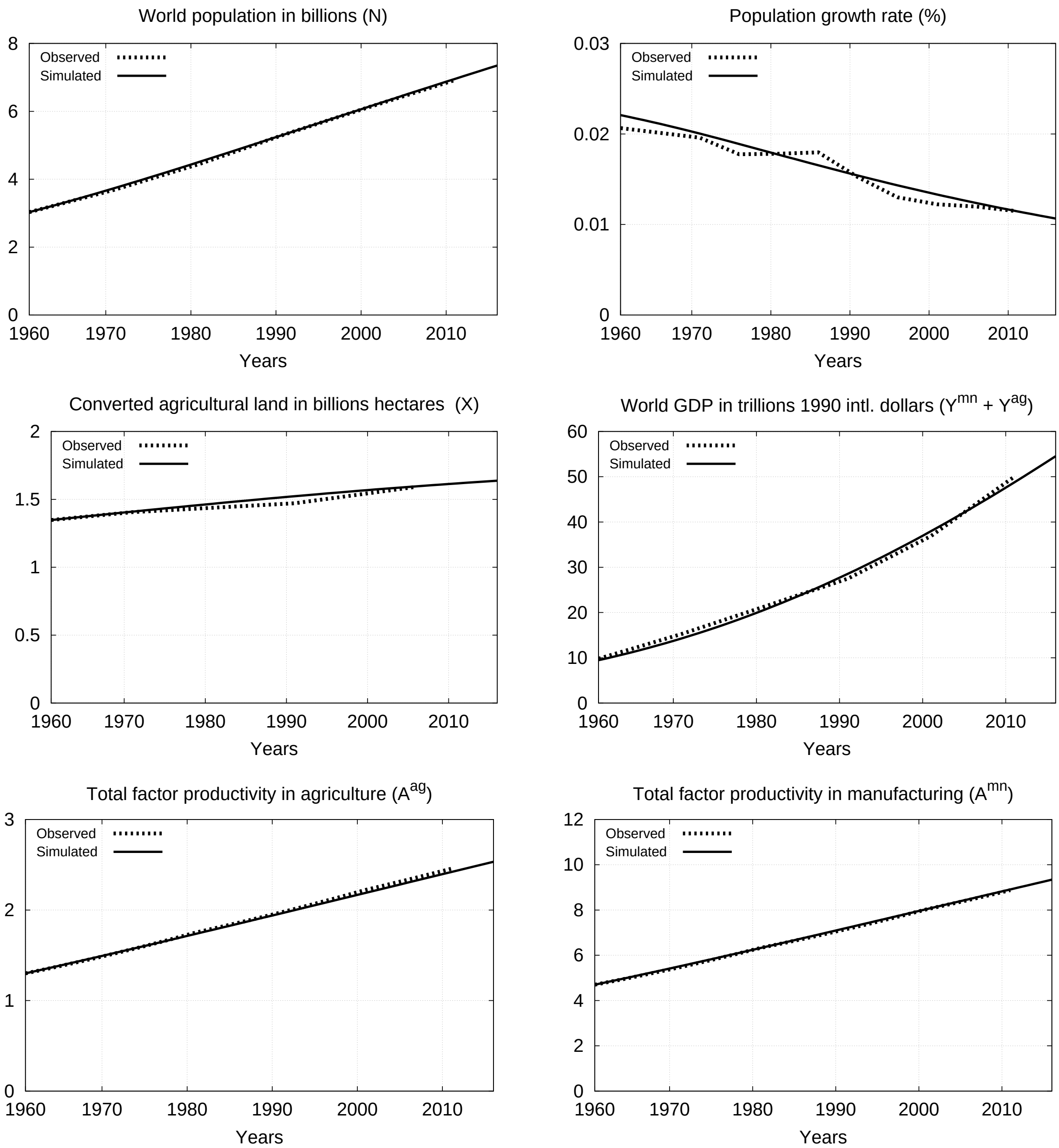
Appendix Estimated parameters and model fit

The vector of parameters that minimize equation (10) are 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 pictures, 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 A1 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: Estimation results: Parameters

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., 2016).



References

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

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

Alston, J. M., J. M. Beddow, and P. G. Pardey (2009) "Agricultural research, productivity, and food prices in the long run," *Science*, 325, 5945, pp. 1209–1210.

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

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

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

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

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

Bolt, J. and 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), pp. 722 – 755.

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

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

Cai, Y., J. Steinbuks, J. Elliott, and 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, and C.-H. Liao (2013) "Endogenous fertility and human capital in a schumpeterian growth model," *Journal of Population Economics*, 26, pp. 181 – 202.

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

——— (1999) "Scale effects in schumpeterian models of economic growth," *Journal of Evolutionary Economics*, 9, pp. 157 – 185.

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

Evans, L. (1993) *Crop Evolution, Adaption and Yield*: Cambridge: Cambridge University Press.

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

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

Fuglie, K. and 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. and D. N. Weil (2000) "Population, technology, and growth: From malthusian stagnation to the demographic transition and beyond," *American Economic Review*, 90 (4), pp. 806 – 828.

Gerland, P., A. E. Raftery, H. Sevcikova, N. Li, D. Gu, T. Spoorenberg, L. Alkema, B. K. Fosdick, J. Chunn, N. Lalic, G. Bay, T. Buettner, G. K. Heilig, and J. Wilmoth (2014) "World population stabilization unlikely this century," *Science*, 346, 6206, pp. 234–237.

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

Goeschl, T. and T. Swanson (2003) "Pests, plagues, and patents," *Journal of the European Economic Association*, 1 (2), pp. 561 – 575.

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

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

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

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

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

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

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

——— (1995b) "Time series tests of endogenous growth models," *Quarterly Journal of Economics*, 110, pp. 495 – 525.

——— (2001) “Was an industrial revolution inevitable? Economic growth over the very long run,” *The B.E. Journal of Macroeconomics*, 1 (2), pp. 1–45.

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

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

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

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

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

Lanz, B., S. Dietz, and T. Swanson (2014) “The expansion of modern agriculture and global biodiversity decline: An integrated assessment.” CIES working paper 29.

——— (2016) “Global population growth, technology, and land conversion: A quantitative growth theoretic perspective,” *International Economic Review*, forthcoming.

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

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

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

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

Ngai, L. R. and C. A. Pissarides (2007) “Structural change in a multisector model of growth,” *American Economic Review*, 97 (1), pp. 429 — 443.

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

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

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

Scheffer, R. (1997) *The Nature of Disease in Plants*: Cambridge: Cambridge University Press.

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

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

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

——— (2014) "How child costs and survival shaped the industrial revolution and the demographic transition: A theoretical inquiry," *Macroeconomic Dynamics*, 18, pp. 114 – 144.

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

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

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

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

United Nations (1999) "The world at six billion." Department of Economic and Social Affairs, Population Division.

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

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

Weitzman, M. (2000) "Economic profitability versus ecological entropy," *Quarterly Journal of Economics*, 115 (1), pp. 237 – 263.

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

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