



Research Paper 29 | 2014

THE EXPANSION OF MODERN AGRICULTURE AND GLOBAL BIODIVERSITY DECLINE: AN INTEGRATED ASSESSMENT

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The expansion of modern agriculture and global biodiversity decline: An integrated assessment*

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This version: May 2016

Abstract

Modern agriculture relies on a small number of highly productive crops and its continued expansion has led to a significant loss of biodiversity. In this paper we consider the macroeconomic consequences of this land conversion process from the perspective of agricultural productivity and food production. We employ a quantitative, structurally estimated model of the global economy in which economic growth, population and food demand, agricultural innovations, and land conversion are jointly determined. We show that even a small impact of global biodiversity on agricultural productivity calls for both a halt in agricultural land conversion and increased agricultural R&D.

Keywords: Global biodiversity; Agricultural productivity; Endogenous innovations; Land conversion; Population dynamics; Food security; Quantitative growth model

JEL Classification numbers: N10, N50, O31, O44, Q15, Q16, Q57.

*We thank Alex Bowen, Derek Eaton, Sam Fankhauser, Timo Goeschl, David Laborde, Robert Mendelsohn, Anouch Missirian, David Simpson, Marty Weitzman, and seminar participants at LSE, University of Cape Town, IUCN, SURED 2014, Bioecon 2013, and the Foodsecure Workshop. Excellent research assistance was provided by Arun Jacob. Funding from the MAVA foundation is gratefully acknowledged. All errors are ours.

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1 Introduction

After hundreds of thousands of years of relative constancy, the human population has exploded with the advent of agriculture. Even more impressively, with the advent of a modern agricultural R&D sector, population has increased three hundred per cent over the last seventy-five years. Increasing food production has been achieved through the selection by humans of a small number of crops with high-yield properties and their application to an ever growing geographical area. The uniformity of the genetic material supporting food production implies that agricultural land expansion is associated with a reduction of biodiversity at the global level.¹ This paper is an attempt to study the macroeconomic consequences of declining global biodiversity in a world where economic growth, population and food demand, agricultural innovations, and the process of land conversion are jointly determined.

There is an inherent tendency for the erosion of agricultural knowledge over time which derives from the evolutionary pressure placed upon existing technology by the selection of successful pests and pathogens (Evans, 1993; Scheffer, 1997).² The tendency of agricultural technology to depreciate through these biological processes implies that agricultural R&D represents a contest between man-made innovations and biological hazards. As the land area allocated to high-yield crops expands, genetic uniformity favors negative feedback effects on agricultural output (e.g. Cardinale, 2012; Reich et al., 2012), including an increased likelihood of pests and pathogens adapting and proliferating on the relatively small number of crop varieties (Tscharnkte et al., 2005; Bianchi et al., 2006). The decline of global biodiversity associated with an expanding agricultural area will thus accelerate technology depreciation and in turn reduce agricultural productivity.

The uniformity of genetic material at the global level results from individual-level decisions: Individual farmers seeking to maximize economic profitability will tend to select high yield

¹ The intensive agriculture production process by definition results in a reduction in the number of crops or livestock species, or both, often leading to monoculture (Matson et al., 1997). Despite the constitution of seed banks in different locations (see Koo et al., 2003, for example), in the last fifty years 75 percent of crop biodiversity has been lost (FAO, 2010).

² This is a standard result from evolutionary biology, whereby applying a treatment to a particular pest population selects resistant individuals. Over time, reproduction with disproportionate prevalence of resistant individuals leads to a decline in the effectiveness of the initial treatment. See Neve et al. (2009) and Delye et al. (2013) for a discussion in the context of weed resistance to herbicides, and also Laxminarayan and Brown (2001) for a discussion in the context of antibiotics resistance.

crops, leading to monoculture and the loss of global biodiversity. In this process, individuals do not take into account their marginal impact on global biodiversity, and thus on global agricultural productivity. Decisions at the individual level about crop selection and the geographical expansion of modern agricultural practices thus imply an externality through an integrated human-biological R&D sector (Weitzman, 2000). In other words, individual decisions that reduce global biodiversity favor the occurrence and diffusion of pests and pathogens, thereby accelerating the depreciation of agricultural technology available to all other producers and affecting aggregate agricultural productivity. However, the local land conversion decisions do not factor in the fact that avoiding an expansion of the agricultural system by retaining reserve lands acts as an input to agricultural R&D.³

To study the socially optimal expansion of agricultural land associated with the decline in global biodiversity, we employ a quantitative two-sector endogenous growth model of the global economy, which distinguishes agriculture from other economic activities to characterize its role producing food and sustaining population (Lanz et al., 2016). On the one hand, the demand for food in the model is proportional to the size of the population and increases with per capita income to capture changes in diet (e.g. Subramanian and Deaton, 1996). Population dynamics are endogenously determined by fertility choices, which derive from households' preferences for fertility à la Barro and Becker (1989), as well as the opportunity cost of raising children. On the other hand, the supply of food derives from the availability of primary inputs, among which the conversion of agricultural land from a reserve base plays a central role, and agricultural technology. We incorporate R&D activities through the Schumpeterian innovation model of Aghion and Howitt (1992), in which total factor productivity (TFP) growth requires labor as an input. The model is structurally estimated to fit 1960-2010 data on world GDP, population, TFP growth and agricultural land area, providing an empirical framework to study the socially optimal allocation of land associated with the growth in the demand for food over time.

The contest between between man-made and biological innovation in agriculture, whereby man-made R&D addresses biological hazards as they appear or nature annihilates technolog-

³ Expanding land area dedicated to intensive agriculture also reduces natural reserve lands, so that the pool of genetic material that can potentially be used as an input to R&D activities decreases (Simpson et al., 1996; Rausser and Small, 2000). As we discuss below, this additional cost of biodiversity reduction is indirectly captured by our analysis.

ical progress by rendering innovations obsolete, is introduced in the agricultural R&D sector. Following Goeschl and Swanson (2003), we represent the occurrence of biological hazards in agriculture as a depreciation of agricultural TFP. More specifically, we posit a function describing how the depreciation of agricultural TFP increases with the scale of agriculture. Thus in our investigation the *rate* at which biological hazards erode agricultural technology and at which agricultural TFP depreciates increases with agricultural land area. Conversely, retaining natural reserve lands away from agriculture contributes to agricultural TFP growth by avoiding TFP depreciation. This representation integrates traditional man-made R&D activities with innovations coming through biological hazards along a single technology ladder, capturing the outcome of the contest between humans and nature.

Given the negative relationship between land conversion and agricultural TFP growth, we illustrate the working of the land conversion externality with three alternative scenarios. In the first scenario, there is no externality associated with an expansion of agricultural area. This represents the continuation of the state of the world prevailing over the period 1960 to 2010. Relative to 2010, baseline projections from the model indicate a 40 percent increase in world population by 2050, a doubling in world GDP, and a 7 percent increase in total agricultural area.⁴ In the second scenario, a social planner responds to the land conversion externality by allocating land to reserves as a means of mitigating the rate of flow of hazards (i.e. reducing the land-use externality), and increases the flow of man-made innovation by allocating more labor to the agricultural R&D sector. This represents the social optimum in the presence of a land conversion externality, and our results suggests that even if the scale of the land conversion externality is relatively small the planner is willing to allocate a substantial amount of land as a buffer against the occurrence of biological hazards. In the third scenario, we solve the model under the assumption that fertility and land conversion choices are made by households and do not take into account the land use externality. Thus the paths for land conversion and population dynamics are exogenous and correspond exactly to the paths prevailing in the absence of a land conversion externality. However, R&D firms respond by increasing the pace of man-made

⁴ A detailed discussion of these baseline projections, together with extensive sensitivity analysis, is provided in Lanz et al. (2016). Here we just note that our projections are consistent with the latest population projections by the United Nations (United Nations, 2013) and those on food and land by the Food and Agriculture Organization (Alexandratos and Bruinsma, 2012). The key qualitative difference is that our projections bring together different processes in a natural framework provided by economic growth theory.

innovation to counter TFP depreciation. The resources required to make up for the increased arrival of biological hazards generate a substantial welfare cost, suggesting a significant value associated with a global policy for land conversion.

The remainder of the paper is structured as follow. In Section 2 we describe the basic structure of the model. Section 3 describes the externality and the policy scenarios we consider. Section 4 reports our results and discusses implications. Some concluding comments are provided in Section 5.

2 The model

This section summarizes the key components of the model and estimation procedure. A comprehensive discussion of the structure of the model, selection and estimation of the parameters, the ensuing projections from the model, as well as sensitivity analysis on the structure of the model is reported in Lanz et al. (2016).⁵ A schematic representation of the model is provided in Figure 1.

