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Trade in Technology: A Potential Solution to the Food Security Challenges of the 21st Century*

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Abstract

Notwithstanding the secular decline in world food prices, the recent rise in caloric undernutrition in Sub-Saharan Africa (SSA) is an indication that the Malthusian footrace between food availability and population remains relevant today. Sluggish growth in farm productivity in SSA has brought to the fore the key role of agricultural technology in alleviating future food insecurity. In this paper, we develop a theoretical model of technology, food security and international trade in which there are three distinct channels for technology to benefit food security in SSA. The first is via greater domestic R&D investment in the SSA region – a long run path to enhance productivity. An alternative is to import technologies from other countries where significant knowledge capital has already been established. The third role for technology to resolve the Malthusian dilemma in SSA is that of 'virtual technology trade', i.e., importing the benefits of technological investments elsewhere through cheaper food. To assess the relative contribution of each channel to food security in Africa, we employ a partial equilibrium, quantitative trade model, augmented by a temporal relationship between R&D investments, knowledge capital and agricultural productivity. We find that the importance of the three technology-food security linkages varies depending on the extent of SSA integration into global markets. Even with the current state of food trade friction, we find that virtual technology trade will be the most important vehicle for reducing undernutrition in Africa between the present and 2050. Investments in national agricultural R&D play a significant role as well. And, if SSA researchers can successfully adapt technologies from the emerging markets, technology 'spill-in' effects could rival in importance their own R&D investments. Furthermore, we find there is significant interaction between technology spill-ins within the rest of the world and virtual technology trade when it comes to alleviating hunger in Africa.

Keywords: Population growth, technological progress, Undernutrition, Malthus, Agriculture
JEL codes: Q16, Q17, Q56

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1. Background and Motivation

With the path of 20th century food prices now comfortably in the rearview mirror (*Figure 1*), the question of whether agricultural technological progress would be able to keep pace with growing population appears to have been put to rest. The global agricultural price index in the year 2000 was only one-quarter of its value in 1900, and just 40% of its average value at the end of the 1970s. This is clear evidence that, over the course of the entire 20th century, improvements in agricultural technology led to strong output growth, outpacing population growth (*Figure 1*). Of course, there were many commodity price spikes that arose during this time, with the most dramatic being in the wake of the Russian crop failure during the early 1970s when this price index more than doubled. A later doubling occurred at the beginning of the 21st century, when a perfect storm of growing bioenergy demands, low commodity stocks and crop failures led to the index rising from less than 40 to more than 80 over a decade's time (Abbott, Hurt, and Tyner 2011). As with the earlier price spikes, this led to a flurry of concern about Malthusian scarcity scenarios, and a burst of investments in agricultural research and development. However, as with the earlier price booms, all indications are that this one is also on the wane (*Figure 1*), aided by the slowdown in the rate of growth in global population (Baldos and Hertel 2016).

While the outcome of the global footrace between food supply and demand seems no longer in doubt, this is not the case within particular regions and nations – most notably Sub Saharan Africa (SSA), where virtually all of the world's net population growth is expected to occur between today and the end of this century (UN Population Division 2015). Indeed, the reluctant decline in fertility in this region has caused the United Nations Population Division to revise upward these global population forecasts. Niger is the poster child for this challenge with a fertility rate of 7.5 children per woman – a figure which has been found to be *below* the desired rate of fertility in that country (INS/Niger and International 2013) If productivity growth in agriculture were also proceeding at a record-breaking pace this demographic anomaly would be of lesser concern. However, lack of investment in national agricultural research, poor dissemination of new technologies, weak institutions and civil unrest have resulted in below average rates of agricultural productivity growth (Fuglie and Rada 2013). It is this combination of high population growth and low productivity growth that has allowed the Malthusian challenge to re-enter the debate in SSA. Indeed, in the past three years, rates of undernutrition in this region have begun to rise, after more than a decade of steady decline (FAO et al. 2018).

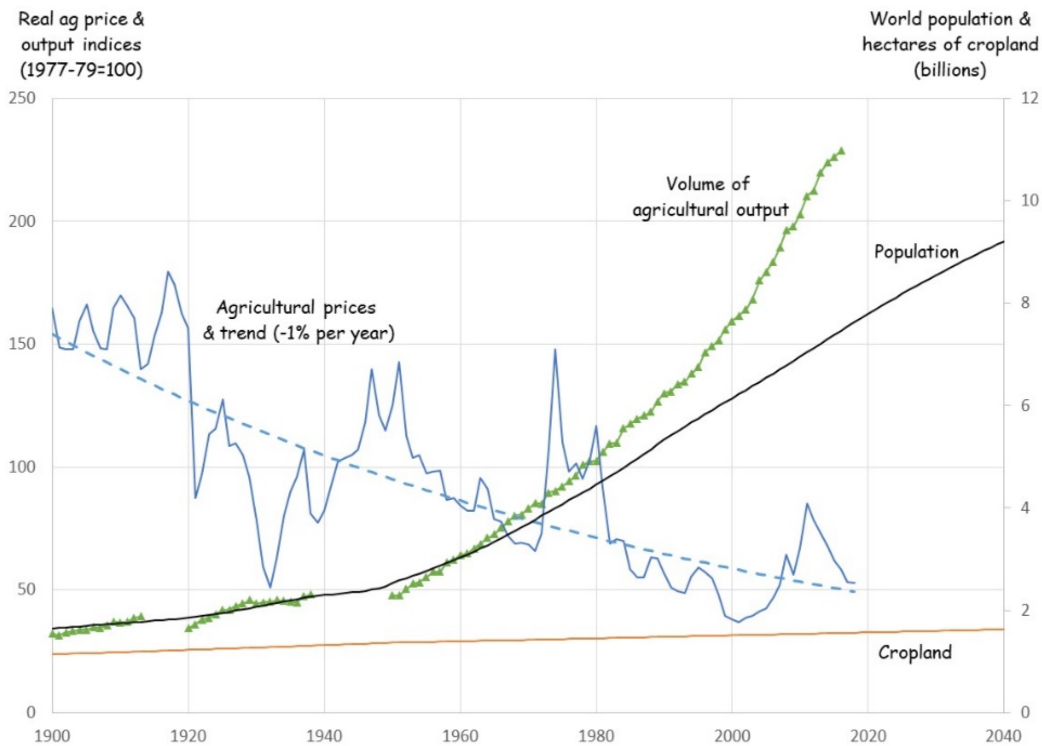

Figure 1. Evolution of global cropland, real agricultural output and price indices, and world population since 1900. Source: Fuglie et al. (2019, forthcoming). The real agricultural price index is the Grilli-Yang price index of traded agricultural commodities divided by the US GDP price index.

Absent a dramatic shift on the demographic front, we must look to the technology side of this regional footrace for a solution. Direct investments in national agricultural research in Africa is clearly an important part of picture. However, given the extremely long lag between public R&D investment in agriculture and improved productivity growth – historically in the United States it has taken two decades for R&D spending to achieve peak impact (Baldos et al. 2018) – this will not solve the near-term challenge. This brings us to the topic of trade – more specifically: trade in agricultural technology. In this paper we will distinguish between two types of trade in technology. The first, dubbed *direct trade in technology*, focuses on the transfer of knowledge from overseas. Historically, direct trade in technology has been hampered by the challenges of adapting solutions from one agro-ecosystem and economic environment to another. This has limited the spillovers from rich to poor nations. Technologies developed in the high income countries or for irrigated Asian agriculture have generally proven ineffective in SSA (Pingali 2012), and the empirical evidence shows little in the way of 'technology spill-ins' from spending in the rich countries (Fuglie 2018; Hayami and Ruttan 1985). However, R&D in the emerging economies may prove more transferable to SSA. We focus on this type of technology spill-in as we consider the potential for direct trade in technology.

We have named the second type of trade in technology '*virtual technology trade*' as it is fully in the spirit of the growing literature on virtual water trade (Allan 1998; Yang and Zehnder 2007). That literature points out that water-intensive crops can be imported in lieu of growing them domestically – hence the idea that these countries are importing 'virtual water'. In the case of agricultural technology, we suggest that one solution to the Malthusian challenge in the SSA region is to import food from regions where technological improvements are outpacing population growth. In section 3 below, we will develop a precise definition of what we mean by virtual technology trade. Historically, virtual trade in technology has been limited by restrictive agricultural trade policies, motivated by self-sufficiency targets as well as concerns about food safety, genetically modified crops, and a host of other factors. Therefore, in the results section of this paper, we will show how the potential for virtual technology trade is critically dependent on the extent to which the SSA region is integrated into global agricultural markets.

While a number of models have produced long-term projections of supply and demand balances in global agriculture (see von Lampe et al, 2014 for a summary and comparison of 10 of the more prominent ones), almost all have assumed exogenously determined rates of productivity growth. Only a few studies have attempted to model future productivity as a function of R&D spending (Lobell, Baldos, and Hertel 2013; Nelson et al. 2010). These models assume a single parameter that indicates the efficiency with which R&D investment produces technical change, i.e., the percentage change in agricultural productivity expected from a 1% change in R&D spending, and restrict this relationship to a particular country or geographic region. State-of-the-art models of R&D capital, however, take account of the substantial lag between R&D spending an boosts in farm productivity growth. This lag is typically one or two decades, beyond which these productivity effects wear off due to R&D capital depreciation (Alston et al. 2010; Baldos et al. 2018). Only Nelson et al. (2010) allowed for eventual R&D capital depreciation, and none of these studies have taken into account how the pattern of past R&D spending may affect future productivity. Clearly, with long R&D lags, countries like China that have increased R&D spending rapidly in recent years will likely have a different productivity trajectory than countries with more stable R&D spending, such as the United States. The present paper extends prior work by (i) projecting future growth in R&D capital stock, taking into account past R&D spending patterns and allowing for R&D capital depreciation, (ii) accounting for differences in the quality and capacity of national agricultural R&D systems by allowing R&D elasticities to vary by global region, based on a review of more than 40 econometric studies (Fuglie 2018);

and (iii) incorporating the potential for international R&D spillovers – that productivity growth in one region depends on not only that region's R&D spending but also on technology transfer from other parts of the world.

In the next section of the paper, we provide a review of the evidence on technological progress in agriculture, its role in driving growth in farm output, the determinants underlying these productivity improvements, and the evidence regarding international technology spillovers. We then introduce our theoretical framework and identify the roles of direct and virtual technology trade in overcoming the Malthusian challenges faced by many countries in Africa. This leads naturally into our quantitative trade model, which is a high-dimensional version of the theoretical model, with geographic heterogeneity and explicit temporal linkages from R&D spending and spillovers to regional productivity growth in agriculture. We then turn to our empirical findings, focusing specifically on the potential for trade in technology to bolster food security in those countries currently experiencing the fastest population growth in the world.

2. Determinants of Agricultural Productivity

Globally, raising agricultural output has come to rely on improving efficiency rather than on increasing the use of land, labor or industrial inputs. As the growth decomposition in *Figure 2* shows, since the 1990s improvement in total factor productivity (TFP) has accounted for about three-quarters of the growth in world agricultural output (Fuglie 2015).[1] The acceleration in

[1] Given data limitations, the growth decomposition in *Figure 2* is only approximate. Output is the value of crop and livestock commodity production at 2005 global average farmgate prices, land includes area in crops and pasture, measured as hectares of 'rainfed-equivalent cropland', where areas under irrigation and pasture are quality-adjusted, labor is number of persons working on farms, capital consists of stocks of farm machinery and animals, and intermediate inputs include inorganic fertilizers and animal feeds. The contribution of each input to output growth is the growth rate of that input multiplied by its cost share. TFP is the difference in growth between output and aggregate inputs. See Fuglie (2015) for a discussion of methods and limitations.

agricultural TFP growth since the 1990s primarily occurred in developing countries and to a lesser extent in transition economies of the former Soviet bloc (where, prior to 1990, agricultural TFP growth had been negative). In highly industrialized countries, TFP was already the primary source of agricultural growth as early as the 1950s or 1960s. Worldwide, use of industrial inputs like inorganic fertilizers grew very rapidly in the 1960s and 1970s, and this growth continues today but at a much slower pace. Most of the growth in agricultural land has come through quality improvement (converting pastures into cropland or extending irrigation) rather than expanding farming to new lands. The growth rate of agricultural labor has slowed sharply since the 1980s, turning negative in the early years of the 21st Century.

