POLICY RESEARCH WORKING PAPER 8257

Economic Growth, Convergence, and World Food Demand and Supply

Emiko Fukase
Will Martin

Abstract

In projecting global food demand to 2050, much attention has been given to rising demand due to the projected population increase from the current 7.4 billion to more than 9 billion. An increasingly important source of the increase in food demand is per capita demand growth induced by rising income per person. Since the proportion of income spending on food decreases as incomes rise, growth in global food demand will be greater if incomes grow faster in developing countries than in high-income countries. Such a pattern of income convergence has become established in recent years, making it important to assess the implications for food demand and supply. Using a resource-based measure of food that accounts for the much higher production costs associated with dietary upgrading, this paper concludes that per capita demand growth is likely to be a more important driver of food demand than population growth between now and 2050. Using the middle-ground International Institute for Applied Systems Analysis Shared Socioeconomic Pathway projections to 2050, which assume continued income convergence, the paper finds that the increase in food demand (102 percent) would be roughly a third greater than without convergence (78 percent). Since the impact of convergence on the supply side is much more muted, convergence puts upward pressure on world food prices, partially offsetting a baseline trend toward falling world food prices to 2050.

Economic Growth, Convergence, and World Food Demand and Supply

Emiko Fukase[*] and Will Martin[**]

[*] World Bank. e-mails: emikof2@aol.com, efukase@worldbank.org.
[**] International Food Policy Research Institute. e-mail: w.martin@cgiar.org.

Economic Growth, Convergence, and World Food Demand and Supply

The projected increase in world population from 7.4 billion in 2017 to well over 9 billion in 2050 has received a great deal of attention as an influence on world demand for food (United Nations 2017). However, as the rate of growth in the world's population is slowing, the importance of growth in food consumption per person, induced by income growth, has become an increasingly important driver of food demand. Engel's law points to a declining share of food in total expenditures as incomes grow. Another important influence on food demand is Bennett's law, under which the proportion of the food budget spent on starchy-staple foods declines while spending on animal-based products increases as incomes grow in developing countries (Godfray 2011). This dietary change puts pressure on agricultural resources since animal-based food requires disproportionately more agricultural resources in production (Rask and Rask 2011).

This relationship between food demand and income, established by Engel's and Bennett's laws, implies that income distribution matters for aggregate food demand. Cirera and Masset (2010) show that, given the same level of aggregate income, an increase in income inequality is likely to reduce aggregate food demand, while a decrease in inequality may lead to an increase in aggregate food demand.[1] Cirera and Masset (2010) also point out that—since most global inequality is between rather than within countries—changes in between-country income inequality are likely to have greater impacts on world food demand than changes in within-country inequality. Thus, in projecting long-run food demand changes, the issue of income convergence—with income per person growing more quickly in low- and middle-income countries than in high-income countries—has potentially important impacts on overall demand for food. This question of convergence, and its consequences for the distribution of income, has received considerable attention from macroeconomists, but seems to have been overlooked by economists considering the demand for food.

Neoclassical growth theory predicts that the differences in per capita incomes across countries converge over time, because the high-income countries at the technological frontier can grow only by adopting new technologies, while poor countries can grow both by adopting new

---

[1] Cirera and Masset (2010) show that an income transfer from the rich to the poor, while preserving average income unchanged, will increase average food consumption, as the poor tend to spend more on food than the rich.

technologies and by catching up with the leading economies. However, the earlier literature found that economies did not converge unconditionally. While several studies found evidence of convergence among today's industrial countries (e.g., Baumol 1986; Dowrick and Nguyen 1989), there was little evidence of convergence in broader groups of countries (e.g., Ben-David 1993, 1994). In fact, Pritchett (1997) concluded that the dominant feature of economic growth since the 19th century had been 'income divergence, big time', with initially poorer countries growing much less rapidly than the more advanced countries.

More recently, however, there appears to have been a major improvement in the growth prospects of developing countries (Baldwin 2016; Dervis 2012; Korotayev, Zinkina, Bogevolnov and Malkov 2011). Dervis (2012) identified a 'new convergence' as having commenced around 1990, with more rapid growth in emerging and developing economies relative to advanced economies. Baldwin (2016) argues that a 'Great Convergence' is under way, with developed-country firms unbundling production stages and moving labor-intensive components of production to low-wage countries, allowing developing countries to industrialize without building entire supply chains from scratch. He also notes that many of the opportunities created by this convergence have been exploited by relatively-large developing countries. This is in sharp contrast with the experience of the 1970s, when the most rapid growth was in relatively small economies such as Hong Kong SAR, China; the Republic of Korea; Singapore; and Taiwan, China.