2.1 The economy

2.1.1 Production and capital accumulation

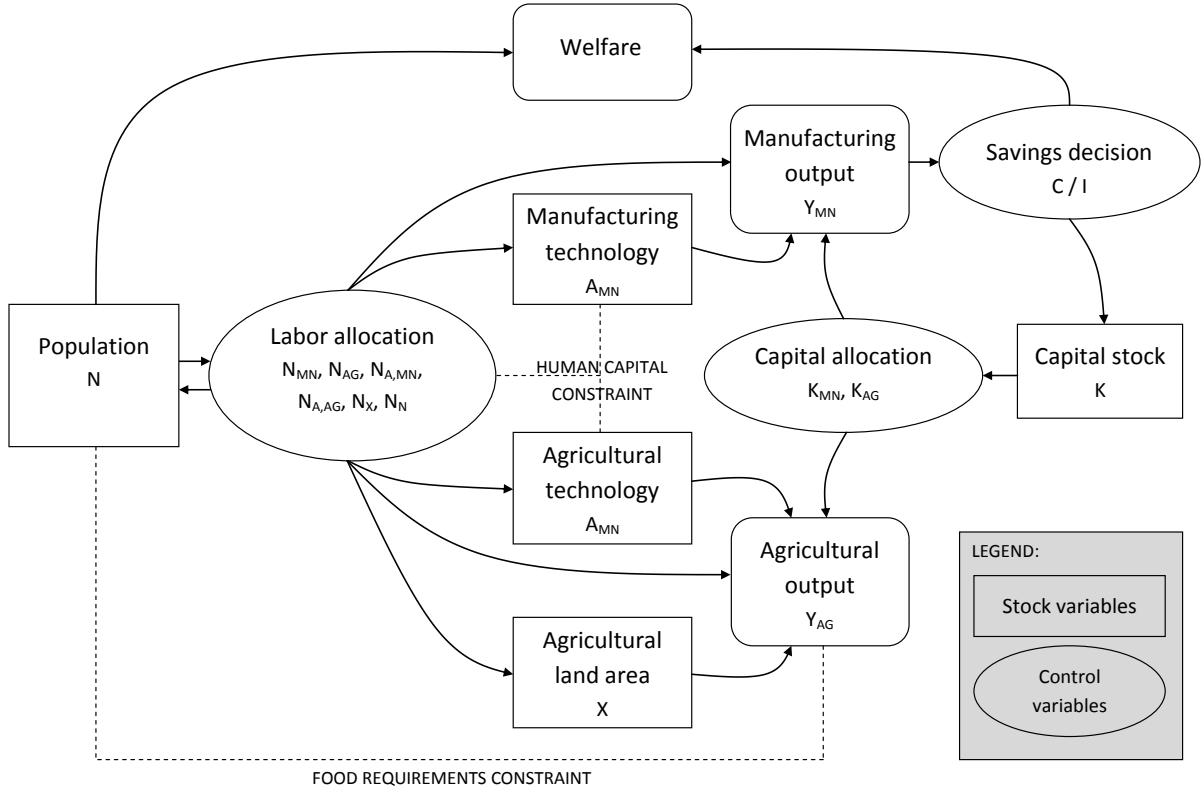
The model comprises two sectors: a manufacturing sector that produces the traditional consumption good in one-sector models, and an agricultural sector that produces food to sustain contemporaneous population. In manufacturing, aggregate output is represented by a standard Cobb-Douglas production function:

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

where $Y_{t,mn}$ is real manufacturing output in time t , $A_{t,mn}$ is an index of productivity in manufacturing, $K_{t,mn}$ is capital allocated to manufacturing, and $N_{t,mn}$ is the workforce allocated to manufacturing. We assume that technology is Hicks-neutral so that the Cobb-Douglas functional form is consistent with long-term empirical evidence (Antràs, 2004), and we use a standard

⁵ The GAMS code of the model is available from Bruno Lanz's website.

Figure 1: Schematic representation of the model



value of 0.3 for the share of capital (see for example Gollin, 2002).

Agricultural production requires land services X_t as an input, and following Kawagoe et al. (1986) and Ashraf et al. (2008) we employ a nested constant elasticity of substitution (CES) function to represent substitution possibilities between land and a capital-labor composite:⁶

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

where σ is the elasticity of substitution between the capital-labor composite and agricultural

⁶ A Cobb-Douglas function is often used for agriculture, notably in Mundlak (2000) and Hansen and Prescott (2002). However, this implies that, in the limit, land is not an essential input in agriculture, as thoroughly discussed in the context of oil scarcity (see Dasgupta and Heal, 1979, for a seminal contribution).

land. We set $\sigma = 0.6$ based on long-run empirical evidence reported in Wilde (2013).⁷ We further set $\theta_X = 0.25$ and $\theta_K = 0.3$ consistent with data reported in Hertel et al. (2012).

2.1.2 Innovations and technological progress

As in the Schumpeterian model by Aghion and Howitt (1992), in each period sectoral TFP evolves as:

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

where S is the maximum growth rate of TFP each period and $\rho_{t,j} \in [0, 1]$ is the arrival rate of innovations each period. Effectively then, sectoral TFP growth is represented as the share of the maximum feasible TFP growth (we set $S = 0.05$ in light of Fuglie, 2012) and depends on the number of innovations arriving within each time period.⁸ The rate at which innovations arrive in each sector is a function of labor allocated to sectoral R&D:

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

where N_{t,A_j} is labor employed in R&D for sector j , $\lambda_j > 0$ is a productivity parameter and $\mu_j \in (0, 1)$ is an elasticity. This formulation implies that TFP growth increases with the share of labor allocated to the R&D sector. As shown by Chu et al. (2013), scaling the labor force in R&D by N_t neutralizes the scale effect and is in line with micro-foundations of more recent representations of technological change such as Dinopoulos and Thompson (1998), Peretto (1998) and Young (1998).⁹ Furthermore, our representation of R&D implies decreasing returns to labor in R&D

⁷ The estimate by Wilde (2013) is based on 550 years of data from pre-industrial England, thus reflecting long-term substitution possibilities, and is estimated in a way that is consistent with our CES functional form assumption (2). However, external validity may be an issue, in particular when applying results for pre-industrial England to developing countries with rapidly growing population. In the discussion of the results we consider the case of $\sigma = 0.2$.

⁸ In the original work of Aghion and Howitt (1992) time is continuous and the arrival of innovations is modeled as a Poisson process. Our representation is qualitatively equivalent, but somewhat simpler, as $\rho_{t,j}$ implicitly uses the law of large number to smooth out the random nature of innovations over discrete time periods.

⁹ In models by Dinopoulos and Thompson (1998), Peretto (1998), and Young (1998), R&D activities simultaneously develops new products and improve existing ones, and the number of product grows with population thereby diluting R&D inputs and avoiding the population scale effect. An other strategy to address the scale effect involves postulating a negative relationship between labor productivity in R&D and the existing level of technology, giving rise to “semi-endogenous” growth models (Jones, 1995, 2001). In this setup however, long-run growth is only driven by population growth, which is also at odds with the data (Ha and Howitt, 2007).

through the parameter μ_j , which captures the duplication of ideas among researchers (Jones and Williams, 2000).

The parameter λ_j is normalized to 1 to ensure that TFP growth is bounded between 0 and S , and the parameters μ_{mn} and μ_{ag} are estimated as described below.

2.1.3 Labor and population dynamics

In each period, the change in population derives from fertility n_t and the rate at which population exits the labor force denoted by δ_N :

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

Because population equals total labor force, δ_N is the inverse of the expected working life time, which we set to 45 years (hence the ‘working mortality rate’ is $\delta_N = 0.022$).

Fertility derives from the allocation of labor to child rearing activities, so that child rearing competes with other labor-market activities:

$$n_t N_t = \bar{\chi}_t \cdot N_{t,N},$$

where $N_{t,N}$ is labor allocated to child rearing activities and $\bar{\chi}_t$ is an inverse measure of the time cost of producing effective labor units. We characterize the well-documented complementarity between human capital and the level of technology (Goldin and Katz, 1998) by postulating an increasing relationship between the time cost of child rearing and the level of technology: $\bar{\chi}_t = \chi N_{t,N}^{\zeta-1} / A_t^\omega$, 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 index of technology, and $\omega > 0$ measures how the cost of children increases with the level of technology.

This formulation implies that, as the stock of knowledge in the economy grows, additions to the stock of effective labor units become increasingly costly. The positive relationship between technology and child rearing costs is consistent with a complementarity between technology and skills (Goldin and Katz, 1998) and imply that, over time, a demographic transition will occur as education requirements increase. In other words, while we do not explicitly model the accumulation of human capital, our model is consistent with the mechanism of (Galor and Weil,

2000), whereby the ‘quality’ of children required to keep up with technology will be favored over the quantity. Furthermore, ζ captures the fact that the costs of child rearing over a period of time increases more than linearly with the number of children (see Barro and Sala-i Martin, 2004, p.412 and Bretschger, 2013). The parameters determining the cost of fertility and how it evolves over time (χ , ζ and ω) are estimated from the data, as described below.