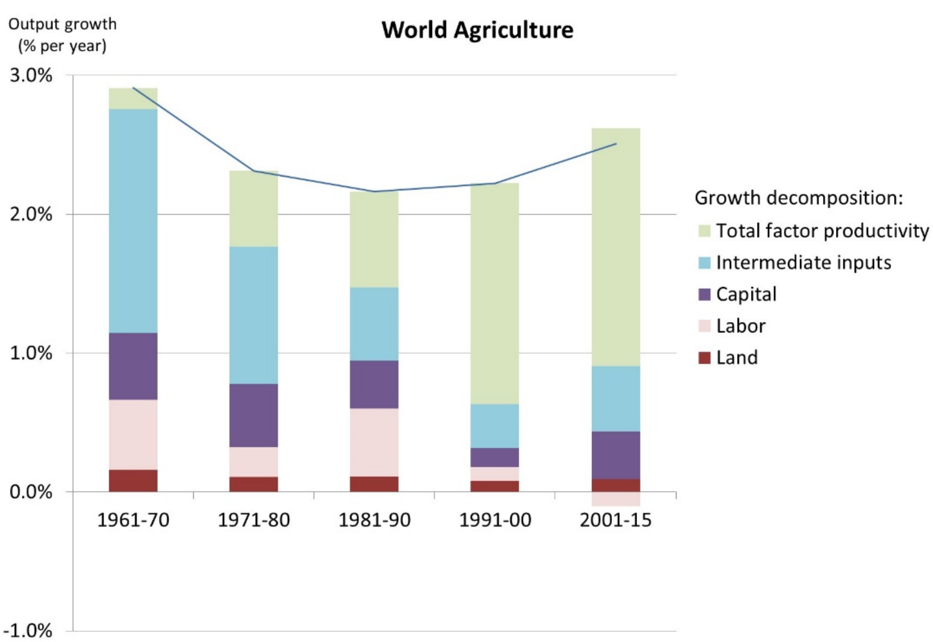

Figure 2. Sources of global agricultural growth, 1961–2015, showing the increasing importance of TFP. Source: USDA-ERS (2019).

The increasing importance of TFP to agricultural growth raises an important question. Is the improved efficiency in agriculture due primarily to reallocating resources (transferring excess labor out of agriculture, consolidating farms to achieve economies of scale, etc.), or to adoption of new technologies and practices that do a better job of converting resources - energy, water, and nutrients - into commodities? If it is the former, then encouraging reallocation of resources may stimulate further improvement in productivity, at least until such opportunities are exhausted. If it is the latter (technological change), then prospects for sustaining growth require an adequate pipeline of new technologies under development. However, the extent to which investments in research and development (R&D) are needed in all countries or regions would seem to depend greatly on the prospects for trade in technology, either in its direct or virtual form.

Empirical research on the drivers of past TFP growth in agriculture have found both resource reallocation and adoption of new technology to be important. Changes in relative factor prices, market liberalization, and institutional or policy reforms that incentivized improved use of resources have often provided a powerful though short-term boost to productivity. Boserup (1965) and Hayami and Ruttan (1985) documented the effect of changing factor scarcity in inducing improvements in agricultural productivity. Perhaps the most dramatic example of how institutional reform can stimulate productivity was the decollectivization of Chinese agriculture begun in 1978. Productivity advanced quickly once farms were once again managed by individual households, who retained the benefits of their own efforts (Lin 1992). Fuglie and Rada (2013) also found positive though more modest productivity gains from structural adjustment reforms in SSA. But such gains from resource adjustment face diminishing returns, and growth may not be sustained after the initial response to new opportunities. Countries that have been able to keep agricultural TFP rising over the long-term have largely been those that have invested resources in agricultural R&D and encouraged the private sector to manufacture productivity enhancing industrial inputs for farms (Hayami and Ruttan 1985; Fuglie 2012)

Because environmental conditions (rainfall, temperature, humidity, soils, topography, etc.) have such an important influence on agriculture, direct spillover of agricultural technologies is likely to be restricted across global geographies. Socio-economic and market factors also constrain spillovers. Farmers in isolated areas with limited access to urban or international markets, for example, are not likely to be able to achieve similar efficiency gains from scale and specialization as farmers with ready access to such markets.

Empirical studies on sources of agricultural TFP growth have found few cases of international R&D spillovers between developed and developing countries, or between developing countries themselves, although spillovers have occurred between temperate-zone developed countries (Fuglie 2018). For example, using patent data, Johnson and Evenson (1999)show that most international technology transfer in agriculture occurs between high-income, temperate countries, and Eberhardt and Teal (2013)find that agricultural TFP growth is strongly correlated across similar agro-climatic environments.

One factor that may be have constrained trade in agricultural technology within tropical zones is the limited capacity of national R&D systems in these regions. Hayami and Ruttan (1985) characterized three stages of national capacities in agricultural research – the ability to screen, adapt and invent. Nascent R&D systems are limited to testing or screening technologies developed elsewhere, while somewhat more advanced systems can adapt them to local conditions, such as crossing an imported crop variety with a local cultivar to get an improved varieties adapted to local conditions. Most agricultural R&D systems in developing countries are at this second stage, while a few, namely those in the large emerging economies of Brazil, China and India, are rapidly moving toward the inventive stage. At this third stage, they are capable of developing general purpose technologies that may have broad application elsewhere, especially in agro-climatic zones not too dissimilar from their own. The development of the tropical soybean by the Brazilian national agricultural research institute, EMBRAPA, and hybrid rice by the Chinese national research system, provide examples of this inventive capacity. This raises the prospect of boosting productivity in the SSA region through new opportunities for direct trade in technology, a prospect we consider in our analysis below.

Another factor complicating growth trajectories in agriculture is the role of environmental policies. Engels Law suggests that, at the margin, non-agricultural demands for environmental resources like land, water and greenhouse gas emissions will become relatively more important than food as societies become wealthier. This is already manifesting itself in many high income countries, where environmental restrictions and conservation measures are a significant part of agricultural policies. Reforms since the 1990s to the EU's Common Agricultural Policy (CAP), for example, have reduced price supports for agricultural commodities while at the same time increasing payments to farmers for retiring land from production and adopting other conservation measures. Several countries have also tightened regulations on nutrient loadings and chemical use by farms, and placed restrictions on the use of certain technologies, such as genetically modified (GM) crops and animal growth hormones (OECD 2011).

One result of EU agricultural policies has been to pull more resources out of the agricultural production. According to statistics compiled by USDA/ERS (2019), between 1990 and 2014, the aggregate amount of land, labor, capital and intermediate inputs employed in northwest European agricultural declined by about one fourth. However, continued improvement in TFP kept farm output from following suit – it remained roughly constant in real terms over this period (*Figure 3*). In contrast, in the US and Canada, aggregate inputs remained almost constant over the 1990-2014 period and steady TFP growth led to rising agricultural output. In a sense, Europe used TFP growth to improve environmental outcomes rather than increase the supply of food, while North America chose to boost food output at the expense of potential ongoing environmental damages.

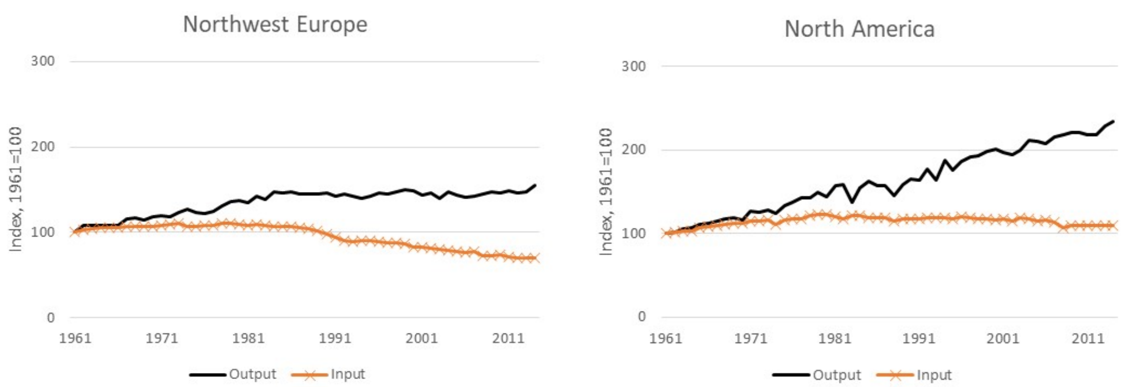

Figure 3. Indices of real agricultural output and aggregate input use in Northwest Europe and North America since 1961. Source: Heisey and Fuglie (2018) using data from USDA/ERS (2019).

In the context of a global trading equilibrium, differential rates of TFP growth among countries or regions can be expected to affect competitiveness and comparative advantage, leading some countries to expand their agricultural sector and others to contract. In our quantitative analysis below, we consider the possibility that rich countries may impose environmental restrictions that constrain virtual trade in agricultural technology, and we explore how this might affect the Malthusian outcome in SSA.

3. Theoretical Framework

Our theoretical framework is designed to be as simple as possible while still addressing all of the key mechanisms determining the role of technology trade in resolving the food security dilemma in SSA. To introduce notation and key concepts, we begin by exploring the Malthusian footrace in the context of a single region, closed economy, thereupon moving to a two-region model to introduce virtual trade in technology.

3.1 Single Region Model

Consider an aggregate, agricultural sector comprised of many farms subject to entry/exit based on profitability. Regardless of the farm level technology, free entry and exit in the context of cost minimization will lead to the aggregate industry operating in the neighborhood of constant returns to scale (Diewert 1981). In the spirit of simplicity, we group the determinants of food output into three distinct components: technology, the key factors constraining long run expansion (climate, land and water – dubbed 'land'), and non-land inputs (including labor, capital and purchased inputs). With just two inputs, the Constant Elasticity of Substitution (CES) production function is sufficiently flexible to locally approximate any technology, leading to the following relationship:

$$Q_O = A(\phi_L Q_L^{-\rho} + \phi_N Q_N^{-\rho})^{-1/\rho} \quad (1)$$

If we further assume that the land input is supplied inelastically, with the non-land inputs in perfectly elastic supply over the long run, then the Malthusian challenge can be formulated in terms of the percentage change in food prices, which evolve according to the following relationship (for all derivations, see supplementary material):

$$p_O = [\Delta_D - a(\varepsilon_S + 1)]/[\varepsilon_S + \varepsilon_D] \quad (2)$$

Where lower case variables denote percentage changes, i.e., $p_O = 100 * dP_O / P_O$ is the growth in food prices and $a = 100 * dA / A$ is the rate of growth in total factor productivity (TFP) in agriculture. This stands in opposition to the percentage growth in food demand due to rising population (and income), Δ_D. The sign and magnitude of the equilibrium price change depends on the elasticity of supply, $\varepsilon_S = \theta_L^{-1}\nu_L + \sigma(\theta_L^{-1} - 1)$, along with the (assumed constant) price elasticity of demand for food, ε_D. The price elasticity of supply for agricultural products, depends, in turn, on the potential to expand area: $\theta_L^{-1}\nu_L$, where θ_L is the cost share of land and water in production, ν_L is the responsiveness of harvested area to land returns, and $\sigma(\theta_L^{-1}-1)$ is the potential for further intensification of production, which, in turn, depends on the elasticity of substitution between land and non-land inputs, $\sigma = 1/(1+\rho)$.

Equation (2) highlights the Malthusian footrace between growing demand and growth in agricultural productivity, where the latter is modulated by the responsiveness of supply to scarcity. If agricultural supplies are price-inelastic, then the outcome of this footrace simply boils down to a question of whether TFP can grow at a faster rate than food demand. As noted in the introduction, the problem at present in the SSA region is that population growth remains stubbornly high, while agricultural TFP growth has historically been amongst the lowest in the world. This mismatch has resulted in food scarcity, rising prices, and rising undernutrition in many parts of SSA.

Fortunately for SSA, the empirical evidence suggests that there exists significant supply response to price in the agricultural sector, once transactions costs are taken into account (Magrini, Balié, and Morales-Opazo 2018). This means that, in addition to the impact of an outward supply shift due to TFP growth, the ensuing increase in profitability in the sector will further boost production by drawing additional land and non-land inputs into the sector. This point is highlighted in the following expression for equilibrium agricultural output growth as a function of increasing demand as well as TFP growth:

$$q_O = [a\varepsilon_D(\varepsilon_S + 1) + \varepsilon_S \Delta_D] / [\varepsilon_S + \varepsilon_D] \qquad (3)$$

This supply response notwithstanding, it is critical to improve TFP growth rates in the region if one hopes to attract sufficient resources and boost output fast enough to keep prices from rising.

Indeed the food security goal in this region is to significantly reduce food prices – particularly during the ‘lean season’ – in order to reduce undernutrition in SSA.

Within this framework, there are four obvious points of entry to overcome the Malthusian threat in the SSA region. The first is to slow population growth ($\Delta_D \downarrow$). This has been successful in some parts of the continent. For example, Ethiopia has reduced its population growth rate by a full percentage point since 1990 (Ethiopia Population 2019), but in the poorest countries in West Africa, (INS/Niger and International 2013) and there is significant resistance to discussion of family planning, let alone implementing a program targeting fertility rates. The next point of entry in equation (1) is to boost TFP growth ($a \uparrow$). As discussed in the introduction, this has been the primary driver of agricultural output growth in the industrialized countries since the end of WWII (Hayami and Ruttan 1985; Fuglie 2015). However, it can take decades for public spending on agricultural R&D to actually boost TFP growth. Indeed, Baldos et al. (2018) estimate that the productivity impacts of public R&D spending in the United States peaks 22 years after the initial investment. And it persists for nearly 50 years! With half of its population under 15 years of age and entering the child-bearing stage of their life cycle, countries like Niger (INS/Niger and International 2013) cannot wait that long for improvements in agricultural TFP.