Whether economic convergence has major implications for world food demand is an important question if we are to fulfill the United Nations' Sustainable Development Goals (SDGs). Several of the 17 SDGs, including goals to end poverty and hunger, to promote inclusive economic growth and to reduce inequality within and between countries, pertain directly to the convergence and food demand question. For instance, if the world is successful in substantially raising the incomes of the poor during the time horizon of the SDGs (2015-2030) and beyond, what would be the impact on world food demand and supply? If populous middle-income countries continue to grow and upgrade their diets, will this put strong upward pressure on world food prices, potentially even threatening the access of some poor people to essential foods? This question was framed by Pan Yotopoulos (1985) in the aftermath of the food price crisis of the 1970s, but it is not clear that we are much better placed to answer it now than we were more than thirty years ago.

Substantial efforts have been made in the modeling community to forecast the global supply and demand for food to the middle of the century, typically using large global agricultural models.[2] However, the projections for food output and prices vary widely across the models, depending on their underlying supply and demand specifications, choices of key parameters such as price and income elasticities and their treatments of technical change. For instance, reviewing modeling approaches from twelve global agricultural economic models, Hertel *et al.* (2016) report that modelers' projections for increases in global crop output between 2005 and 2050 range from 52 percent to 116 percent, while estimated changes in crop prices vary from a decline of 16% to a rise of 46% (Table 2, p. 429).

Surveying the literature on the relationship between income distribution and food demand, Cirera and Masset (2010) conclude that most existing models for projecting food demand fail to incorporate sufficient Engel flexibility, except for some models with flexible demand systems such as an Implicitly Directly Additive Demand System (AIDADS) (Rimmer and Powell 1996). An important new paper by Gouel and Guimbard (2017), which uses the highly-flexible Modified Implicitly Directly Additive Demand System (MAIDADS), projects an increase of 95 percent in consumption of animal-based food, as against an 18 percent increase in demand for starchy staples, with the latter being largely driven by population growth towards 2050.

One way to disentangle the divergent results from modeling is to focus on a small number of key economic drivers that affect long-run crop output, price and land use changes. Pioneering work in this direction was undertaken by Hertel (2011) and Hertel and Baldos (2016) with the Simplified International Model of agricultural Prices, Land use and the Environment (SIMPLE) model. The model relies on price responsive demand and supply of agricultural goods with extensive (area expansion) and intensive (yield growth) margins. Using the SIMPLE model, Hertel and Baldos (2016) find that long-run crop prices will most likely resume their downward trend between 2006 and 2050 but that these results are subject to a wide range of uncertainty.[3]

---

[2] See Cirera and Masset (2010), Hertel, Baldos and van der Mensbrugghe (2016), Lampe *et al.* (2014), and Valin *et al.* (2014) for reviews.

[3] After specifying distributions for the underlying parameters and drivers of demand and supply, Hertel and Baldos (2016) undertake a Monte Carlo analysis and find a very broad range of potential outcomes for their global variables. They find that about 72 percent of the outcomes foreshadow a crop price decline while the remaining 28 percent correspond to price rises between 2006 and 2050 (Figure 11.7).

The objective of this paper is to explore the evolution of world food demand and supply to 2050, extending a simple econometric model developed by Fukase and Martin (2016). In Fukase and Martin (2016), this model allowed us to assess the prospects for net import demand for food in China. Here, we extend our approach to the global level and focus on the implications of income convergence on long-term food demand and supply. On the demand side, per capita consumption of the aggregate food is modeled as a function of real income only, with a functional form developed to allow for consumption that asymptotically approaches a ceiling level (Rask and Rask 2004, 2011). On the supply side, we specify a production equation as a function of real income and agricultural land endowment per capita. This enables us to estimate a simple relationship between the productivity-driven growth of income per capita, declining per capita availability of agricultural land, and the growth of food output for each country.

Following Yotopoulos (1985) and Rask and Rask (2004, 2011), we convert all food items into a resource-based measure of food, a cereal equivalent (CE). The key advantages of the CE demand model (Fukase and Martin 2016; Rask and Rask 2011) are its parsimony and transparency. It accounts for the greater agricultural resource requirements associated with dietary upgrading, in particular, the resources required to produce animal-based products (e.g., cropland to produce feedstuff and pastures to graze animals). In our analysis, we consider only non-price influences on supply and demand, evaluating both consumption and production in cereal equivalent *quantities*. We then use a gap approach, i.e., examining the implications of different income growth scenarios for gaps in supply and demand for food and the resulting pressures on food prices.