Population dynamics are further constrained by food availability, as measured by agricultural output.¹⁰ Specifically, in each period, agricultural production is consumed entirely to sustain contemporaneous population: $Y_t^{ag} = N_t \bar{f}_t$, where \bar{f}_t is per capita demand for food, i.e. the quantity of food required to maintain an individual in a given society. We further specify per capita demand for food as a concave function of per capita income: $\bar{f} = \xi \cdot \left(\frac{Y_t^{mn}}{N_t} \right)^\kappa$, where ξ is a scale parameter and $\kappa > 0$ is the income elasticity of food consumption. Food demand thus captures both physiological requirements (e.g. minimum per capita caloric intake) and the positive relationship between the demand for food and per capita income.

The parameters determining the demand for food are the following. the income elasticity of food demand is 0.25, which is consistent with evidence across countries and over time reported in Subramanian and Deaton (1996), Beatty and LaFrance (2005), and Logan (2009). The parameter measuring food consumption for unitary income (ξ) is calibrated such that the demand for food in 1960 represents about 15% of world GDP, which corresponds to the GDP share of agriculture reported in Echevarria (1997). This implies $\xi = 0.4$.

2.1.4 Land

As a primary factor, land input to agriculture has to be converted from a total stock of available land \bar{X} by applying labor. Over time the stock of land used in agriculture develops as:

$$X_{t+1} = X_t(1 - \delta_X) + \psi \cdot N_{t,X}^\varepsilon, \quad X_0 \text{ given}, \quad X_t \leq \bar{X}, \quad (5)$$

¹⁰ Food consumption does not contribute directly to social welfare. As discussed below however, the level of population enters the social welfare criterion (together with the utility of per capita consumption of the manufacturing good). Thus through the impact of the subsistence requirements on population dynamics, food availability will affect social welfare. For a similar treatment, see Strulik and Weisdorf (2008), Vollrath (2011) and Sharp et al. (2012).

where $N_{t,X}$ is labor allocated to land clearing activities, $\psi > 0$ measures labor productivity in land clearing activities, $\varepsilon \in (0, 1)$ is an elasticity, and the depreciation rate δ_X measures how fast converted land reverts back to natural land. We assume the period of regeneration of natural land is 50 years, so that $\delta_X = 0.02$. The parameters ψ and ε are estimated from the data as described below.

2.1.5 Preferences and savings

The utility function of a representative household is defined over own consumption of the manufacturing good c_t , fertility n_t and the utility its children will experience in the future $U_{i,t+1}$.¹¹ More specifically, we represent household preferences with the recursive formulation of Barro and Becker (1989):

$$U_t = \frac{c_t^{1-\gamma} - 1}{1-\gamma} + \beta n_t^{1-\eta} U_{i,t+1},$$

where γ is the inverse of the intertemporal elasticity of substitution, β is the discount factor and η is an elasticity determining how the utility of parents changes with n_t . The objective function is given by the utility function of the dynastic head and obtained by successive substitution of the recursive utility function (see Lanz et al., 2016, for the detailed derivation):

$$U_0 = \sum_{t=0}^{\infty} \beta^t N_t^{1-\eta} \frac{(C_t/N_t)^{1-\gamma} - 1}{1-\gamma}, \quad (6)$$

where $C_t = c_t N_t$ is aggregate consumption in t .

The parametrization of the objective function is as follows. First, the elasticity of intertemporal substitution is set to 0.5 in line with estimates by Guvenen (2006). In the model, this corresponds to $\gamma = 2$. Second, given the constraint on η to maintain concavity in the objective function, we set it to 0.01, so that altruism towards the welfare of children remains almost constant as the number of children increases. This implies that the objective function is very close

¹¹ The fact that we solve the model as a social planner problem simplifies the notation and allows us to exploit efficient solvers for constrained non-linear optimization. However, it abstracts from externalities that would arise in a decentralized equilibrium (see Romer, 1994, for example). As discussed below, however, market imperfections prevailing over the estimation period will be reflected in the parameters that we estimate from observed trajectories.

to a standard Classical Utilitarian objective. Third, we set the discount factor to 0.99, which corresponds to a pure rate of time preferences of 1 percent per year.

Aggregate consumption derives from manufacturing output, which alternatively can be invested into a stock of capital:

$$Y_{t,mn} = C_t + I_t, \quad (7)$$

where C_t and I_t are aggregate consumption and investment respectively. The accumulation of capital is then given by:

$$K_{t+1} = K_t(1 - \delta_K) + I_t, \quad K_0 \text{ given}, \quad (8)$$

where δ_K is the per-period depreciation rate. Because we solve for the social planner solution of the problem, savings cum investments decisions mirror those of a one-sector economy (see Ngai and Pissarides, 2007, for a similar treatment of savings in a multi-sector growth model).

2.2 Estimation of the model

We consider the planner's problem of selecting the allocation of labor and capital as well as the saving rate to maximize the utility of a representative dynastic household. Specifically, a representative household chooses paths for $N_{t,j}$, $K_{t,j}$, and C_t by maximizing (6) subject to technological constraints (1), (2), (3), (4), (5), (7), (8) and resource allocation constraints for capital and labor:

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

The numerical model is solved as a constrained non-linear optimization problem and thus mimics the welfare maximization program by directly 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.¹²

¹² The numerical problem is formulated in GAMS and solved with KNITRO (Byrd et al., 1999, 2006), a specialized software for constrained non-linear programs.

As mentioned in the text previously, 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) are estimated by fitting the model to 1960 – 2010 trajectories 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). The estimation procedure includes three main steps, and is discussed in some more detail in Appendix A. First, we impose specific parameter value for a number of quantities that are standard in the literature (see discussion above). Second, we calibrate values for the state variables to initialize the model in 1960. Third, we define a minimum distance criteria for GDP ($Y_{t, mn} + Y_{t, ag}$), population (N_t), crop land (X_t), and TFP ($A_{t, mn, ag}$) as a way to select the vector of parameters that best fit observed trajectories. Using simulation method to find the vector of parameters that minimize our criteria, we find that the model closely fits the targeted data (see goodness-of-fit measures in Appendix A).

3 Land-use externality: Scenarios

In this section we introduce the contest in agricultural technology. In a first step, we expand upon the intuition underlying the existence of an externality associated with agricultural land conversion. We then explain how biological hazards are integrated in the representation of agricultural R&D.

3.1 Intuition for the land use externality

The agricultural sector also has an inbuilt force for *technological regression*. Technological regression occurs by reason of the erosion of the effectiveness of an existing man-made innovation, so that its productivity impact is no longer experienced (e.g. Evans, 1993; Scheffer, 1997). In effect, in the agricultural sector, upward steps on the technology ladder achieved by man-made innovations may be lost through backwards steps (Goeschl and Swanson, 2003). This tendency for technological regression over time, or depreciation of the current state of technology, derives from the evolutionary selection process allowing pests and pathogens to adapt to a given innovation. Thus with the passage of time alone, it would be expected that technological progress in

agriculture would be eroded by virtue of these biological processes.

We assume that, as the amount of land allocated to the agriculture expands, the increased uniformity of the genetic material used in production directs the process of evolution and favors biological innovations (e.g. Weitzman, 2000). This is based on the notion of resilience of ecosystems, one aspect of which is that only individuals resistant to a particular innovation reproduce and thus, over time, become disproportionately prevalent. As the genetic material supporting agriculture declines, pests and pathogens become more likely to adapt to crops and proliferate, increasing crop losses to biological hazards (Cardinale, 2012; Reich et al., 2012). The continued conversion of lands to modern agriculture increases opportunities for the proliferation of pests and pathogens, and hence reduces overall agricultural productivity in the agricultural system (Tschamntke et al., 2005; Bianchi et al., 2006). Allocating land to reserves (i.e. reducing the rate of conversion) then serves as a means of mitigating the rate of flow of biological hazards (i.e. conservation reduces the global land-use externality).

The expected growth rate of agricultural TFP is the net result of the rate of innovations out of the man-made R&D and the inflow of problems into the agricultural sector. Because of the depreciation of agricultural technology over time, investments in the agricultural R&D sector are required to be positive just to keep TFP constant in that production sector. However, we posit that cost of biological hazard, in terms of technological regression, is determined by a convex relationship between the extent of agricultural land conversion and the occurrence of pests and pathogens. Thus the net outcome of the technological contest in agriculture is determined by (i) the quantity of labor allocated to agricultural R&D, determining the rate of arrival of man-made innovations, and (ii) the scale of the modern food production system, as measured by the amount of land used for agriculture, determining the rate of arrival of biological problems (pests and pathogens).

Of course there are many other potential costs that might be associated with the increased scale of agriculture and reduced global biodiversity. One important cost is the loss of biodiversity associated with the conversion of natural land towards agricultural land, which reduces the resources from which R&D solutions to biological hazards could be found (Simpson et al., 1996; Rausser and Small, 2000). This provides an alternative channel by which land conversion reduces agricultural technology growth, as it makes future man-made innovation more difficult

to achieve. An other cost associated with the expansion of modern agriculture is likely to occur through the correlation of yields across increasingly uniform areas. As will become clear below, these related processes have a very similar impact, in terms of agricultural technological progress, as the one determining the occurrence of pests and pathogens. Hence the interpretation of our results can be extended to the case where natural land areas are preserved as a way to preserve the pool of genes to be used for R&D, or reduce correlation in yields.