This brings us to the idea of *trade in technology* – the vehicle for delivering the last two options for resolving the Malthusian dilemma in SSA. As noted above, the first, and most obvious, type of technology trade involves importing existing technologies from other regions. This is typically termed ‘technology spillover’ and this idea inspired many foreign aid projects in the 1950’s – for example introducing new breeds of livestock and new seed varieties into Africa. Unfortunately, most of these efforts failed miserably with the livestock falling prey to local disease and lack of management infrastructure and the new seed varieties failing due to insufficient nutrients, irregular precipitation and vulnerability to local pests. This poor track record is evident in the empirical work that finds only very limited evidence of direct agricultural technology transfers from OECD countries into the tropical regions of Africa (Johnson and Evenson 1999; Eberhardt and Teale 3103; Fuglie 2018). However, with growing capacity for research discovery in emerging economies like Brazil, China, and India, that share more characteristics with Africa, the potential for R&D spillovers increases. We explore below the potential for such 'direct technology trade' to solve the Malthusian challenge in Africa.

As noted above, we dub the second type of technology trade, as 'virtual trade in technology' – drawing inspiration from the literature on 'virtual water trade' (Allan 1998; Yang and Zehnder 2007). In this case, rather than importing the technology itself, we explore the role of international commodity trade in allowing agricultural products produced elsewhere with new technologies to resolve the upward price pressures resulting from rapid population growth in the face of sluggish TFP growth in SSA agriculture. In order to render this idea more concrete, we expand the model introduced above to two regions and consider the impact of TFP growth in the rest of the world (RoW) on food prices, production and imports in SSA. Specifically, we evaluate the percentage change in SSA net imports, relative to worldwide production, as a function of technological innovation in the rest of the world. To address this issue, we turn to the two region model.

3.2 Two Region Model

We begin with the following expression for the change in net imports into SSA:

$$t = 100 * dM^{SSA} / Q^{W} = \beta qo_{D}^{SSA} - \alpha qo_{S}^{SSA} \quad (4)$$

Where $M = Q_{D}^{SSA} - Q_{O}^{SSA}$, reflects net imports into the SSA region, $T = M / Q^{W}$ expresses these net imports as a portion of global supply, $\alpha = Q_{O}^{SSA} / Q^{W}$ is SSA's share of global supply (which equals global demand by virtual of global market clearing) and $\beta = Q_D^{SSA} / Q^W$ is SSA's share of global demand (which equals supply in this equilibrium model). Solving for percentage change in the global price, we have:

$$p_O = -(\varepsilon_S^{RoW} + 1)a^{RoW} / (\{(\varepsilon_D^W + \alpha\varepsilon_S^{SSA}) / (1-\alpha)\} + \varepsilon_S^{RoW}) = -\gamma_O a^{RoW} \quad (5)$$

where the superscript RoW denotes rest of world and so a^{RoW} is TFP growth in the non-SSA region. This expression is quite similar to (2), only now the productivity growth only applies in the non-SSA, RoW region.

Utilizing this equilibrium outcome allows us to solve for the elasticity of net imports into SSA as a function of TFP growth in the rest of the world, yielding the following:

$$t / a^{RoW} = 100 * dM / Q^W = [\alpha\varepsilon_S^{SSA} + \beta\varepsilon_D^{SSA}]\gamma_O \quad (6)$$

where $\gamma_O = (\varepsilon_S^{RoW} + 1)a^{RoW} / [\{(\varepsilon_D^W + \alpha\varepsilon_S^{SSA}) / (1-\alpha)\} + \varepsilon_S^{RoW}]$. Not surprisingly, the elasticity of virtual technology trade with respect to RoW productivity growth, t / a^{RoW}, depends on all of the supply and demand elasticities in the two region model, as well as the relative size of SSA and in the global food economy, through the (negative of the) price multiplier: γ_O. Once the world price effect is determined, then the trade elasticity is increasing in the price elasticities of demand and supply in the SSA region. If consumers and producers in this region are highly responsive to price, then the elasticity of virtual technology trade will be larger.

In the quantitative trade model developed in the next section, we will elicit the magnitude of this elasticity. In an empirical context, we will see that this elasticity also depends critically on the degree to which the SSA food economy is integrated into global markets. The foregoing, two region model assumes full market integration, but in reality, the extent of SSA integration into world agricultural markets remains limited. Furthermore, in the context of a more disaggregated representation of the global economy we expect that virtual technology trade will emanate from just a few highly innovative regions, not the entire rest of world.

3.3 Adding Natural Resource Conservation

The final consideration that we bring to bear in this theoretical model is the emerging trend in some of the world's richest economies to use TFP growth to reduce input use in agriculture. This reduces the growth in output in food production in the RoW region, as can be seen in the following expression in which agricultural land and water resources are withdrawn from agriculture through a set of environmental programs, thereby resulting in a backward shift in land supply of (percentage) magnitude: Δ_L:

$$q_O = \varepsilon_S p_O + (\varepsilon_S + 1)a - \Delta_L \tag{7}$$

From this expression it can be seen that such an environmental program can potentially be large enough to neutralize the growth in output and eliminate the virtual technology trade altogether. Indeed, this has been the case in much of Europe as well as in high income East Asia (REF Heisey and Fuglie, 2018). In the special case where: $\Delta_L = a(\varepsilon_S + 1)$, these conservation programs fully offset the effect of TFP on output growth. Another way of thinking about this is that regions like the EU can withdraw resources from agriculture up to this point without having an adverse impact on output. However, if TFP growth slows beyond that point, or if the conservation practices are more aggressive, output -- at constant world prices -- will fall.

In the context of the two-region trade equilibrium, the world price change as a function of the combined TFP growth and conservation measures in the non-SSA region becomes:

$$p_O = [(1-\alpha)\Delta_L^{RoW} - (1-\alpha)(\varepsilon_S^{RoW} + 1)a^{RoW}] / [\varepsilon_D^W + \varepsilon_S^W] \tag{8}$$

The first term in the numerator (backward supply shift due to conservation measures) offsets some of the price reducing effect of the innovation in RoW and therefore dilutes the amount of virtual technology trade which will follow from the innovations in RoW agriculture.

4. Quantitative Trade Model

In order to explore the potential for trade in technology to resolve the Malthusian challenge in SSA, we turn to a numerical implementation of the theoretical framework discussed above. This higher dimensional implementation of the model allows us to relax a number of critical assumptions. These include: (i) increasing the number of regions to allow for isolation of key sources of technology spillovers (ii) development of explicit R&D spending scenarios and the ensuing profile of TFP growth across these regions over time, (iii) heterogeneous rates of population and income growth, and (iv) relaxing of the assumption of perfectly elastic supplies of non-land factors of production.

4.1 Model Dimensions

The quantitative trade model used here is dubbed SIMPLE: a Simplified International Model of Prices Land use and the Environment, in recognition of the barebones nature of the model (Baldos and Hertel, 2013; Hertel and Baldos, 2016). It has been used to analyze the long run drivers of future food production, prices and land use change (Baldos and Hertel 2013; T.W. Hertel, Baldos, and van der Mensbrugghe 2016), adaptation to climate change (Baldos and Hertel 2015; Lobell, Baldos, and Hertel 2013), the role of R&D and productivity growth in ensuring food security and environmental sustainability (Baldos and Hertel 2014; Thomas W. Hertel, Ramankutty, and Baldos 2014) and the market impacts of reducing food waste and post-harvest losses (Hertel and Baldos, 2016). As its name suggests, this has been designed around the principle that a model should be no more complex than is absolutely necessary to understand the basic forces governing the global supply and demand for crops, cropland and food prices.

The SIMPLE model disaggregates the world economy into sixteen regions, each producing an aggregate crop commodity using a variable combination of land and nonland inputs (Fig. A1 in supplementary material). Substitution of non-land inputs (e.g., fertilizers, farm labor and machinery) for land in crop production offers scope for endogenous intensification of production, allowing for crop yield growth even in the absence of technological change under increasing scarcity. Expansion of cropland requires that the land be bid away from competing uses, with the size of this area response varying across geographic regions. Crop production in SIMPLE has four potential uses: direct consumption, livestock feed, food processing, and biofuel feed-stocks. Food demands are price- and income-sensitive, but become less as per capita incomes rise (Muhammad et al., 2011). Rising incomes also cause consumers to diversify their diets, which, at early stages of economic development, means adding relatively more livestock and processed foods. Production of both these commodities requires crop inputs – the demand for which can be altered by exogenous technological progress in those sectors (e.g., more feed efficient livestock technology).

4.2 Endogenizing Crop Productivity

In the crops sector, we allow for endogenous growth in productivity, driven by exogenously specified time paths for investments in agricultural research. To implement this we modify the production function in (1) as follows:

$$Q_O = A_O R_O^{\delta_O} R_S^{\delta_S} (\phi_L Q_L^{-\rho} + \phi_N Q_N^{-\rho})^{-1/\rho} \qquad (9)$$

where initial productivity, A_O, is enhanced by growth in the stock of own-research capital, R_O, and spill-in research capital, R_S. These provide factor-neutral productivity shocks, directly contributing to TFP growth in the region. The parameters δ_o and δ_s are elasticities that specify the percentage change in TFP from a 1% increase in research capital from a given source.

Research capital $R_i$accumulates from past research expenditures $r_i(t)$ in region i according to:

$$R_i = \int_{-\infty}^{t-L} exp^{-\lambda(t-g)} r_i(g)\ dg \qquad (10)$$

where λ is the capital depreciation rate and L represents the lag time for research expenditures to mature into useable technologies that are adopted on farms. The general expression in (10) can take on a variety of forms. It weights each past year's research expenditure by a value ranging from 0 and 1 (0 when the technology is not yet in use or has been replaced or fully depreciated, and 1 when it is fully operational and adopted). In our application we assume a 35-year research lag structure where the weights have a gamma distribution that reaches a maximum value after 14 years. See Alston et al. (2010) for a discussion of measuring research capital in the context of agriculture.

Sources of data on historical expenditures for public and private agricultural research are described in Fuglie (2018), who also reports elasticities estimated by more than 40 studies on how agricultural R&D capital affected TFP growth in different regions of the world. These elasticities describe how public and private research within countries, research in other countries, and research by international agricultural research centers, affected agricultural TFP growth in particular countries. From this list, Fuglie (2018) developed a "synthesis" set of R&D elasticities for major global regions and compared the predicted TFP growth from R&D spending to actual TFP growth for those regions. Fuglie's (2018) results are reproduced in *Figure 4*, which give an indication of the share of historical TFP growth that can be attributed to R&D, as opposed to other factors. In developed regions, changes in R&D capital explain nearly all of agricultural

TFP growth, and R&D spill-ins are significant. In developing regions and transition economies, R&D capital accounts for only part of the observed growth in TFP, and R&D spill-ins are important only for the LAC region. The CGIAR system of international agricultural research centers, which focuses on improving food crops in low income countries, has had a measureable impact on agricultural productivity across all developing regions. The gap between observed and predicted TFP growth in China, Africa and elsewhere can be explained in part by reforms in these regions that encouraged more efficient utilization of existing resources.

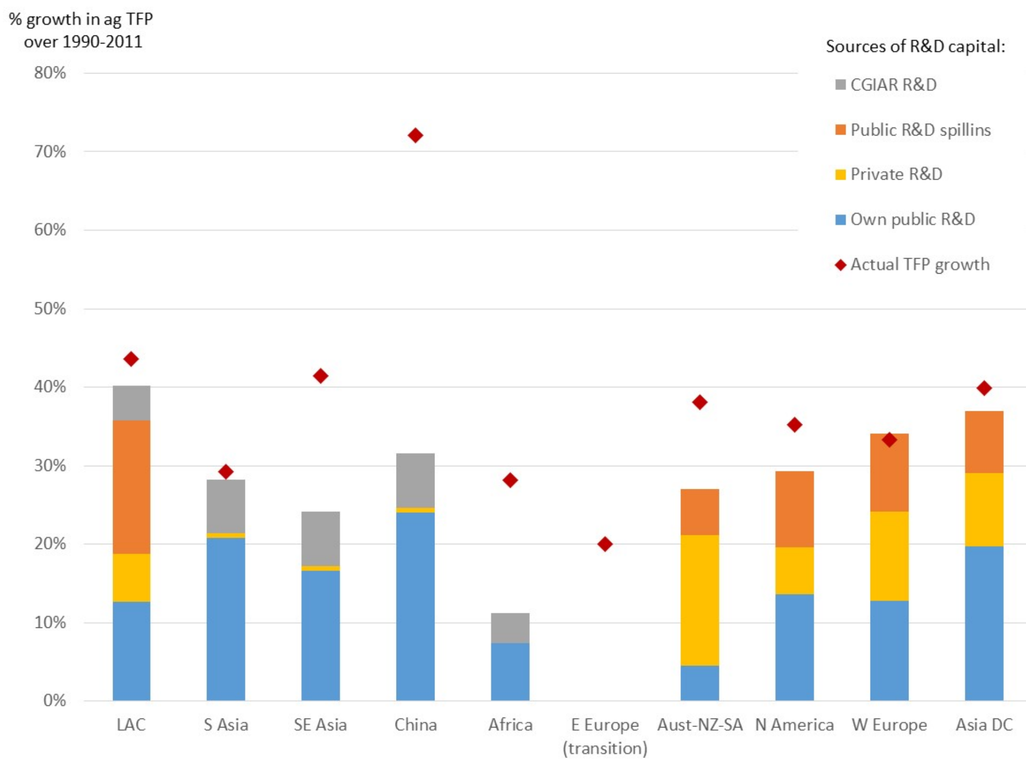

Figure 4. Observed changes in agricultural TFP for major global regions over 1991-2011 and predicted TFP growth from changes in R&D capital over same period. Source: Fuglie (2018).