Following this introduction, the second section examines the relationship between income growth, population growth and demand for food. The third section quantifies the extent of income convergence and its impact on food demand. The fourth section presents the relationship between economic growth, land availability and the supply of food. The fifth section projects supply and demand of food towards 2050 and considers the implications of income convergence for the supply-demand balance and for food prices. The final section presents a brief conclusion.

Modeling Food Demand

Because we focus on the impacts of economic growth and convergence, we first examine the pattern of economic growth since 1992. Figure 1 shows the evolution of annual per capita GDP

growth rates in 2005 constant prices by 'high-income' and 'developing' countries[4] between 1980 and 2013 (World Bank 2015). The figure shows that the high-income countries as a group grew faster than developing countries in the 1980s, at 2.4 percent and 1.8 percent per year respectively. By contrast, average growth for developing countries in the 1990s, at 3.0 percent, exceeded that for high-income countries at 1.7 percent. In the first decade of the new millennium, the growth rate for developing countries was 3.8 percent, well ahead of the 1.2 percent growth rate in high-income countries. Higher economic growth in developing countries has potentially important implications on food demand, given the declining share of income spent on food as incomes rise.

To evaluate how food consumption patterns evolve with income growth, we consider two measures of food consumption, namely, cereal equivalents (CE) (Yotopoulos 1985; Rask and Rask 2004, 2011) and calorie measures. Cereal equivalent measures convert foods into cereal equivalents in terms of their dietary energy equivalents. The approach accounts for a central feature of food demand under income growth—the shift from reliance on direct consumption of grains and other starchy staples into more diversified diets including edible oils and protein-rich animal products. This dietary upgrading imposes greater burdens on agricultural resources since production of more diversified, and particularly animal-based, diets requires much more agricultural output than plant-based diets (Fukase and Martin 2016; Rask and Rask 2011).

Figure 2a shows the estimated global CE consumption curve along with the actual changes in CE consumption between the beginning of the period (1992) and the end (2009), for the World Bank's regions. The CE consumption-income relationship is specified using the coefficient estimates in Fukase and Martin (Table 2, 2016), which extends the food demand analysis developed by Rask and Rask (2011) to 1980-2009.[5]

---

[4] Under the World Bank country classification, all countries above a certain threshold Gross National Income (GNI) are classified as 'high' income countries (https://datahelpdesk.worldbank.org/knowledgebase/articles/906519). Only 'developing' countries are included in the 'regions', namely East Asia and the Pacific (EAP), Europe and Central Asia (ECA), South Asia (SA), Latin America and the Caribbean (LAC), Middle East and North Africa (MENA) and Sub-Saharan Africa (SSA). We classify countries into high and developing countries based on their 1992 income levels. This is because defining country groups at the end introduces systematic bias into growth rate comparisons by consistently subtracting better performers from the lower income group and adding better performers to the higher income group.

[5] In Fukase and Martin (2016), this equation was also re-estimated adding the wedges between domestic and international prices created by Consumer Transfer Equivalents (Anderson and Nelgen 2013). While this variable was statistically significant, its inclusion did not change the coefficients for the income variable, and substantially reduced the size of the estimating sample. Thus, we focus on the specification without the price distortion variable.

$$y = 2.2 - 1.7 \cdot exp\,(-5.8*10^{-5} \cdot x) \qquad\qquad\qquad\qquad\qquad (1)$$

$$[0.16]\ \ [0.15]\quad [1.1*10^{-5}]\ ^6$$

where y is CE consumption per capita and x is Purchasing Power Parity (PPP) Gross Domestic Product (GDP) per capita in 2005 constant prices. The estimated CE curve shows a concave relationship between CE food consumption and real income levels: with demand rising much more rapidly at low income levels when consumers are likely to spend a large proportion of increases in their incomes on food; CE consumption continues to increase as incomes grow, albeit at a slower rate, as consumers substitute foods with relatively high income elasticities (such as animal products) for cereals and tubers; and finally, CE consumption growth tapers off at higher levels of income (Rask and Rask 2011).

For most regions, the levels of per capita CE consumption and their growth between 1992 and 2009 are consistent with the estimated curve in the relevant income ranges. Two exceptions were the ECA region and the high-income regions. In the ECA region, consumption of livestock products fell drastically following the move away from central planning, as the high cost of these products became evident (Rask and Rask 2004). In high-income regions, there has been a shift away from the most resource-intensive meats, such as beef, and towards more efficiently-produced products such as poultry. In contrast, all non-ECA developing regions increased their consumption as their incomes grew. China's high economic growth saw a rapid increase in CE food consumption, with its per capita CE consumption increasing by about 70 percent over the period. China's ongoing dietary shift, which reflects increasingly affluent life-styles induced by high income growth, appears to have been a major driver behind this change (Fukase and Martin 2016).[7] Figure 2a reveals much lower levels of income and CE consumption for the South Asia (SA) and Sub-Saharan Africa (SSA) regions than others. Despite the recent relatively high economic growth of the SA region, it continues to be the one in which food consumption in cereal equivalents is lowest, perhaps partly reflecting habit formation patterns of the type analyzed by Atkin (2013) and/or cultural factors (Alexandratos and Bruinsma 2012).