3.2 Specification of the land use externality

As described in Section 2.1.2, man-made innovation in agriculture derives from the allocation of labor to R&D activities, while land acts as an input to agricultural production (Section 2.1.1). We now introduce the critical second role for land allocation, and that is to determine the manner in which technology evolves. Following Goeschl and Swanson (2003), we represent the occurrence of such a pest-related event as the potential reduction of land productivity (i.e. a depreciation to agricultural TFP).¹³

The rate of *technological depreciation* for the agricultural R&D sector is endogenous and depends on the size of the agricultural system. Hence technological progress in agriculture, and by extension agricultural output (equation 3), is augmented to include depreciation associated with the occurrence of biological hazards:

$$\tilde{A}_{t+1,ag} = \tilde{A}_{t,ag} \cdot (1 + \rho_{t,ag}S - \phi_t S), \quad (9)$$

where ϕ_t measures the rate at which man-made R&D depreciates. Similar to man-made innovation growth, TFP depreciation associated with biological hazards is proportional to the maximum rate of change in TFP $S = 0.05$.

This augmented representation of agricultural technology integrates the biological world into man-made technological progress. The relationship between the amount of land allocated to agriculture and the depreciation of agricultural TFP is then written as an increasing and

¹³ In the continuous time framework of Aghion and Howitt (1992) this can be interpreted as a discrete step down on the technology ladder. However, as we work on discrete time we work with a continuous rate of TFP depreciation, effectively integrating discrete downwards steps occurring over time intervals.

convex function of the amount of land used in agriculture:

$$\phi_t = \lambda_D (X_t)^{\mu_D} , \quad (10)$$

where $\lambda_D \geq 0$ and $\mu^D > 1$. The implied convexity captures non-linearities in the value of biodiversity (e.g. Brown and Goldstein, 1984) and is reminiscent of threshold effects that characterize many ecological processes. The expected growth rate of agricultural TFP is the net result of the flow of innovations out of man-made R&D (or moves up the TFP ladder) and the arrival of biological hazards associated with the scale of agriculture (moves down the technological ladder).

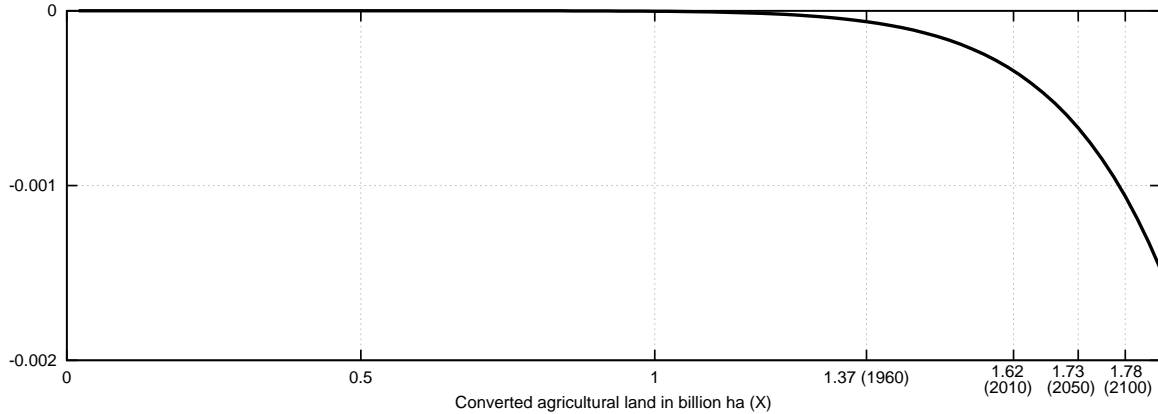
The biological process underlying Equation (10) is well documented, but there exists little empirical evidence that could guide the parametrization of (10). Indeed identifying separately the processes determining the evolution of agricultural TFP, whether man-made innovations respond to biological hazard or the opposite, is challenging.¹⁴ For example, Oerke (2006) provides a quantitative overview of crop losses to pests and pathogens and Bennett et al. (2012) provides evidence about the yields lost due to the use of monoculture. While they do not make a link with agricultural area, these two studies suggest that the potential loss in worldwide agricultural output due to pests and pathogens is large, with actual losses around 30 percent and potential losses (i.e. without any control) around 50 percent (Oerke, 2006). At the micro-level, Veres et al. (2013) provides a recent overview at the landscape level, while Okada et al. (2013) reports empirical evidence that the area over which herbicides is applied is positively correlated with genetic resistance by weeds. However, empirical evidence at the micro level is difficult to extrapolate at the global level.

We therefore select the parameters determining the scale of the externality, λ_D and μ_D in (10), in order to illustrate the processes at play and how these impact the macroeconomic system. Our main specification, displayed in Figure 2, implies that TFP depreciation rate is small (indeed almost insignificant) given 2010 agricultural land area, but rises sharply with additional land conversion projected to take place in the future.

Specifically, we select the parameters such that, along our baseline projection for agricultural

¹⁴ However, because the model is fitted to the last fifty years of data on agricultural TFP growth, estimates determining labor productivity in agricultural R&D will reflect the occurrences of biological hazards. This is because man-made innovations are directed at existing pests and pathogens, and that these threats have been adapting over time to the technological solutions.

Figure 2: Land conversion and expected rate of agricultural TFP depreciation



land, the land conversion externality reduces baseline 2100 agricultural agricultural output by 10 percent. The corresponding numerical values for the parameters are $\lambda_D = 3.5e - 5$ and $\mu_D = 10$. As shown in 2, per period TFP depreciation rate due to biological hazards starts at 0.025 percent in 2010, and gradually increases to 0.1 percent by 2100. Given the projected rate of TFP *growth*, which starts around 1 percent in 2010 and declines over time towards 0.5 percent, the assumed schedule for TFP depreciation are small but significant.

4 Results: Optimal control and simulations

4.1 Decision-making scenarios: Centralized and decentralized choices

Trajectories for agricultural land and population at the global level stem from decentralized decisions on land conversion and fertility. When individual decision-makers do not internalize the increasing inflow of problems associated with land conversion, the decentralized allocation will differ from the social optimum. For this reason it is important to consider alternative assumptions concerning the possible responses to the land conversion externality.

We consider three alternative scenarios: (i) a baseline path in which there is no externality; (ii) a path in which land conversion has a negative impact on agricultural TFP, and a social planner can respond to it with both land conservation policies and increased man-made agricultural innovations resulting in the social optimum (labeled “Technology and conservation”); and (iii)

a path in which land conversion has a negative impact on agricultural TFP, but land conversion and fertility decisions by individual households do not take it into account, making man-made innovation the only possible response (labeled “Technology only”). We now discuss these in turn.

The *Baseline* pathway is based on the assumption that land conversion does not generate an increased inflow of hazard to agricultural production. Therefore $\lambda^D = 0$. This pathway would prevail, for example, if the risk of biological hazard did not increase with farther expansion of the agricultural system. Along this pathway the sole cost associated with the expansion of agricultural land is the allocation of labor to land clearing. We evaluate the magnitude of the cost associated with the land conversion path under the label “*Baseline with externality.*” This provides a measure of the scale of the externality if there is no attempt to control it.

The *Technology and conservation* outcomes are derived under the assumption that a social planner controls all the variables of the problem and that he takes into account the impact of land conversion on agricultural TFP. In this case the negative feedback of converting land in terms of TFP is internalized, and agricultural land and population are optimally determined given the social cost of expanding agricultural land. Resources devoted to R&D can also be modified to increase the pace of man-made innovation and counter the incoming biological hazards. Intuitively, this is the social optimum derived in the presence of a land conversion externality.

The *Technology only* pathway focuses on the problem of decentralized choice regarding fertility and land conversion. In particular, individual decisions about fertility and land conversion fail to recognize the negative feedback from land conversion on agricultural TFP. In the simulations, trajectories for population and land are exogenously set to those determined under the *Baseline* scenario. Given trajectories for population and land, we solve for the allocation of resources that takes into account the land conversion externality induced by decentralized fertility and land conversion choices. Thus in this scenario, the external cost of land conversion can solely be addressed by an increased allocation of resources to the agricultural R&D sector in order to increase the pace of man-made innovations. The land conversion externality thus implies that these pathways are suboptimal as private and social objectives diverge.

To summarize, the *Baseline* pathway thus represents the evolution of an unconstrained the

world in terms of biodiversity and biological hazards. The *Technology only* pathway demonstrates how the pursuit of individual interests that abstract from the external cost associated with land conversion conflict with the social objective and result in the need to divert resources towards R&D to alleviate the impact of biological hazard. The *Technology and conservation* pathways demonstrate how the social optimum might instead reduce the scale of land conversion in response to the association between land conversion and biological hazard.