4.3 Estimating Undernutrition

Our principal Malthusian metric is the extent of macronutrient malnutrition, specifically, daily caloric intake. Based on estimates from UN FAO (2012), we postulate a distribution of caloric intake across the population in SSA. The solid line in *Figure 5* shows this distribution for the year

2006. By integrating under this density function up to the minimum caloric requirement, we obtain the undernutrition index for that year. Multiplying by total population in the region, we obtain the poverty headcount. Following the approach originally develop for poverty measures by Foster, Greer and Thorbecke (1984), we can also compute the average depth of undernutrition or the 'undernutrition gap'. As income rises, food consumption increases, along with caloric intake, and this density function shifts to the right. The hypothetical 2050 density shown in *Figure 5* shows a lower undernutrition headcount ratio. The absolute number of undernourished people in the region will depend on the population growth rate, changes in per capita income, and the price of food.

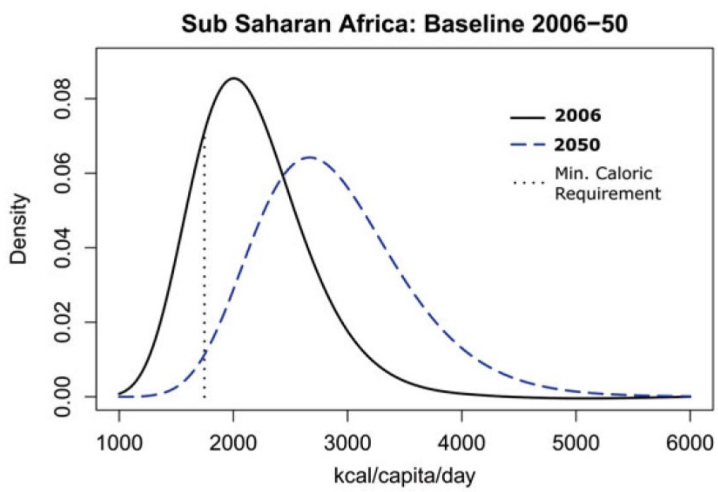

Figure 5 Distribution of caloric consumption for Sub Saharan Africa in 2006 (solid black line) and in 2050 (dashed blue line). The dotted line represents the minimum required daily caloric intake. Source: Authors' calculations using 2006 data from UN FAO (2012) and 2050 projections from Authors' calculations.

4.4. International Trade

The standard implementation of SIMPLE incorporates market segmentation following the idea originally proposed by Armington (1969) who postulated that domestic and imported products were differentiated goods, albeit potentially close substitutes. This trade specification has since garnered considerable empirical support in agricultural trade (e.g., Villoria and Hertel, 2011). The constant elasticity of substitution specification is also consistent with market demand when individual households make a discrete choice between purchasing international vs. domestic commodities and consumers' ideal characteristics are distributed according to the multinomial logit (Anderson, Palma, and Thisse 1989). In this case, the elasticity of substitution is inversely related to the measure of heterogeneity in the underlying population's preferences. So, for example, a country in SSA with a significant population in an urban seaport, exposed to international products, and also many people still living in remote rural areas with limited exposure to world markets, would have a lower elasticity of substitution that one in which nearly everyone lived in cities along the coast with ready access to international markets.

We apply the same segmented markets specification to domestic producers where suitable aggregation across agricultural producers with limited market access gives rise to a constant elasticity of transformation between domestic and international goods. When many of a country's farmers face high transport costs and have poor access to world markets, the absolute value of this transformation elasticity is small, and domestic producers are relatively unresponsive to world price changes. On the other hand, when farmers are well- integrated into the world market, we expect a strong supply response to international prices.

The extent of market segmentation is captured by the elasticities of substitution and transformation between domestic and international goods as well as the initial shares of international goods in the consumption and production bundles. The absolute value of the trade elasticities are set to 3, in keeping with the broad thrust of the empirical evidence for international substitution of crops (Hertel et al., 2007). In the Armington specification, the initial extent of market penetration (the share of spending on international goods (CES), or the share of sales to the global market (CET) – see Figure S1) also plays a central role in determining the degree to which the global and regional crop markets are linked. If no international goods are available (zero share), then domestic and international consumer prices will not be linked at all.

4.5 Model Validation

SIMPLE has been validated over historical periods via backcasting, focusing on global changes in food production, prices and cropland (Baldos and Hertel 2013), regional output changes (Hertel, Ramankutty, and Baldos 2014; Hertel and Baldos 2016), as well as changes in undernutrition (Baldos and Hertel 2014). And the model has been applied to the analysis of a variety of food and environmental issues, including adaptation to climate change (Lobell et al. 2012; Baldos and Hertel, 2015), and the impact of reducing food waste and post-harvest losses (Hertel and Baldos, 2016).

Figure 6 summarizes observed changes as well as model outputs over the period 1961–2006. Model outputs are generated using historical changes in population, income as well as agricultural total factor productivity growth (see Table S1). In general, the model does well in capturing the historical changes in crop production and crop price at the global level (actual changes at 196% and -23% vs model output at 183% and -23%, respectively). SIMPLE also captures the partitioning of global crop supply growth between global cropland expansion and global average crop yield growth (see Figure S2). However, relative to the global changes the model does less well at capturing historical changes at the regional level (see Figure S3) due to the importance of local and regional policies, civil conflict and many other factors omitted from SIMPLE.

Figure 6 also shows the contribution of population, income and agricultural productivity growth to the historical changes output. Here, we see that the simulated increase in global crop production is mainly due to the historic population growth over this period (red bar – left panel,

Figure 6). Increased food demand due to population growth place pressure to increase global crop price (red bar, right panel, *Figure 6*) but due to the impressive growth in agricultural productivity (green bar, right panel, *Figure 6*) food prices over this long run historical period have fallen sharply.

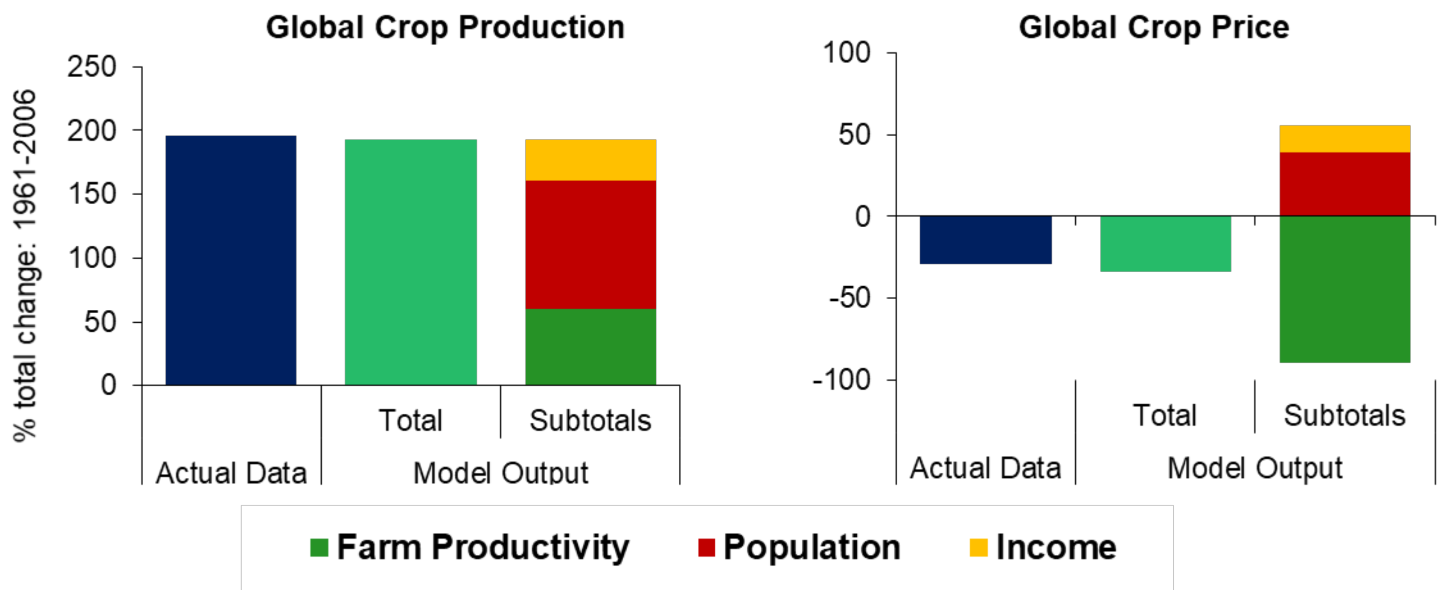

Figure 6. Historical validation and decomposition of key drivers of global crop production and prices. Historical data on crop production and crop prices from FAOSTAT *(2019)* and World Bank GEM Database *(2019)*, respectively.

5. Results

5.1 Experimental Design

To understand the potential for trade in technology to alleviate the Malthusian pressures in the SSA region, we run a series of six experiments (**Error! Reference source not found.**) with rows corresponding to the state of market integration and the columns corresponding to the extent of technology spillovers. For example, the first cell in this experimental design matrix captures the intersection of historically segmented markets (first row) and historical spillover coefficients (first column). We dub this *Seg-HSpill* which we consider as our future baseline scenario. In contrast, the diagonally opposing cell is dubbed *Int-ESpill,* denoting fully integrated markets (second row) and enhanced spillovers without environmental restrictions (second column), as described in Section 2 above. By contrasting rows in this matrix we obtain insights into the role of market integration in the determination of technology's impacts on undernutrition in Africa. By contrasting columns in this matrix, we see the effects of enhanced spillovers on direct and virtual technology trade and their consequences for undernutrition in SSA. The final (third) column in this experimental design box corresponds to the case in which environmental restrictions are added to the shocks applied in the second column's experiments.

Table 1. Experimental Design

Experimental Design		**Technology Spillovers**		
		Historical Spillovers	Enhanced Spillovers	
			No Environ Restrictions	With Environ Restrictions
Market Integration	Historical Segmentation	*Seg-HSpill*	*Seg-ESpill*	*Seg-Espill-Restrict*
	Full Integration	*Int-HSpill*	*Int-ESpill*	*Int-Espill-Restrict*

5.2 Global Baseline Results

Before taking a closer look at the regional results in SSA, we first examine the changes in key global variables in our future baseline scenario - *Seg-HSpill*. *Figure 7* shows projected changes in global crop production and prices (upper panel). These projections are generated using key assumptions on how population and per capita income as well as agricultural total factor productivity will grow between 2006 and 2050 (see Table S2). Under the future baseline.

future growth rates in total factor productivity for the crops sector are based on expected increases in public R&D spending in agriculture as well as 'Historical North' technology spillovers as defined in Section 4.1. Relative to the historical changes, we see that the future increases in global crop production over 2006-2050 (99%) is much less rapid (in percentage terms) than the increase in over 1961-2005 (190% - see *Figure 6*). Global food prices are expected to continue their long-term decline (by another 39% from 2006 levels). The key to these outcomes is a slowdown in demand growth as global population stabilizes (annual average growth of 2.6% in 1961-2006 vs 0.8% in 2006-2050). With this slower population growth, we now see that the relative contribution of per capita income growth to total food demand is becoming greater (orange bar – upper right panel, *Figure 7*). Globally, average caloric consumption is expected to increase by 36% (mostly through increased consumption of meat, biofuel, and processed food products) while undernutrition count is predicted to fall by almost 82%. Greater food availability due to future improvements in farm productivity as well as increased food affordability, given rising per capita incomes, are key to attaining these strong gains in future food security outcomes.

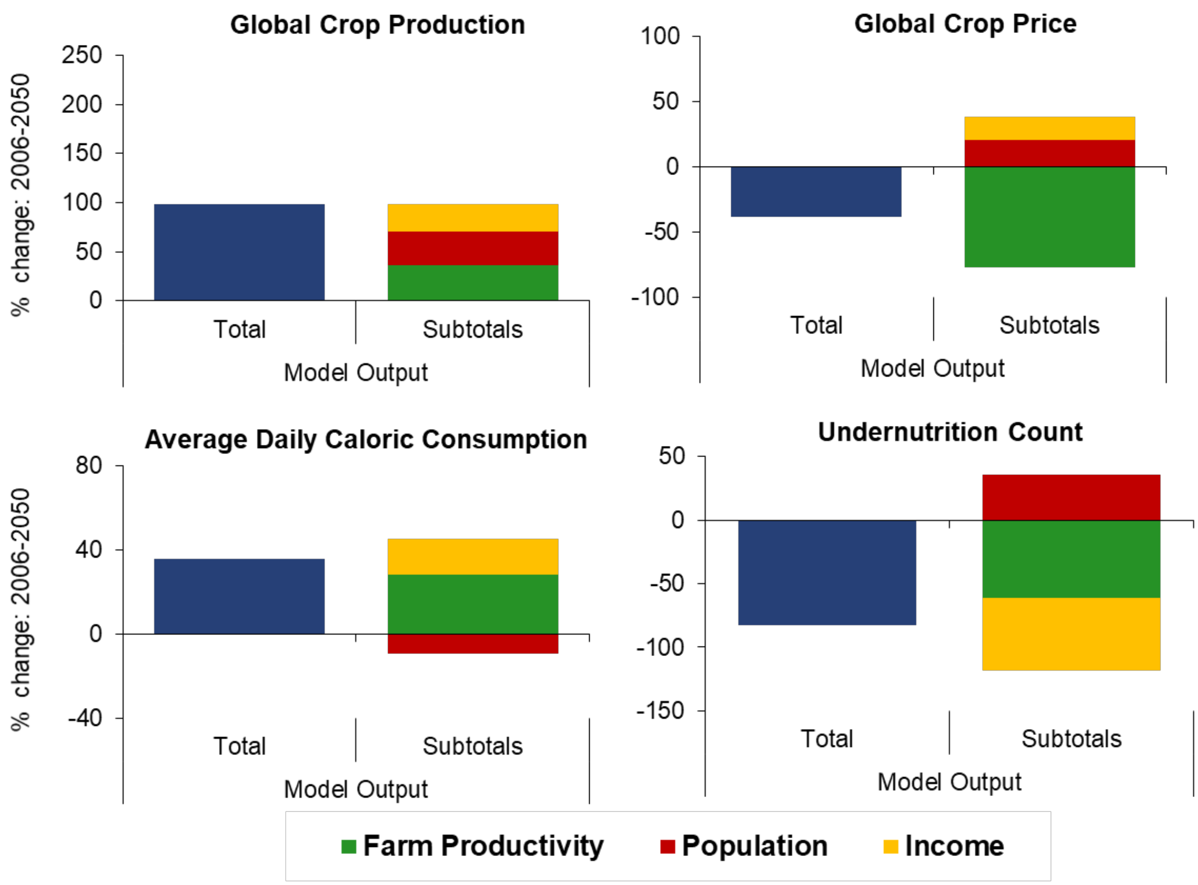

Figure 7. Projected baseline and decomposition of key drivers of global crop production, prices, caloric consumption and undernutrition count.