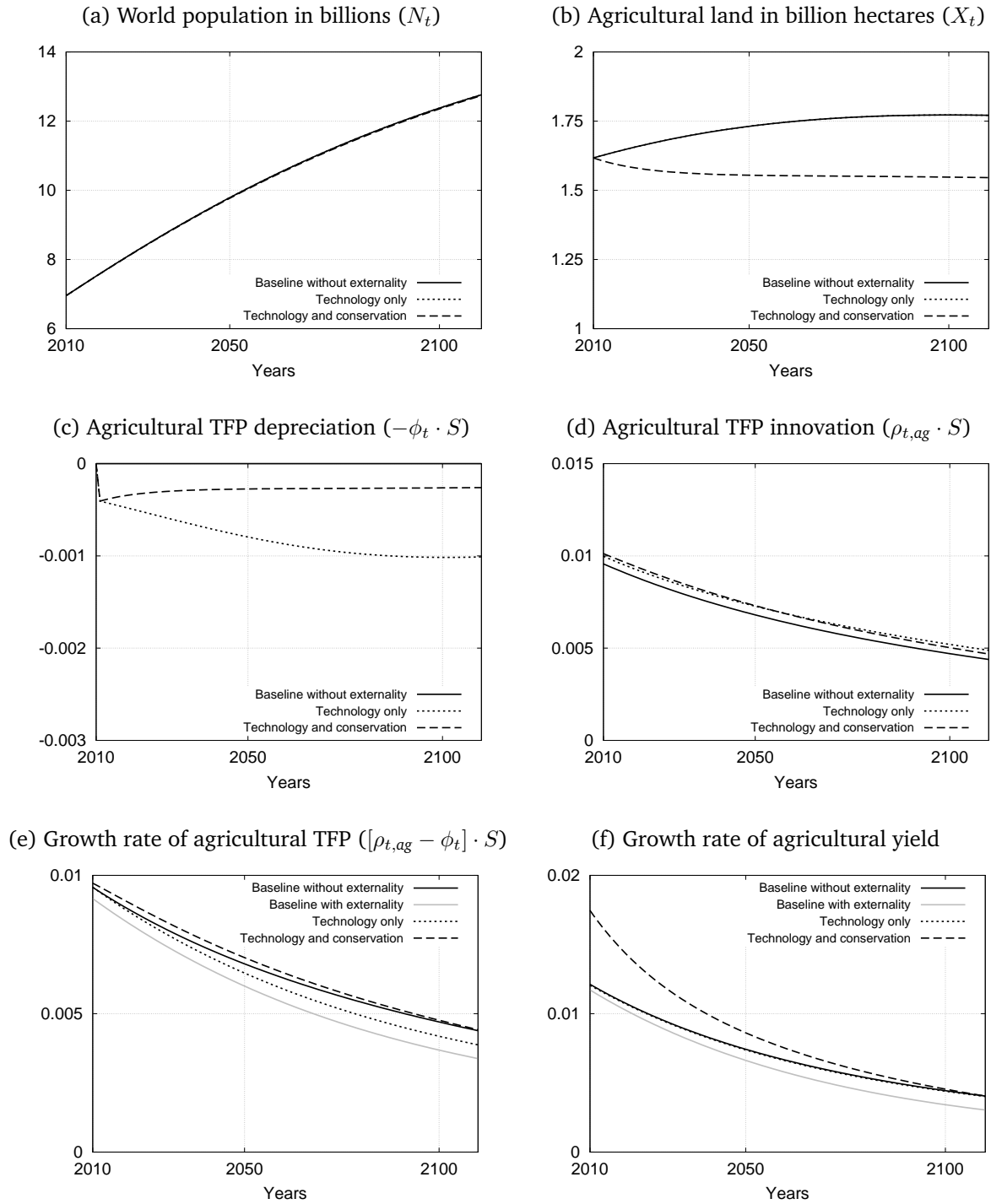
4.2 Aggregate impacts of the land conversion externality

Figure 3 reports trajectories for population (panel a) and agricultural land (panel b). By definition, these paths are the same under the *Baseline* and *Technology only* scenarios. The main implication of baseline projections from the model is a world population of 9.85 billion by 2050 and 12 billion by 2100. Agricultural land area reaches 1.73 billion hectares in 2050 and stabilizes at 1.77 billion hectares shortly after that. As discussed in Lanz et al. (2016), these figures lie towards the upper end of projections by the United Nations (2013) and by the Food and Agriculture Organization (Alexandratos and Bruinsma, 2012). We find that a steady state in land conversion is consistent with sustained growth in agricultural output even though we are only mildly optimistic about future technological progress.¹⁵ Indeed sectoral TFP growth in 2010 is around one percent per year and declines from 2010 onwards (see Figure 3, panel e).

An important feature of these projections is that the growth rates of the variables decline towards a balanced growth trajectory where population, land and capital reach a steady state. Thus our results confirm the widespread expectation that the long-standing processes of growth in population and land conversion are in decline. This is resulting from the quality-quantity trade-offs, shifting from quantity-based economies with large levels of population growth and associated land conversion toward quality-based economies with investments in technology and education for lower levels of fertility. Importantly, the decline in growth rates is a feature of the data over which the model is estimated.

¹⁵ Between 1960 and 2010, agricultural output in the model increased by 279 percent, and increases by a further 67 percent between 2010 and 2050. Without being targeted by the estimation, these figures are consistent with an observed two percent annual growth rate in global agricultural output reported in Alexandratos and Bruinsma (2012) for the period 1960 to 2010, and very close to the 72 percent increase in agricultural output projected by the same authors between 2010 and 2050. Between 2050 and 2100, agricultural output increases by a further 31 percent.

Figure 3: Projections for population, land conversion and agricultural technology, 2010 – 2100



However, while the population growth rate declines over time, it is still significantly positive in 2100. One key implication of our model is therefore that population does not reach a steady state in the foreseeable future, and in particular that the decline of population growth is slower

compared to what is implied by existing population projections from the United Nations (2013) and Lutz and Samir (2010) for example. The finding of sustained population growth over the coming century is plausible because of the amount of inertia in the system, and because better economic prospects will sustain the demand for children despite an increasing cost associated with child rearing and education.

Turning to the impact of land conversion on agricultural TFP, it is obvious that the path for population is almost unaffected. The difference between population under *Baseline* and *Technology and conservation* is less than 1 percent by 2100 (or around 100 million). However the externality has a large impact on socially optimal land conversion choices (panel b). Under *Technology and conservation* agricultural land area immediately declines and reaches a steady state at around 5% below the 2010 level. This corresponds to a reduction of agricultural land by 70 million hectares relative to 2010, as opposed to an increase by around 150 million hectares under the baseline *scenario*. The planner thus leaves a portion of agricultural land used in 2010 to convert back to natural land in order to mitigate the negative impact of agricultural land expansion.

The impact of land conversion on the agricultural TFP growth is illustrated in panels (c) and (d). The pace of technological depreciation (panel c) associated with the baseline level of agricultural land reaches around 0.1 percent by 2100, as shown by the path for the *technology only* scenario. In contrast, under *technology and conservation* the decline in agricultural land area gradually brings depreciation close to zero. At the same time, the level of man-made innovation in agricultural R&D under both the *technology only* and *technology and conservation* scenarios is higher relative to the *Baseline* scenario. As shown in panel (e), the resulting growth in agricultural TFP is higher under *Technology and conservation* than *Baseline*, thus compensating for the lower amount of land input used in agriculture. Under the *Technology only* scenario however TFP growth is lower relative to the baseline, but slightly higher than the path for *Baseline with externality*.

In the final panel of Figure 3, we report the growth rate of agricultural yield (panel f), which measures the rate of change in agricultural output per unit of agricultural land area. This is an important measure of the resources allocated to agriculture for a given agricultural land area in use. The paths for *Baseline* and *Technology only* are almost identical, with agricultural yield

growth starting at around 1.2 percent per year in 2010 and declining towards 0.5 percent per year in 2100. This is expected because both the amount of land and the amount of population that has to be fed is the same under both scenarios. The growth rate of agricultural yield derived under the *Technology and conservation* scenario is initially high at around 1.8 percent, and converges to the same growth rate as the *Baseline* path by 2100. This suggests an important reallocation of factors to increase agricultural yield in early period, but a convergence of the two paths in the long run. We also note that, under the *Baseline* scenario, the implied externality would mean that agricultural yield growth would be lower by around 0.1 per cent per year by 2100.

Before turning to the sectoral allocation of labor and capital, Figure 4 reports an index for agricultural output (panel a) and the associated growth rate (panel b).¹⁶ This Figure demonstrate that agricultural output is virtually the same across all scenarios, despite differences in the composition of inputs (recall that population is almost identical across all scenarios). Our model suggests an increase of agricultural output by 67 percent in 2050 relative to 2010, and a doubling of agricultural production by 2100. Note that these figures are broadly in line with the 60 percent increase projected by Alexandratos and Bruinsma (2012), the difference seeming mostly from slightly higher population projections. The simulated impact of the externality that would prevail under a myopic allocation of resources (*baseline with externality*) implies that around 10 percent of agricultural output would be lost due to the negative feedback of land conversion.

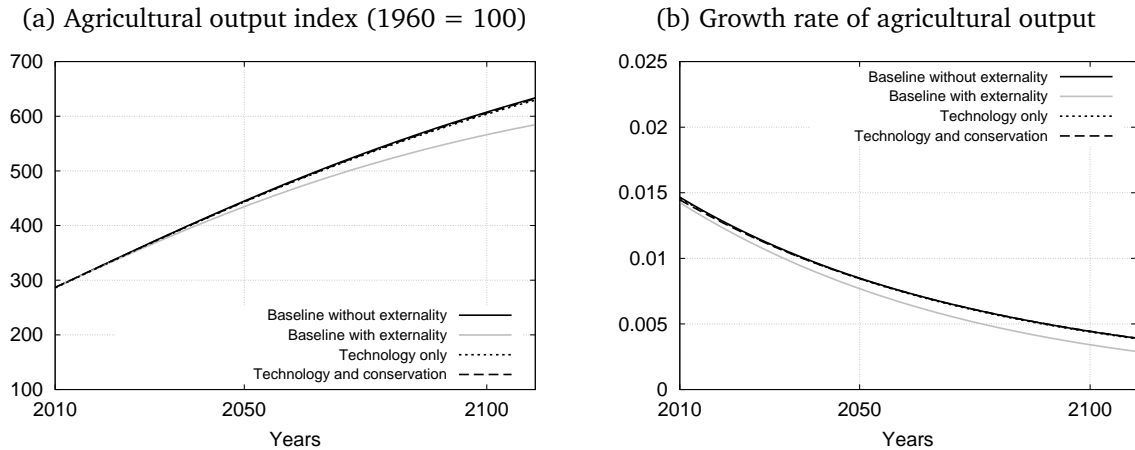
4.3 Changes in sectoral labor allocation

Figure 5 reports on how the allocation of labor differs across scenarios. Specifically, we report the difference in percentage points between labor *shares* allocated to different activities using *Baseline* as the benchmark.¹⁷ The *Technology only* path shows that the share of labor allocated to agricultural R&D increases in order to support a higher pace of man-made innovations. The

¹⁶ The base year of the index is 1960 suggesting that agricultural output increases by a factor of 2.8 over the estimation period. While this figure is not directly targeted by the estimation, it is very close to the factor of 2.7 reported in Alexandratos and Bruinsma (2012) over the same period.

¹⁷ Thus if the path for the *technology only* scenario is 0.2 above zero, this implies that the share of labor allocated to that particular sector is 0.2 percentage point higher under the *technology only* scenario relative to the *baseline*.

Figure 4: Agricultural output and associated growth rate, 2010 – 2100



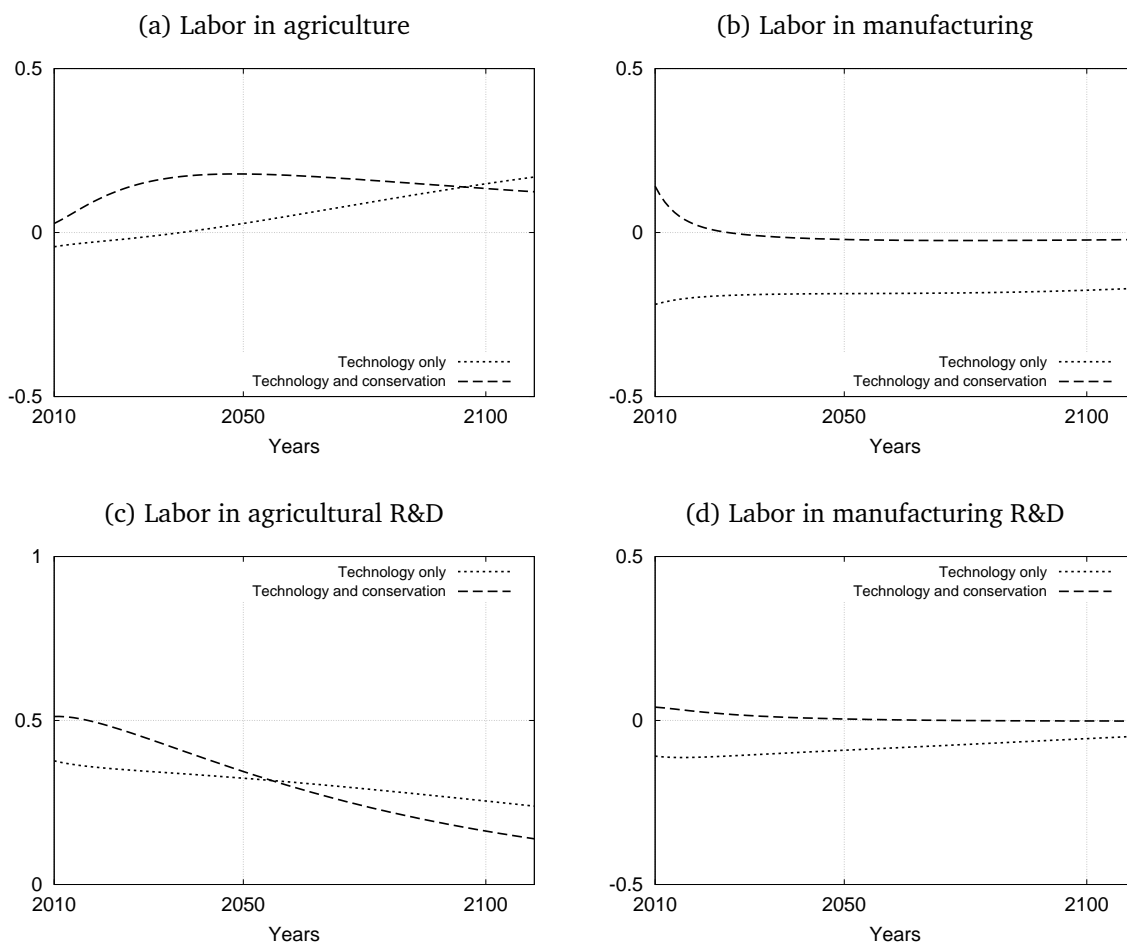
share of labor allocated to agricultural R&D is around half a percent higher relative to *Baseline*, which corresponds roughly to a 10 percent increase of the workforce allocated to agricultural R&D.¹⁸ Similarly, the share of labor in agriculture increases over time to compensate lower TFP growth resulting from TFP depreciation. Importantly, the *Technology only* scenario implies that labor is diverted away from manufacturing production and R&D, which will induce large welfare costs.

Under the *Technology and conservation* path, the social planner significantly reduces agricultural land area but maintains food supply by increasing the share of labor in both agricultural production (panel a) and R&D (panel c). Specifically, more labor is allocated to agricultural production in order to make up for the lower land input, and also in agricultural R&D in order to compensate for remaining TFP depreciation. Labor shares allocated to manufacturing and manufacturing R&D are, however, almost identical between *Technology and conservation* and *Baseline*. The share of labor allocated to both land conversion and fertility is lower under the *Technology and conservation* scenario, which translates into a slightly lower population.

Finally, panel (f) shows that the share of capital allocated to agriculture is higher under both *Technology and conservation* and *Technology only* scenarios relative to the *baseline*.

¹⁸ While the proportion of labor employed in agricultural R&D (around 5 percent) may appear to be high, it should be noted that it includes any labor time dedicated at improving factor productivity. This includes many informal activities taking place in developing economies, such as seed selection or improving irrigation practices.

Figure 5: Sectoral labor shares relative to *Baseline* (in percentage points)

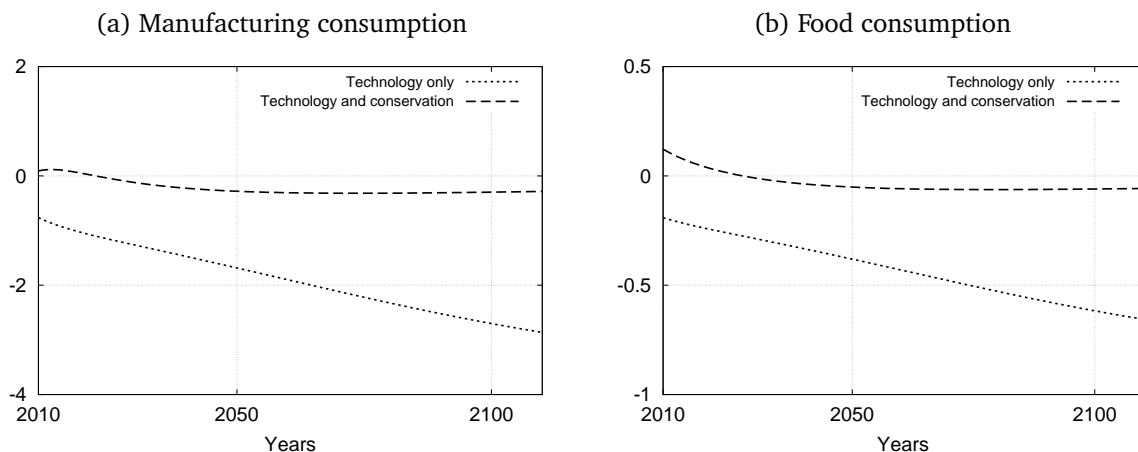


4.4 Per capita consumption and social welfare

Figure 6 shows the implications of reallocating labor away from the manufacturing sector in terms of per capita consumption. Specifically we report paths for per capita manufacturing consumption (panel a) and food consumption (panel b) derived under *Technology only* and *Technology and conservation* as a percentage *Baseline* consumption level each period.