5.3 The Role of Technology in Reducing Undernutrition in SSA

Figure 8 reports four sets of results from our experiments with the two variants of the SIMPLE model: segmented and integrated markets for crop commodities, varied across two different technology scenarios: historical spillovers and enhanced spillovers. Focusing first on the model with segmented markets and historical spillovers (our 'baseline' version of the current world, or *Seg-HSpill*), the model projects a 60% decline in the undernutrition headcount in SSA over the 2006-2050 period (the far left blue column in *Figure 8*). If markets become fully integrated then undernutrition falls by 93% (the far left orange column in the figure). The underlying drivers include: population growth (increases undernutrition headcount at constant income), per capita income growth (shifts the consumption distribution in *Figure 5* to the right, thereby reduction undernutrition, and technology (boosts supplies and lowers prices, thereby reducing undernutrition). In this first experiment, population and income growth have numerically offsetting effects on SSA undernutrition, so the net decline in undernutrition is almost all due to technology (i.e., the height of the blue 'all tech' bar is almost identical to the total reduction), which is pure coincidence and not the case with the other experiments.

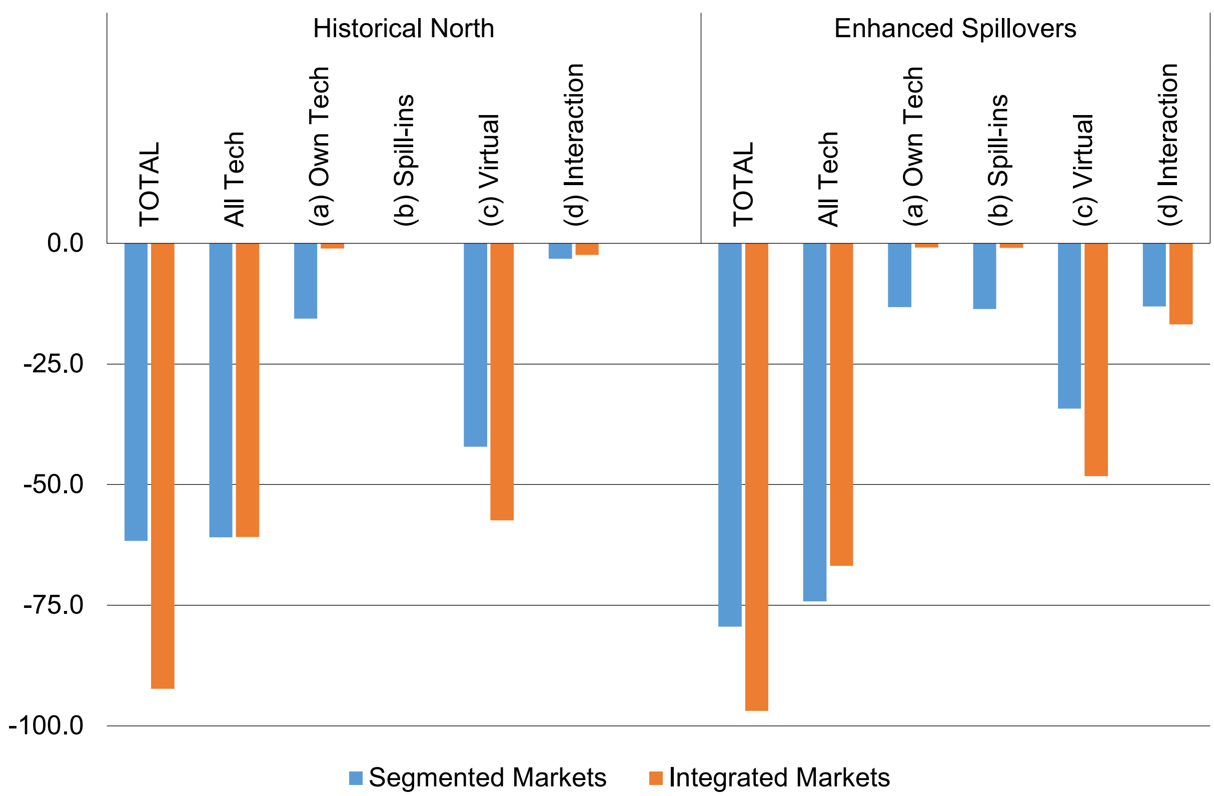

Figure 8. Contribution of technological change to the reduction in undernutrition in Sub Saharan Africa. Source: Authors' calculations.

The remaining bars in Figure 8 decompose the impact of technology into the components identified in the theory section above. The first is the contribution of SSA's own technological innovations on undernutrition in the SSA region. The second set of bars refer to the impact of direct trade in technology between RoW and SSA (*spill-ins*). This is absent in the context of historical spillovers, so no bars appear here. The third component of this decomposition refers to the impact of *virtual* technology trade. This refers to the growth in availability of food in the SSA region due to technological improvements elsewhere in the world. This is the dominant factor in the experiment wherein historical market segmentation and historical spillovers are maintained. The fourth and final component of this decomposition is the result of interactions between spillovers amongst regions in RoW and virtual technology trade with SSA. When technology spills over from (e.g.) US to Argentina, and Argentinian producers expand exports to SSA, SSA benefits indirectly from the spillovers within RoW. This *interaction effect* would not have arisen if the initial spillovers had not taken place. And it is facilitated by international commodity trade with SSA.

It is interesting to contrast these results with those from the *Seg-ESpill* experiment in which commodity markets remain segmented, but technology spillovers are enhanced, allowing for low income countries, including those in SSA, to benefit from technological advancements in the emerging economies. These results are displayed in the blue bars in the right hand panel of Figure 8. Enhanced spillovers boost the undernutrition reduction by nearly 20%, from 60% to 80%. The added contribution comes in equal parts from the spill-ins from emerging economies' technology to the SSA region, and from the interaction effect. With greater spillovers amongst developing countries elsewhere, there are significant indirect (virtual) benefits to undernutrition reduction in the SSA region.

The orange bars in Figure 8 report the results for SSA undernutrition changes from 2006-2050 in the context of fully integrated world markets. This is an extreme case, whereby one price prevails, worldwide, for the composite crop commodity. This scenario, although not very realistic, is intended to foreshadow future differences in the impact of technology trade, were agricultural markets to become more globalized. There are clearly many obstacles to achieving greater international integration, including transportation costs and infrastructure limitations, government policies aimed at maintaining some degree of self-sufficiency in food, and differing sanitary and phyto-sanitary standards. As shown in Figure 8, the removal of segmented markets for agricultural products shifts most of the improved nutritional status in SSA to the virtual technology category. Regional improvements in SSA technology have little impact on world prices, and therefore limited impact on SSA nutritional outcomes. Given the large and growing role of technological investments in Latin America, China and South Asia, enhanced spillovers from those regions have a significant impact on world prices and therefore make a contribution of the reduction of undernutrition in SSA under the *Int-ESpill* scenario. Indeed, under this final scenario, undernutrition in SSA is nearly eliminated by 2050 (total = -97%).

The other interesting point about the integrated markets experiments is the sizable gap between the 'Total' and 'AllTech' contributions to undernutrition reduction. When markets are segmented, rapid growth in demand in SSA tends to push up prices in that region, relative to world markets. SSA is where a large share of the world's population will be added over next century, and many countries in the region are also experiencing rapid income growth. On the other hand, if consumers in Africa can access food from anywhere in the world (integrated markets), this regional demand growth has a far more modest impact on food prices in SSA. In this case, the benefits of rising income overcome the pressure placed by growing population on the undernutrition headcount, leading to additional reductions in undernutrition in the region beyond those offered by improvements in technology.

5.4 The Role of Environmental Stringency in the North

Thus far, we have assumed that rising productivity in the wealthier countries, here dubbed 'North' as a shorthand, translates into increasing output and therefore virtual technology trade.

However, as we saw in Section 2, in some regions this improved technology has instead translated into reduced inputs instead of higher output. In particular, by limiting the use of land, water and chemicals in agriculture, the European Union has sought to make farmers stewards of the environment, with special payments to provide the necessary incentives. The theory developed in Section 3 shows the potential for such environmental restrictions to offset the impact of productivity growth on prices and virtual technology trade. Of course, the extent to which this actually occurs is an empirical question. It depends on the stringency of the environmental restriction, relative to the rate of productivity growth, the elasticities of supply and demand, as well as the contribution of the restricted region to global output. For this reason, it is important to conduct a quantitative experiment.

In this final pair of experiments, we assume that the EU approach to restricting inputs used in agriculture spreads to other high income economies, including the US, Canada, Australia, New Zealand, Korea and Japan. Furthermore, we assume that crop output ceases to grow in all these countries, using the improved productivity instead to reduce input usage. Figures 9a and 9b report key results for the cases of segmented and integrated markets. These figures plot the contribution of each region of the world to international crop supplies. In the case of segmented markets, this is the share of each region in sales to the global market (gross exports). In the case of integrated markets, this is simply the share of each region in global production.

Consider first, *Figure 9*a. In the absence of environmental restrictions, South America is projected to account for about half of the growth in global crop exports over the 2006-2050 period. This is due to relatively high rates of R&D investment, leading to high productivity growth, as well as ample fertile land that can be brought into production. China, as the world's largest agricultural economy, with extremely high rates of productivity growth and essentially zero population growth, follows with just under 30% of gross export growth. Other economies contribute far smaller shares to the growth in international crop availability, with the EU contributing about 7% of this growth, and the US and Canada just 2% of this export growth.

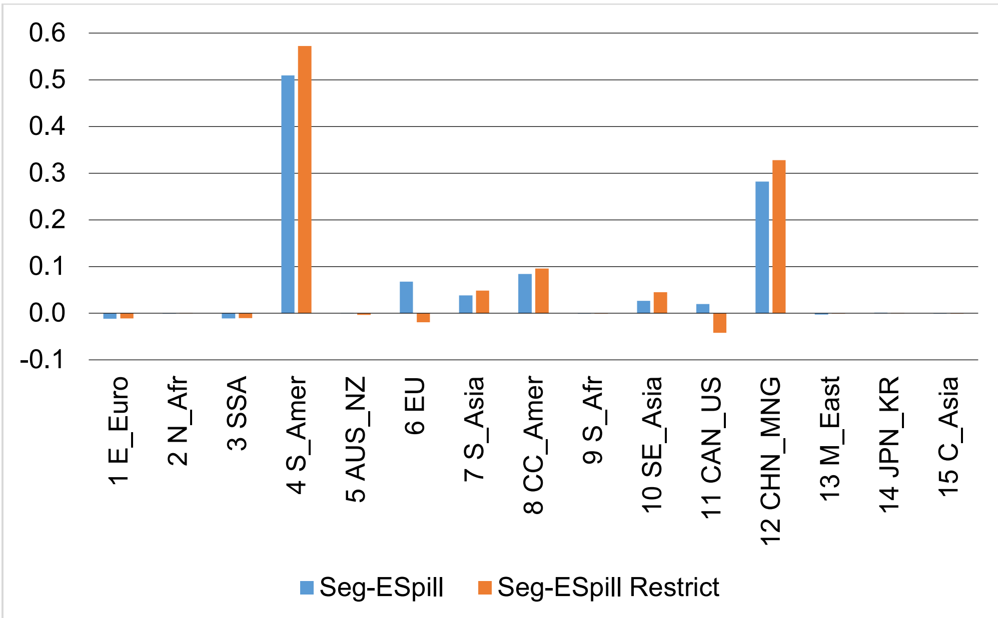

Figure 9a. Regional contributions to growth in international supplies of crop commodities over 2006-2050 with segmented markets (share of total growth). Source: Authors' calculations.