The main result is that, under *Technology and conservation*, both manufacturing and food consumption are lower than under *Baseline*, but that the difference is small. Given our representation of preferences, the trajectory reported in panel (a) is a measure of equivalent variation as a percentage of *Baseline* consumption, which is around 0.3 percent. Thus under the social optimum the welfare cost of the externality is small. The slightly lower consumption of food is explained by the fact that manufacturing output under *Technology and conservation* (i.e. income) is slightly lower than under *Baseline* (see Figure 4 panel b), which implies that the per

Figure 6: Per capita consumption relative to *Baseline* (in %)



capita demand for food is lower. In other words, because households in the *Technology and conservation* are slightly less opulent, they consume less food on a per capita basis.

On the contrary, differences in manufacturing consumption (and hence welfare) between *Baseline* and *Technology only* start at around 1 percent and increase over time. These results suggest a large value for global land use management, as maintaining land reserves generates a substantial gain in welfare over time. In other words, the cost associated with a reduction of the land area dedicated to agriculture is not very high, whereas remaining on the same path for land conversion implies a costly re-allocation of resources. This result is mainly driven by the assumed substitution possibilities between primary factors in agriculture, in particular the elasticity of substitution σ , and we return to the importance of this parameter in next section. But more fundamentally, this result reflects the fact that, over the 50-year period during which the model is estimated, land only plays a relatively minor role in the growth of agricultural output.

4.5 Interpretation and discussion

The results of the simulations demonstrate how the three basic scenarios drive very different futures in terms of land management and welfare. The *Baseline* scenario is based on the assumption that there is no negative feedback from land conversion towards modern agriculture. This scenario is mostly a continuation of what has been observed in recent history, with significant (although declining) rates of land conversion and population expansion. Continuing along this

pathway would imply further land conversion by around 10% relative to 2010. However, given developed countries will likely experience a decline in agricultural land area (Alexandratos and Bruinsma, 2012), the amount of land brought into agriculture from within developing countries will amount to more than that, and these are precisely the areas that hold the most valuable and diverse genetic resources.

The *Technology only* scenario takes the fertility and land conversion decisions resulting from the *Baseline* scenario as a given, but assumes that the social planner can reallocate resources in response to the negative externality of land-use. The basic result is that the cost of the unmanaged global land is large and must be divided between consumption and R&D. In particular, under the assumption that individuals make fertility and land conversion decisions without consideration of the negative externality, the labor allocation must compensate through increased allocation to the R&D sector. This drives a large gap between the *Baseline* and *Technology only* scenarios in terms of consumption and in turn welfare.

Under the *Technology and conservation* scenario the social planner can control both fertility and land conversion decisions to manage the external cost of land conversion. In this case the decision maker will harness the expansion of the agricultural area in order to avoid a costly increase in the arrival of hazards. The overall impact is a reduction in agricultural land area, which is compensated by devoting more resources to agricultural production and R&D.

A striking feature of the *Technology and conservation* path is that the social planner immediately starts to build up land reserve as a buffer against agricultural TFP depreciation. In Figure 7 we show how the path in which the level of externality is selected such that the socially optimal amount of agricultural land is roughly that of 2010. This corresponds to a decrease of λ_D from $3.5e-5$ to $1e-5$. The implications in terms of per capita manufacturing consumption (welfare) are reported in panel (b) and show that the welfare cost of such land conversion policy is around 0.1 percent. The model thus suggests that land conservation policies are relatively cheap in so far as they are associated with higher resource allocated to agricultural R&D as well as more capital and labor allocated to agricultural activities.

One key assumption underlying this result is the assumed substitutability between factors in agricultural production, and the importance of this assumption is illustrated in Figure 8. In particular, assuming $\sigma = 0.2$ instead of $\sigma = 0.6$, so that it is more difficult to substitute the

Figure 7: Impact of λ_D on land conversion and welfare

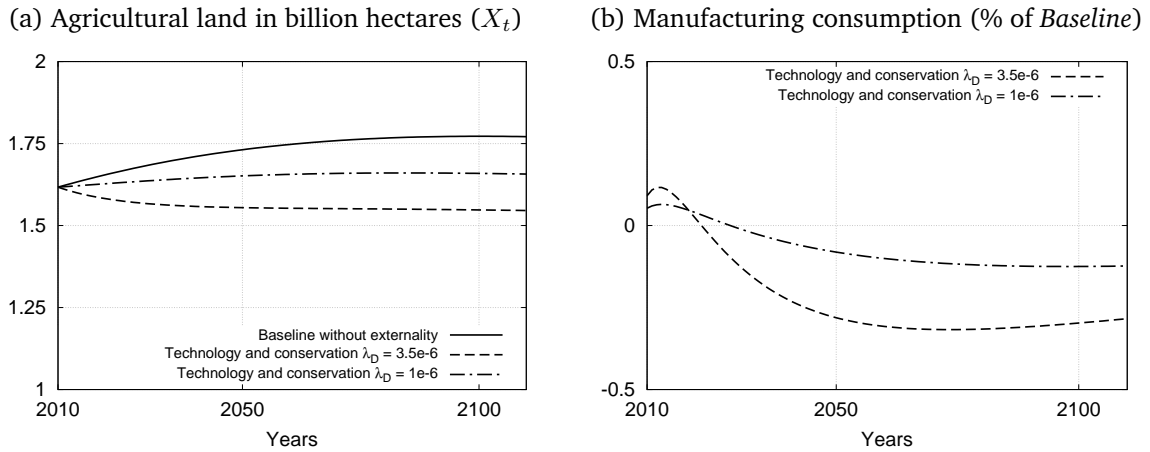
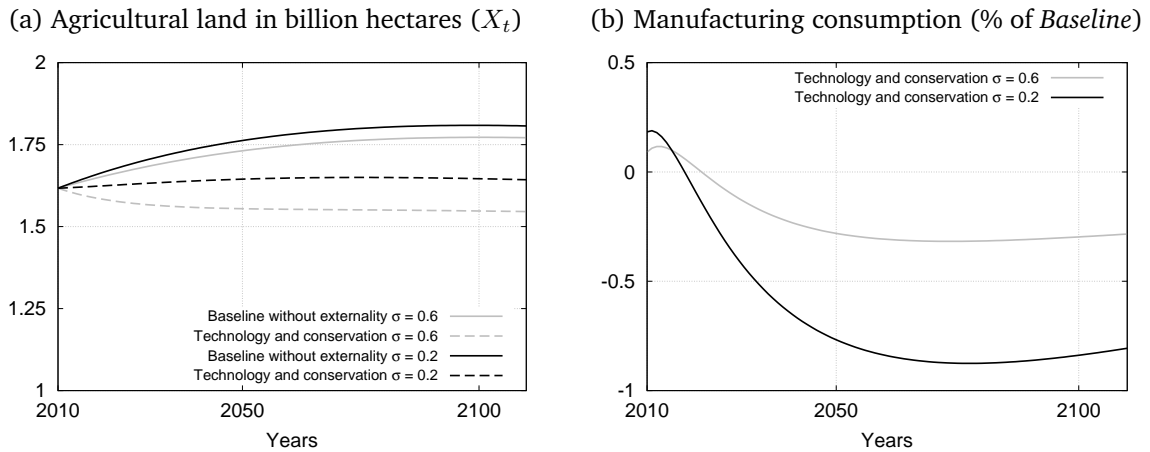


Figure 8: Impact of σ on land conversion and welfare



capita-labor composite for land, has two effect. First, in the *Baseline* scenario, as agricultural production grows to meet the growing demand for food, a lower σ implies that factor inputs in agriculture are more complementary and thus the demand for land conversion is larger. To assess this effect, we first re-estimate the model using $\sigma = 0.2$ so that it fits the data over the period from 1960 to 2010 (see Lanz et al., 2016, for more details). However, while the level of land conversion is indeed higher under the assumption that $\sigma = 0.2$, the increase in agricultural land relative to $\sigma = 0.6$ is small.

The second effect arises when we introduce the land use externality, as a lower σ implies that it is more costly to substitute out of the land input. The proportional response in terms of land conservation is thus lower when $\sigma = 0.2$ as compared to $\sigma = 0.6$. But in addition to a

lower reduction in agricultural land input, more capital and labor have to be diverted from other sectors in order to maintain food production, as inputs are more complementary. This implies that the welfare cost of the externality is significantly larger, as shown in Figure 8, panel (b).