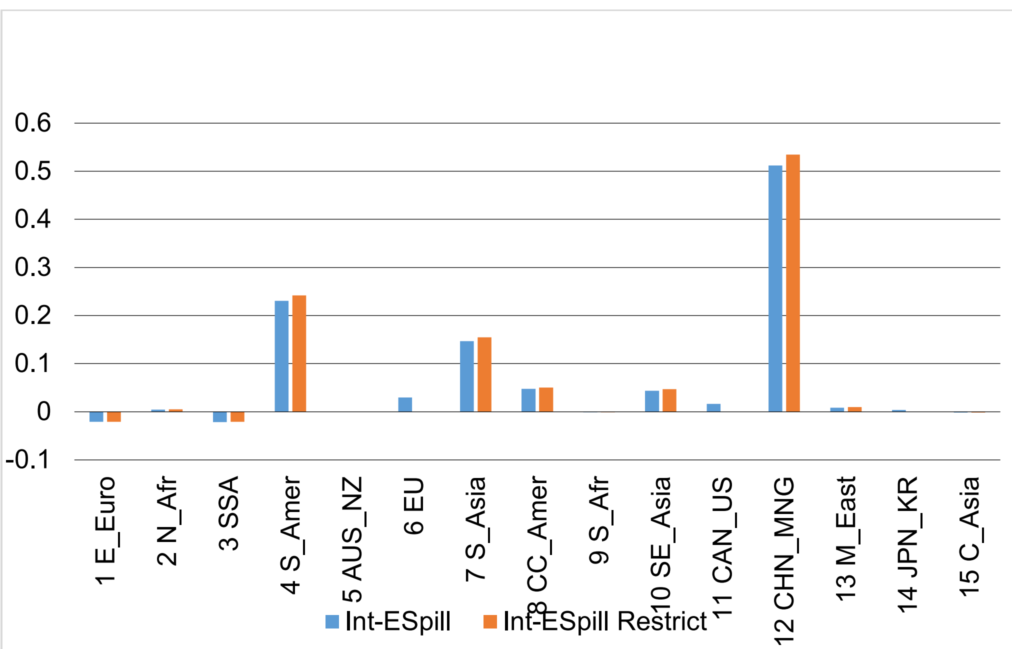

Figure 9b. Regional contributions to growth in international supplies of crop commodities over 2006-2050 with integrated markets (share of total growth). Source: Authors' calculations.

When environmental restrictions are put in place, the affected economies cease to contribute to global crop supplies, instead reducing gross exports in favor of domestic consumption. When these reductions are summed across these regions, they account for a slowdown of nearly 9% in global export growth. However, other regions expand exports in response to the relatively higher commodity prices and largely make up for this reduction. As a consequence, global prices fall less under this scenario, but the magnitude of this reduction is just 3 percentage points, relative to baseline in 2050. Therefore the impact on undernutrition in SSAS is modest, falling by 77% under *Seg-Espill-Restrict* as opposed to a 79% decline under the *Seg-Espill* experiment.

This impact of environmental restrictions on agriculture in the 'North' is even more modest in the case of integrated markets (Figure 9b) since the contribution of the affected economies to global supply growth is less than their contribution to global export growth. The restricted economies reduce global supplies by about 5% under the environmentally constrained scenario, and the impact on world prices in 2050 is just one percentage point, with a negligible impact on SSA undernutrition. In short, while these environmental restrictions are potentially significant, in practice their effect could be readily offset by increased investment in SSA technology (segmented markets) or enhanced spillovers (integrated markets).

6. Summary and Conclusions

The recent rise in caloric undernutrition in Sub-Saharan Africa is an indication that the Malthusian footrace between food availability and population remains relevant in some of the world's poorest countries. This has brought greater attention to the role of agricultural technology in ensuring food security in this region. In this paper, we develop a model of technology, food security and international trade in which there are three distinct channels for technology to benefit food security in SSA. The first is via greater domestic R&D investment in the SSA region. This is the primary channel through which the industrialized and newly emerging economies, including Brazil and China, have boosted farm productivity in their own countries. However, the lag between current investments and future productivity can be a long one, and historical neglect of the agricultural research infrastructure as well as civil strife make this relatively difficult in SSA. An alternative is to import technologies from other countries where significant knowledge capital has already been established. Empirical evidence suggests that technology 'spill-ins' from the wealthy economies, largely located in the temperate climatic zones has hitherto been very limited. However, there is significant potential for greater success by transferring technologies from emerging tropical economies such as Brazil which shares similar agro-ecologies. The third role for technology to resolve the Malthusian dilemma in SSA is that of 'virtual technology trade', i.e., importing the benefits of technological investments elsewhere through cheaper food, a channel possible if food exporting countries are willing to maintain considerable environmental resources in agriculture.

In order to assess the relative contribution of each channel to food security in Africa, we employ a partial equilibrium, quantitative trade model, augmented by a dynamic relationship between R&D investments, knowledge capital and agricultural productivity. Not surprisingly, we find that the importance of the three technology-food security linkages varies depending on the extent of global market integration. With fully integrated agricultural markets, virtual technology trade is far and away the most important vehicle for reducing undernutrition in the SSA region. Given the dominance of R&D capacities outside the SSA region, it makes sense for Africa to simply import cheap food – at least in the context of our partial equilibrium framework. However, agricultural markets in SSA remain highly segmented – far removed from this integrated market ideal. Nonetheless, even with the current state of food trade friction, we find that virtual technology will be the most important vehicle for reducing undernutrition in Africa between the present and 2050. However, investments in agricultural R&D by SSA countries play a significant role as well. And, if SSA researchers can successfully adapt technologies from the emerging markets, this spill-in effect could rival in importance their own R&D investments. Furthermore, we find there is significant interaction between technology spill-ins in the rest of the world and virtual technology trade when it comes to alleviating hunger in Africa.

Given the importance of agricultural output growth in the rest of the world for SSA's food security – via virtual trade in technology -- we also explore the consequences of more widespread adoption of the EU approach to the agriculture-environment interface. Rather than allowing farm productivity growth to be translated into increased food production, Western Europe has used this opportunity to withdraw resources from agriculture, resulting in a relatively flat output profile. We examine the impact on global food production and prices as well as undernutrition in SSA in 2050, of strengthened environmental restrictions in the EU, US, Canada, Japan, Korea, Australia and New Zealand such that their production profile, between the present and mid-century, is flat. Fortunately for the poor in Africa, the impact is modest, as the emerging economies pick up the slack. In short, we find that the food-environment trade-off in the 'North' is not very consequential for undernutrition in SSA.

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Appendices for:
Trade in Technology: A Potential Solution to the Food Security Challenges of the 21st Century

By Thomas W. Hertel, Uris L.C. Baldos and Keith O. Fuglie

Outline:

A. Theoretical Model

1. Core model
2. Single region results
3. Two region results
4. Adding conservation measures

B. Quantitative Trade Model

C. Additional Results:

1. Benchmark data
2. Backcasting and historical validation

A. Theoretical Model

Box A1 outlines the core, long run partial equilibrium model of agriculture in linearized form (lower case variables denote percentage change in the corresponding upper case (levels) variables.

Box A1: A simple, partial equilibrium long run model of agriculture

(1) $qo = -\varepsilon_D p_O + \Delta_D$: demand for agricultural output

(2) $p_O + a = \sum_j \theta_j (p_j - a_j)$: agricultural entry/exit; zero profits

(3) $q_N + a_N = q_O - a - \sigma(p_N - a_N - p_O - a)$: demand for non-land inputs

(4) $q_L + a_L = q_O - a - \sigma(p_L - a_L - q_O - a)$: demand for land input

(5) $p_j = 0, \forall j \neq L$: supply of non-land inputs

(6) $q_L = \nu_L p_L - \Delta_L^S$: supply of land to agriculture

Notation: all price and quantity variables represent percentage changes in the underlying indexes

q_O, q_j : % change in long run agricultural output and input j

a, a_j : cumulative output-augmenting and input-*j* augmenting technical change in agriculture

p_O, p_j : % change in the price of agricultural output and input *j*

$\sigma \geq 0$: elasticity of substitution between land and non-land inputs

$\nu_j \geq 0, \theta_j \geq 0$: elasticity of supply to agriculture and cost share of input *j*

$\varepsilon_D \geq 0$: price elasticity of demand for agricultural output

Δ_L, Δ_D : shifters in land supply, due to conservation measures, and output demand

$\varepsilon_S^X \equiv \theta_L^{-1} \nu_L$: the extensive margin of supply response (area elasticity wrt commodity price)

$\varepsilon_S^I \equiv \sigma(\theta_L^{-1} - 1)$: the intensive margin of supply response (yield elasticity wrt commodity price)

CES production function (upper case variables are *levels* of corresponding lower case variables):

$$Q_O = A(\phi_L Q_L^{-\rho} + \phi_N Q_N^{-\rho})^{-1/\rho}$$

Where: $\sigma = 1/(1+\rho)$ and $\rho > -1$

Equation (1) determines the global demand for food as a function of price (via and constant price elasticity of demand, $\varepsilon_D > 0$, and exogenous shifts in this demand function, Δ_O^D, due to growth in population and income, both of which are determined outside this partial equilibrium model. Equations (2) – (4) are a consequence of cost minimizing behavior in the agricultural sector, subject to the CES production function shown at the bottom of Box A1, coupled with free entry/exit into or out of the agricultural sector, thereby ensuring zero profits (2). For the results derived in this paper, the key elements of equations (2) – (4) are the rate of total factor productivity (TFP) growth (a) and the elasticity of substitution between the land and nonland inputs, $\sigma \geq 0$. We do not exploit the input biased technological change terms in this paper. For the derivation of these three equations, see: https://www.gtap.agecon.purdue.edu/resources/download/1610.pdf

Equations (5) and (6) close the factor markets in this model. Given its long run nature, nonland inputs (labor, capital and industrial inputs) are assumed to be in perfectly elastic supply in this partial equilibrium model. By contrast, land (and water) are inelastically supplied to farming, thus giving an upward slope to the partial equilibrium supply curve. The output supply elasticity, $\varepsilon_S = \theta_L^{-1} v_L + \sigma(\theta_L^{-1} - 1)$, is therefore a function of the land supply response to land returns, v_L, translated through the inverse of the cost share of land, θ_L, which serves to magnify the impact of commodity price changes on land rents, since the nonland inputs are in perfectly elastic supply and cannot benefit from a commodity price increase. This is the extensive margin of commodity supply.

The other component of the commodity supply response is the intensive margin of supply, $\sigma(\theta_L^{-1} - 1)$. It depends critically on the elasticity of substitution between the nonland inputs (e.g., fertilizer) and land. This, too, is a function of the cost share of the inelastically supplied land input. In the case of subsistence agriculture, commercial inputs are likely to be small, capital limited and labor abundant, making this cost share large. This translates into a very limited intensive margin of commodity supply response.

Single Region Analysis: Setting $a_j = 0$ and substituting (4) into (2), and solving for land rents, we obtain:

$$(6) \qquad p_L = \theta_L^{-1}(p_O + a)$$

This is the well-known "magnification effect" in economics whereby any change in output price is magnified as it is transmitted back to the returns to the sector-specific factor, land. Using (1) to eliminate q_O from (3), using (2) to eliminate po and equating (5) and (3) to reflect equilibrium in the land market (assuming no environmental conservation measures: $\Delta_L = 0$) leaves us with one equation in one unknown, namely land rents, which depend on all the economic parameters in the model as well as the productivity shock and population growth:

$$(7) \qquad p_L = [(\varepsilon_D - 1)a + \Delta_D]/[\nu_L + \sigma(1-\theta_L) + \theta_L \varepsilon_D]$$

Plugging (7) into (5), since land supply varies directly with land returns, we have:

$$(8) \qquad q_L = \nu_L[(\varepsilon_D - 1)a + \Delta_D]/[\nu_L + \sigma(1-\theta_L) + \theta_L \varepsilon_D]$$

Equations (7) and (8) are informative. Firstly, we can see that the impact of technological progress in agriculture on land supply is ambiguous. In particular, since all of the parameters in the denominator are non-negative, $a < 0 \Rightarrow p_L > 0$ if, and only if, $\varepsilon_D < 1$. That is, land use will fall following a favorable technological innovation if and only if farm level demand is inelastic. Adding the population growth term, we see that land use will grow in response to the Malthusian factor, but it will grow at less than the rate of population growth due to endogenous intensification of production (nonland substitution for scarce land). Overall, the change in land use remains indeterminate, provided the farm level demand elasticity is less than one.

Equation (7) offers insights into the likely magnitude of such land rental price changes. In particular, the change in land rents, for a given farm level demand elasticity and a given factor-neutral productivity shock, will be greater, the smaller the elasticity of land supply (ν_L) and the smaller the elasticity of substitution between land and non-land inputs (σ). Equation (7) can be re-written in terms of the implied commodity supply elasticity in this model: $\varepsilon_S = \theta_L^{-1}\nu_L + \sigma(\theta_L^{-1} - 1)$, where the first term represents area response to the commodity price change and the second reflects yield response to higher commodity prices. This results in (7'):

(7') $$p_L = \{[(\varepsilon_D - 1)a + \Delta_D] / \theta_L[\varepsilon_S + \varepsilon_D]\}$$

Increasing the land supply elasticity or the elasticity of substitution boosts the aggregate supply responsiveness of output, thereby dampening the resulting price changes.

Plugging (7') into (6) and solving for the equilibrium output price change gives:

(9) $$p_O = [\Delta_D - a(\varepsilon_S + 1)] / [\varepsilon_S + \varepsilon_D]$$

This is equation (2) in the main text. From this equation, we see that the outcome of the long run Malthusian footrace between supply and demand depends critically on the relative rates of population growth and technological progress, whereby the latter is modulated by the price elasticity of supply. If this elasticity is zero, then the long run evolution of prices is simply dependent on the footrace between demand growth and the rate of technological progress. However, the stronger the supply response in agriculture, the more modest is the rate of TFP growth required to keep prices falling, as TFP growth boosts profitability in agriculture, thereby drawing in additional resources in the form of land and nonland inputs. The resulting equilibrium change in agricultural output can simply be read off the demand schedule:

$$(10)\qquad q_O = -\varepsilon_D[\Delta_D - a(\varepsilon_S + 1)]/[\varepsilon_S + \varepsilon_D] + \Delta_D = [a\varepsilon_D(\varepsilon_S + 1) + \varepsilon_S\Delta_D]/[\varepsilon_S + \varepsilon_D]$$

This is equation (3) in the main text. It shows that both TFP growth and population growth will stimulate growth in output, with the magnitude of this increase depending on the size of the demand and supply elasticities.

Two Region Model: In order to understand the impacts of a continental scale technology shock on global commodity prices and undernutrition, we need to factor in not only the changes that arise in the innovating region, but also the response of producers and consumers rest of the world. In the absence of technological spillovers, i.e., keeping the level of technology in the SSA region constant, all of the impacts will be carried through the commodity markets. We call this *virtual trade in technology* to relate it to the popular literature on virtual trade in water. We investigate the determinants of this virtual technology trade first, then progress to the case where some of the technological gains spillover to the rest of the world – a phenomenon which we dub *direct trade in technology*.

With minor modifications, we can adapt the model in Box 1 to analyze the impacts of virtual technology trade. Since we will assume in this section that world markets are fully integrated (an assumption that will be relaxed in the quantitative trade model), equation (1) simply becomes global demand. And we distinguish the two regions using the superscripts: *SSA* and *RoW.* These are attached to the supply-side variables in equations (2) – (5). In order to assess the impact of virtual trade in technology, we evaluate the change in SSA net imports, relative to global consumption, due to the improvement in technology in the RoW region:

(11) $t = 100 * dM^{SSA} / Q_O^W = \beta qo_D^{SSA} - \alpha qo_S^{SSA}$

Where $M = Q_D^{SSA} - Q_O^{SSA}$, reflects net imports into the SSA region, $T = M / Q^W$ expresses these net imports as a portion of global supply, $\alpha = QO_S^{SSA} / Q^W$ is SSA's share of global supply (which equals global demand by virtual of global market clearing) and $\beta = Q_O^{SSA} / Q^W$ is SSA's share of global supply (which equals demand in this equilibrium model). **This is equation (4) in the main text.**

With integrated world markets, an outward shift in the RoW region A's supply curve, in the absence of demand growth, can be represented using the following, reduced form equations:

(12) $q_O^{RoW} = \varepsilon_S^{RoW} p_O + \Delta_S^{RoW}$; $q_O^{SSA} = \varepsilon_S^{SSA} p_O$ and $q_O^W = -\varepsilon_D^W p_O$

Where $\Delta_S^{RoW} = (\varepsilon_S^{RoW} + 1) a^{RoW}$ and the supply response in each region is a function of the region-specific factor supply and demand parameters: $\varepsilon_S = \theta_L^{-1} \nu_L + \sigma(\theta_L^{-1} - 1)$. Global market clearing requires that demand equals global supply:

(13) $q_O^W = \alpha q_O^{SSA} + (1-\alpha) q_O^{RoW}$

Where $\alpha = QO^{SSA} / QO^W$ denotes that share of global production in the affected region.

Solving for the equilibrium change in global price in response to the shift in RoW's supply curve:

$$-\varepsilon_D^W p_O - \alpha(\varepsilon_S^{SSA} p_O) - (1-\alpha)\varepsilon_S^{RoW} p_O = (1-\alpha)\Delta_S^{RoW}$$

$$p_O = -(1-\alpha)\Delta_S^{RoW} / [\varepsilon_D^W + \alpha\varepsilon_S^{SSA} + (1-\alpha)\varepsilon_S^{RoW}] = -(1-\alpha)\Delta_S^{RoW} / [\varepsilon_D^W + \varepsilon_S^W]$$

(14) $p_O = -(1-\alpha)\Delta_S^{RoW} / (\varepsilon_S^W + \varepsilon_D^W) = -\gamma_O^{RoW} a^{RoW}$

where $\gamma_O = (\varepsilon_S^{RoW} + 1)a^{RoW} / [\{(\varepsilon_D^W + \alpha\varepsilon_S^{SSA}) / (1-\alpha)\} + \varepsilon_S^{RoW}]$ and the global supply elasticity is just the weighted combination of the regional supply elasticities: $\varepsilon_S^W = \alpha\varepsilon_S^{SSA} + (1-\alpha)\varepsilon_S^{RoW}$, and similarly for demand: $\varepsilon_D^W = \beta\varepsilon_D^{SSA} + (1-\beta)\varepsilon_D^{RoW}$

We can also relate the two-region problem back to the single region problem dealt with previously by rewriting (14) as follows:

(15) $\quad p_O = -\Delta_S^{RoW} / (\{[\varepsilon_D^W + \alpha\varepsilon_S^{SSA}] / (1-\alpha)\} + \varepsilon_S^{RoW})$

Where first term in the denominator, $[\varepsilon_D^W + \alpha\varepsilon_S^{SSA}] / (1-\alpha)$, is the *elasticity of excess demand* facing producers in region RoW. This reflects the residual demand for region RoW's product, once the supply response in the rest of the world is accounted for. As such, it is larger than the ordinary demand elasticity. Since this combined price response is weighted by the inverse of the share of region RoW's production in the world market, as $\alpha \to 1$, the excess demand elasticity facing these producers becomes infinite. This is simply a formal representation of the one region result in which impacts of a localized innovation in the case where the regional economy is fully integrated into the world economy results in the full benefit of the productivity improvement flowing through to producers in the innovating region. Clearly the relative size of the region where technology is improving will play a key role in determining the importance of virtual technology trade.

Impacts on SSA and trade: Having established the impact of a shock to supplies in region RoW on world prices, we can work our way back to the regional outputs and demands:

(16) $q_O^{RoW} = -\varepsilon_S^{RoW}\gamma_O^{RoW}a^{RoW} + (\varepsilon_S^{RoW} + 1)a^{RoW} = [(1-\gamma_O^{RoW})\varepsilon_S^{RoW} + 1]a^{RoW}$, $q_O^{SSA} = -\varepsilon_S^{SSA}\gamma_O^{RoW}a^{RoW}$, $q_D^{RoW} = \varepsilon_D^{RoW}\gamma_O^{RoW}a^{RoW}$, and $q_D^{SSA} = \varepsilon_D^{SSA}\gamma_O^{SSA}a^{RoW}$

And hence the technology-driven change in trade:

(17) $t = 100 * dM / Q^{W} = \beta(\varepsilon_{D}^{SSA} \gamma_{O}^{RoW} a^{RoW}) - \alpha(-\varepsilon_{S}^{SSA} \gamma_{O}^{RoW} a^{RoW}) = [\beta \varepsilon_{D}^{SSA} + \alpha \varepsilon_{S}^{SSA}] \gamma_{O}^{RoW} a^{RoW}$

Which is equation (6) in the text.

Substituting in the expression for γ_{O}^{RoW} yields:

(18) $t = 100 * dM / Q^{W} = a^{RoW} (\varepsilon_{S}^{RoW} + 1)[\beta \varepsilon_{D}^{SSA} + \alpha \varepsilon_{S}^{SSA}] / (\{[\varepsilon_{D}^{W} + \alpha \varepsilon_{S}^{RoW}] / (1-\alpha)\} + \varepsilon_{S}^{RoW}) > 0$

So the virtual trade in technology is a rather complex function of the regional supply and demand elasticities as well as the shares of the two regions in current demand and supply. As the innovating region looms larger in global supply the excess demand elasticity facing that region: $\{[\varepsilon_{D}^{W} + \alpha \varepsilon_{S}^{R}] / (1-\alpha)\}$, shrinks and the ensuing price change increases. This has the effect of amplifying the demand increase and supply reduction in SSA, therefore increasing the percentage change in technology-driven trade. Conversely, as the technology-affected region shrinks in relative size: $\alpha \to 1$, $\gamma_{O} \to 0$ and the world price change flowing from the technological innovation becomes very small. In this case, the impact on technology-driven trade is small.

Adding conservation programs in the innovating region: We treat the conservation programs as a backward shift in the land supply function in equation (6) in Box A1: $\Delta_{L} > 0$, we can follow the same steps above and derive the new quantity supplied and price equilibrium conditions for the single region model as follows:

(19) $q_{O} = \varepsilon_{S} p_{O} + (\varepsilon_{S} + 1) a - \Delta_{L}$

(20) $p_{O} = [\Delta_{D} + \Delta_{L} - (\varepsilon_{S} + 1) a] / (\varepsilon_{S} + \varepsilon_{D})$

The conservation measure operates as a backward shift in the supply curve and, in terms of equilibrium price, it operates in the same way as a shift in commodity demand. In the case of a wealthy economy (e.g., the Northern Europe), with stable population growth and food-satiated consumers, demand growth may be minimal. In this case, prices can remain stable as long as the conservation measures do not overwhelm TFP growth, i.e., $\Delta_L \leq (\varepsilon_S + 1)ao$. In the context of the two region model, we have the following equilibrium condition for world price (**equation (8) in the main text**):

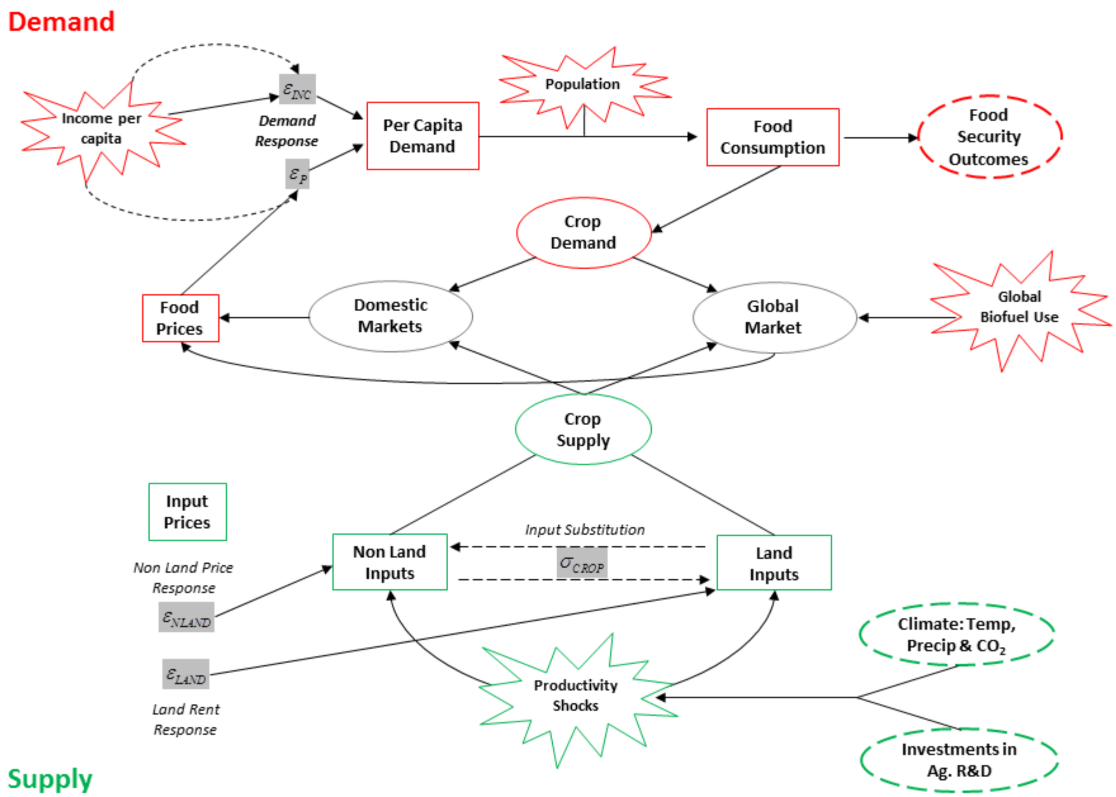
(21) $p_O = [(1-\alpha)\Delta_L^{RoW} - (1-\alpha)(\varepsilon_S^{RoW} + 1)a^{RoW}] / [\varepsilon_D^W + \varepsilon_S^W]$

B. Quantitative Trade Model

The Simplified International Model of Prices Land use and the Environment (SIMPLE) model is a multidimensional extension of the theoretical model in Box 1. Rather than two regions, there are an arbitrarily large number of geographic regions in SIMPLE (15 in the current implementation – see Figure S2). In addition, nonland factor supplies are not perfectly elastic, reflecting the fact that other factors of production (most notably labor) are inelastically supplied to agriculture in many parts of the world. Another key extension is the incorporation of the equation determining current TFP growth as a function of past investments in agricultural R&D (main text, equation (9)). Finally, in the segmented markets version of SIMPLE, there is imperfect price transmission from global markets into the domestic economy. While this quantitative trade model is expressed in linearized form, it is solved using nonlinear methods that capitalize on update formulae based on the underlying cost functions. Thus it can be thought of as a one-shot, comparative static model that takes the global economy from one equilibrium (e.g., 2006) to a future equilibrium (e.g., 2050). It is validated based on its ability to predict historical outcomes (e.g., 1961) for key variables, based on a backcasting exercise (see below).