5 Concluding comments

We have demonstrated in a two sector macroeconomic model the manner in which land/labor allocations interact with per capita income growth under a risk of biological hazards. First, we have explored the *baseline* outcome, in which there is no negative feedback from continued expansion of agriculture. In this case, our quantitative model projects a population approaching 12 billion persons over the next century and an increase of agricultural area by around 150 million hectares.

This outcome seems optimistic, and we have examined a scenario in which there is a negative feedback from the unabated expansion of the agricultural system. Motivated by theoretical and empirical considerations, we have modeled this negative feedback as a convex function of agricultural land area. In our model, the ongoing expansion of agriculture generates an increased flow of hazards within the system, which must be addressed through man-made innovations or experienced through lower agricultural TFP.

We have explored two possible scenarios for addressing this assumed negative feedback. One is the *technology only* scenario in which population and land conversion is determined in a decentralized manner and fixed to their *baseline* pathway, and the decision maker must react through factor allocation. While the R&D sector is used as a means of addressing the resulting biological feedback, the reallocation of resources results in a lower per capita consumption. In turn, the external cost of uncontrolled agricultural expansion thus has significant impact on aggregate welfare.

In the final scenario we have explored, *Technology and conservation*, the decision maker both perceives the negative externality and he can manage the negative feedback through both the R&D sector and also through land conservation. This results in a decline in agricultural land area, although it is associated with a significantly lower welfare impact than the one observed under *Technology only*.

We close by emphasizing that these results are illustrative of the working of a land conversion externality that would affect agricultural technology. As discussed in the text, while there exists empirical evidence supporting the evolutionary mechanisms at the micro level (plot- and landscape-level), further work should provide empirical evidence about the scale of such externality at the macro level. Nevertheless, our empirical framework suggests that land reserves can be constituted at a relatively low cost in terms of per capita consumption. The key message that accompanies this positive outlook is that the constitution of land reserves should be accompanied by investments in both agricultural technology and agricultural capital as a substitute to land in the production of food.

Appendix A Structural estimation procedure and model fit

As detailed in Lanz et al. (2016), the seven parameters $\{\mu^{mn,ag}, \chi, \zeta, \omega, \psi, \varepsilon\}$ are estimated using simulation-based structural methods. The moments we target are taken from observed trajectories over the period 1960 to 2010 of world GDP (Maddison, 1995; Bolt and van Zanden, 2013), world population (United Nations, 1999, 2013), crop land area (Goldewijk, 2001; Alexandratos and Bruinsma, 2012) and sectoral TFP (Martin and Mitra, 2001; Fuglie, 2012).¹⁹ In the model these correspond respectively to $Y_{t,mn} + Y_{t,ag}$, N_t , X_t , $A_{t,mn}$ and $A_{t,ag}$. We target one data point for each 5-year interval, yielding 11 data points for the targeted quantity (55 points in total), and use these to formulate a minimum distance estimator.

Specifically, the parameters minimize the value of the following expression:

$$\sum_k \left[\frac{\sum_{\tau} (Z_{k,\tau}^* - Z_{k,\tau})^2}{\sum_{\tau} Z_{k,\tau}} \right], \quad (\text{A1})$$

where $Z_{k,\tau}$ denotes the observed quantity k at time τ and $Z_{k,\tau}^*$ is the corresponding value simulated from the model. For each parameter to be estimated from the data, we start by specifying bounds of a uniform distribution. For elasticity parameters, these bounds are 0.1 and 0.9 and for the labor productivity parameters we use 0.03 and 0.3. We then solve the model for 10,000 randomly drawn vectors of parameters and evaluate the error between the simulated trajectories and those observed. By gradually refining the bounds of the distribution, this procedure converges to the vector of parameters that minimizes goodness-of-fit objective. This procedure converges and the vector of estimates reported in Table A1.²⁰

¹⁹ Data on TFP is derived from TFP growth estimates and are thus subject to some uncertainty. Nevertheless, a robust finding of the literature is that the growth rate of TFP economy-wide and in agriculture is on average around 1.5-2% per year. To remain conservative about the pace of future technological progress, we assume 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.

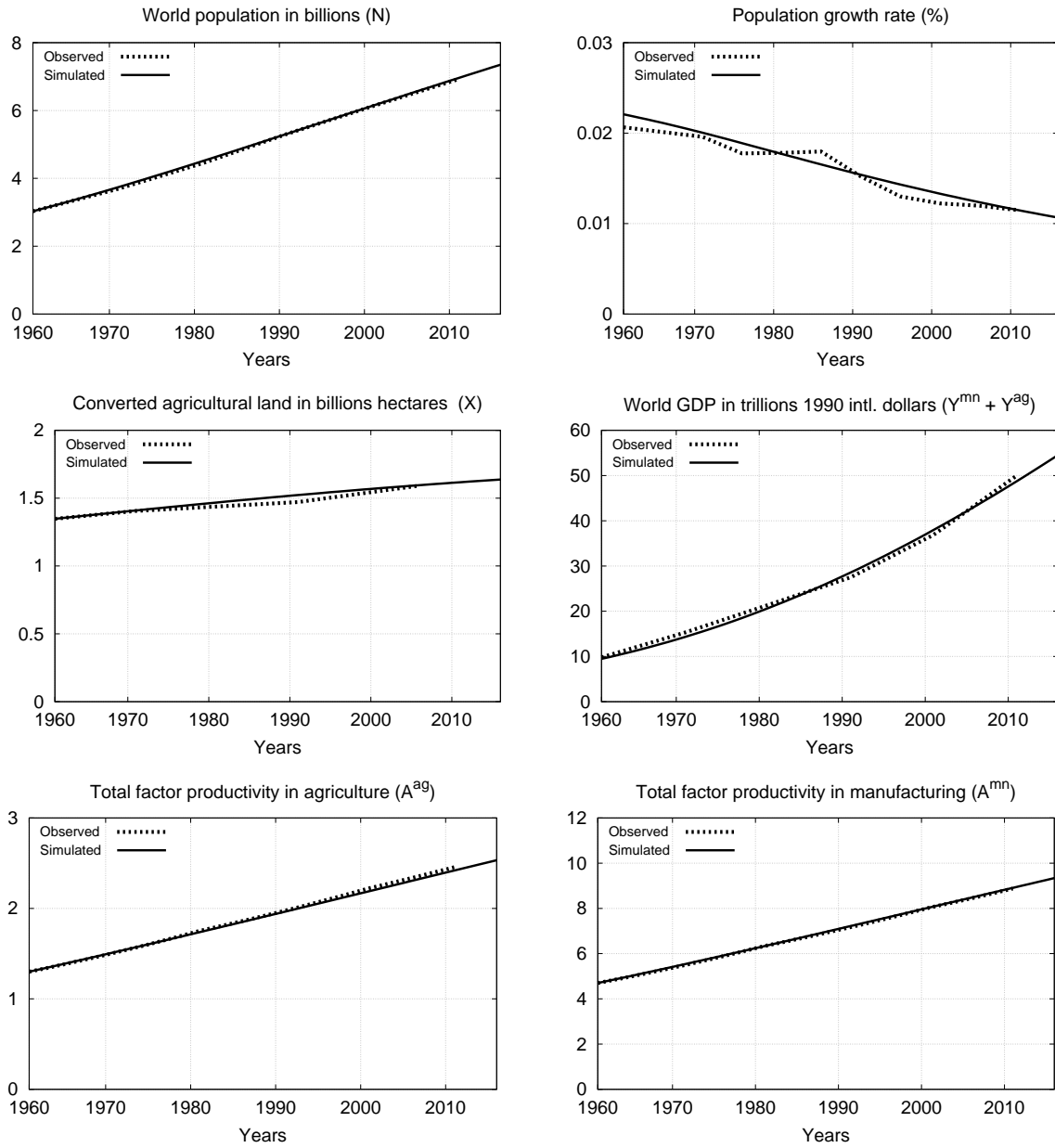
²⁰ As for other simulation-based estimation procedures involving highly non-linear models, the uniqueness of the solution cannot be formally proved (see Gourieroux and Monfort, 1996). Our experience with the model suggests however that the solution is unique, with no significantly different vector of parameters providing a comparable goodness-of-fit objective. In other words, estimates reported in Table A1 provide a global solution to the estimation objective. This is due to the fact that we target a large number of data points for several variables, and that changing one parameter will impact trajectories across all variables in the model, which makes the selection criteria for parameters very demanding.

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

The resulting fit of the model is reported in Figure A1, which compares trajectories that were observed over the period from 1960 to 2010 with the trajectories simulated from the model. As evident from the pictures, the estimated model provides a a very good fit to recent history, and the relative squared error (A1) 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.

Figure A1: Estimation of the model 1960 – 2010 (source: Lanz et al., 2016).



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