In our quantitative trade model (Figure S1), per capita consumer demands are also disaggregated into three food types: crops, livestock and processed foods. These demands are log-linear functions of price and income, with respective food demand elasticities varying as a function of per capita income in each region. Based on international cross-section estimates by Muhammad *et al* (Muhammad et al. 2011), the absolute values of the income and price elasticities for all food types fall as incomes grow. Regional food demand is obtained by multiplying per capita demand by regional population. Since livestock and processed foods are valued-added products, these are produced within the consuming region using crop and non-crop inputs and therefore have region-specific prices. A substantial share of crop demands in the model is *derived demands*, obtained from the consumer demands for value-added food products. This is important, since technological change and factor substitution in the livestock and processed food industries can lead to varying intensities of crop use in these food products. The global demand for crops is the summation of final demands and derived demands summed over all regions. World demand for crop feed stocks in biofuels is exogenously specified and serves as an addition to global crop demand.

Figure A1. Diagram of the SIMPLE model: The bottom panel (green) refers to regional crop production for the aggregate crop commodity. The upper panel (red) refers to regional crop demand. The disposition of crops includes direct consumption, feedstuff use and food processing, as well as biofuels. Under market segmentation, consumers and producers interact in the domestic and international crop markets. Under integrated markets there is just a single global market and one price in all regions.



Notation: The following are key parameters for each region: ε_{INC} and ε_P are the price and income elasticities for each of the four consumption commodities. These vary with per capita income and therefore evolve over time. The elasticity of substitution between land and nonland inputs, σ_{CROP}, and determines the potential for endogenous intensification of production. The supply elasticities of land and nonland inputs to the crops sector, ε_{LAND}, (ν_L in the theoretical model), ε_{NLAND} and are also region-specific.

Global crop production in the model is specified for each of the 15 geographic regions as a CES function of land and non-land inputs, each with different yields and potentially differing rates of technological progress across regions. Cropland supply elasticities, which vary by region, are based on the adjusted estimates of Gurgel *et al* (Gurgel, Reilly, and Paltsev 2007) and Ahmed *et al* (Ahmed, Hertel, and Lubowski 2008). Non-land factor supplies to agriculture are also less than perfectly elastic supply, but are more price responsive than land supply, based on the estimates offered by OECD (OECD 2001). In the standard version of the SIMPLE model, equilibrium is attained in the crop markets when supply equals demand where the equilibrating variable is the global price of crops. In the segmented markets version of SIMPLE model there is a finite elasticity of substitution between crop commodities in the domestic and international markets and similarly a CET function determining supply to the global market.

We the compute the malnutrition headcount as our measure of food insecurity. The index measures the prevalence of undernourishment by reporting the fraction of population whose daily dietary energy intake is below the minimum requirement (FAO 2012). In the literature, it is common to focus on changes in malnutrition incidence (Alexandratos and Bruinsma 2012; Alexandratos 2010). Mathematically, the malnutrition index is equivalent to the poverty index measure proposed by Foster *et al.* (1984). Given this, we can use the concept of poverty-growth elasticity to link this measure to the average per capita dietary energy intake. Widely used in the poverty literature, the growth elasticity measures the percent changes in the indices of poverty given a one percent change in average per capita income (Bourguignon 2003; Lopez and Serven 2006). To apply this concept in the case of dietary energy, we assume that the distribution of per capita dietary energy consumption is lognormal. This is consistent with the traditional assumption used by FAO regarding the distribution of dietary energy intake within a country

(Neiken 2003). The following equation is used to calculate the growth elasticity for the malnutrition index (ε_{MI}).This characterizes the percent change in this indices in the wake of a one percent rise in average dietary energy consumption (DEC):

$$\varepsilon_{MI} = -\frac{1}{\sigma}\frac{\tau}{\pi}\left[\frac{\ln\left(w/y\right)}{\sigma} + \frac{\sigma}{2}\right] \tag{1}$$

In this equation, w is the minimum daily energy requirement (MDER), y is the average per capita DEC, and σ is the standard deviation of the DEC distribution. The operators: τ and π denote the standard normal probability density and cumulative distribution functions, respectively. To compute the updated malnutrition headcount, we simply multiply the malnutrition index by the population headcount. To implement the model, we rely on the food security data published by FAO (2012; 2010).

C. Additional Results:

Figure A2 reports the extent of global market penetration in regional crop consumption and production. These shares play a key role in the segmented markets model. A low rate international market participation will translate into limited international price transmission into the domestic market. This is clearly the case for the SSA region for which both demand and supply shares are quite low.

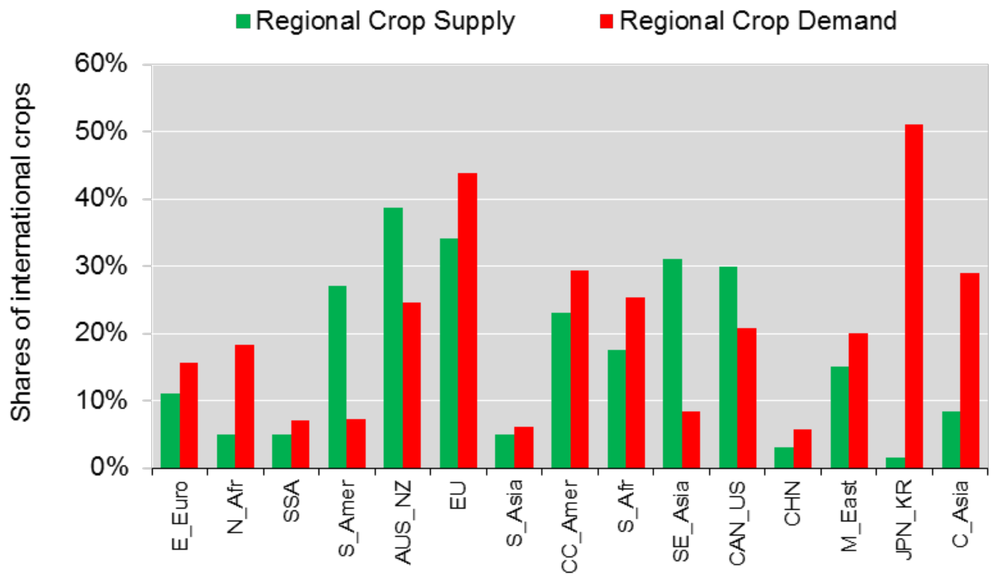


Figure A2. Shares of international goods in the regional demand for (red) and supply of (green) crops in 2006 (Source: FAO).

Table A1 reports the exogenous drivers used in our historical validation of the SIMPLE model for the 1961-2006 period. These include: population, income per capita, TFP for the crops, livestock and processed foods sectors, factor supply shifts for three regions: rural labor supply in Africa and irrigation supplies in South and Southeast Asia, all of which grew at extraordinary rates over this period due to exogenous factors (e.g., the green revolution in Asia).

Figure 6 in the main text compares the actual and model-predicted changes in global crop production and composite world price for crops over this historical period. Figure A3 below provides this same comparison for two other key observables: crop yields and cropland area. These figures demonstrate that SIMPLE does a good job capturing global changes in the agricultural sector over a 45 year period. However, capturing regional changes in such a simple model is more challenging. Figure A4 shows that crop growth in Latin America, in particular, was much more rapid than predicted by the model over this historical period. There are many potential reasons for this, including the opening up of vast areas of farmland in Brazil.

Table A1. Average Annual Growth Rates for Historical Validation: 1961-2006

Region	Population	Per Capita Incomes	Total Factor Productivity			Other Drivers
			Crops	Livestock	Processed Foods	
Eastern Europe	0.51	-1.20	0.40	0.66		
North Africa	4.86	1.80	3.13	0.18		
Sub Saharan Africa	5.39	-0.38	0.84	0.43		3.5
South America	3.34	1.90	2.53	0.96		
Australia+New Zealand	2.04	3.05	1.99	1.14		
European Union	0.47	4.41	2.28	1.14		
South Asia	3.71	4.03	1.51	0.59		3.3
Central America + Caribbean	3.94	2.50	1.20	0.96	1.09	
South Africa	4.07	0.39	1.90	0.43		
South East Asia	3.82	6.77	2.13	1.05		3.3
Canada+United States	1.31	3.68	2.52	1.14		
China	2.36	40.38	3.23	1.05		
Middle East	3.89	4.16	2.34	0.18		
Japan+Korea	1.05	7.89	3.47	1.14		
Central Asia	4.32	-1.51	0.40	0.66		

Sources: The following growth rates are calculated from these sources: Population and Per capita incomes from World Bank's World Development Indicators (2019); Total Factor Productivity Growth for Crops from Fuglie (2012), for Livestock from Ludena et al (2007) and for Processed Foods from Griffith et al (2004). Other shifters non-land input supplies in Sub-Saharan Africa based on Labor force growth rate and South & Southeast Asia to account for areas equipped for irrigation.

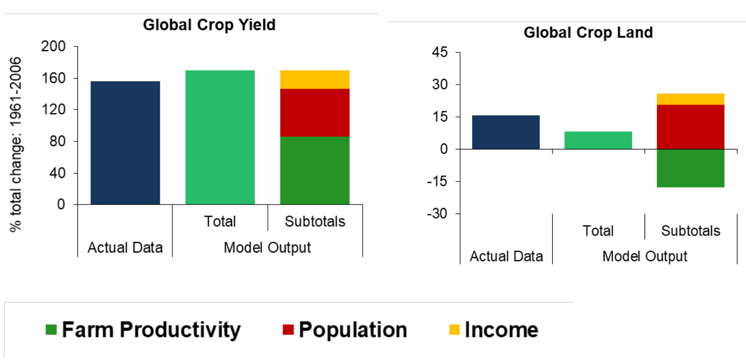


Figure A3. Historical validation and decomposition of key drivers of global crop production and prices. Historical data on crop yield and crop land from FAOSTAT (2019). (See also Figure 6 in the main text.)

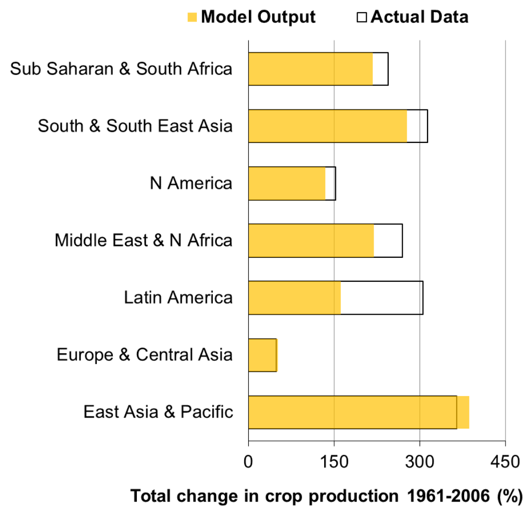


Figure A4. Historical validation of regional crop production over the period 1961-2006. Historical data on crop yield and crop land from FAOSTAT (2019). (See also Figure 6 in the main text.)

Table A2 reports the exogenous drivers of SIMPLE going forward to mid-century, along with their sources. Macro-economic trends are taken from the 'business as usual' Shared Socioeconomic Pathways scenario (SSP2). Productivity growth rates are based on expert projections from the literature (see legend for Table A2).

Table A2. Average Annual Growth Rates for Projections : 2006-2050

Region	Population	Income	Total Factor Productivity			
			Crops			
			Historical North	Enhanced Spillovers	Livestock	Proc Foods
Eastern Europe	-0.33	6.59	0.44	0.44	1.31	
North Africa	1.08	6.65	1.05	1.88	-0.28	
Sub Saharan Africa	3.60	10.93	0.45	1.00	0.47	
South America	0.79	4.43	3.32	5.36	4.89	
Australia+New Zealand	0.84	1.72	1.60	1.60	0.46	
European Union	0.00	1.68	1.97	1.97	0.46	
South Asia	1.01	17.67	2.08	3.50	2.52	
Central America + Caribbean	1.06	3.99	2.88	4.56	4.89	1.09
South Africa	0.39	6.64	0.67	1.32	0.47	
South East Asia	0.79	9.81	1.18	2.06	4.12	
Canada+United States	0.63	1.43	1.78	1.78	0.46	
China	-0.16	15.47	3.04	4.88	4.12	
Middle East	1.63	2.45	1.04	1.86	-0.28	
Japan+Korea	-0.37	2.58	1.87	1.87	0.46	
Central Asia	1.31	10.49	0.63	0.63	1.31	

Sources: The following growth rates are calculated from these sources: Population and per capita incomes from Shared Socioeconomic Pathway (SSP) Projections Database v0.5 (Kriegler et al. 2012, O'Neill et al. 2014) for population and per capita income growth rates; Total Factor Productivity Growth for Crops from authors' calculations, for Livestock from Ludena et al (2007) and for Processed Foods from Griffith et al (2004)