---

[6] Standard errors are in brackets.

[7] For instance, the rise in China's imports of oilseeds (mainly soybeans), which was a major cause of China's agricultural trade deficit since the late 2000s, can be explained by the expansion of its modern livestock sector—which increased demand for protein feeds—along with rising consumer demand for vegetable oils (Fukase and Martin 2016).

Turning to calorie-based measures, Figure 2b shows the changes in food consumption between 1992 and 2009 by region with the global calorie consumption trend curve. The regional changes in calorie consumption are broadly in line with the global calorie trend line, revealing a concave relationship between income and food consumption albeit at a much lower level relative to the CE measure. Figure 2c shows the projected growth of demand for cereal equivalents and for calories on a comparable scale (Fukase and Martin 2016). The figure shows that consumption of calories levels off much earlier and at a much lower level than consumption of cereal equivalents. This is because the latter measure reflects the increasing agricultural resource requirement resulting from dietary shifts which continue after calorie consumption stabilizes.

Past and Future Growth in Global Food Demand

In Table 1, we decompose total growth in global food demand into parts due to population growth and to per capita consumption growth. The first three columns of Table 1 report the evolution of CE food demand for our 134 sample countries, which account for 95 percent of 2009 population.[8] CE food demand grew at 2.3 percent in the 1980s, 2.1 percent in the 1990s and 1.9 percent in the first decade of the new millennium.

Table 1. Changes in CE food demand 1980-2050

	Evolution of CE Food Demand 1980-2009					
	CE Food Demand			Annual Average CE Food Growth		
	Change (mil. Tons)	Initial year (mil. Tons)	Last year (mil. Tons)	Total (%)	Per capita (%)	Population (%)
1980-1991	864	2999	3863	2.30	0.55	1.75
1992-2000	817	4590	5407	2.05	0.69	1.36
2001-2009	878	5455	6333	1.87	0.72	1.15
	Projected Changes in CE Food Demand 2009-2050					
	CE Food Demand			Annual Average CE Food Growth		
	Change (mil. Tons)	Initial year (mil. Tons)	Final year (mil. Tons)	Total (%)	Per capita (%)	Population (%)
2009-2050	7049	6899	13948	1.72	1.03	0.68

Source: Authors' calculations.
Note: Annual % changes are based on log-differences.

---

[8] The figures for the 1980s are not strictly comparable, since we have data only for 115 countries, with most former Soviet bloc countries not reporting.

The next three columns in Table 1 decompose the change in CE food demand annual growth rate into per capita consumption growth and population growth. Table 1 reveals that the annual average growth in per capita food demand has become increasingly important, rising from 0.55 percent per year in the 1980s to 0.69 percent per year in the 1990s and 0.72 percent in the 2000s respectively while annual average population growth has decreased, from 1.75 percent in the 1980s to 1.36 percent in the 1990s, and 1.15 percent in the 2000s.

To explore how CE consumption might evolve to 2050, we use projections for population and GDP (in PPP 2005 constant prices) from the Shared Socioeconomic Pathways (SSP) database developed by the International Institute for Applied Systems Analysis (IIASA).[9] To provide a benchmark, we focus on the so-called 'middle ground' scenario (SSP2) for both GDP and population projection data. Over the period 2009-2050, the SSP2 projection suggests annual world per capita GDP growth of 2.4 percent and world population growth of 0.68 percent per year. This implies annual global GDP growth of 3.1 percent.

Figure 3a shows the growth of the global population in percent log-difference form. This illustrates clearly the rapid decline that has occurred, and is projected, in world population growth rates. However, measures of aggregate population growth mask differing regional population growth rates. Figure 3b shows the projected evolution of population between 1992 and 2050 by region. The proportion of the population living in the two poorest regions, namely the SA and SSA regions combined, is projected to increase from 36 percent in 2009 to 45 percent by 2050. China's population, which accounted for about one-fifth of the world population in 2009, is projected to peak around 2030. Figure 3c reveals that nearly three-quarters of the increase in the global population is expected to be in SSA (44 percent) and SA (29 percent).

An important feature of equation (1) is its implied pattern of income elasticities for total food demand. While income elasticities of demand for individual food items generally decline as income rises (Timmer, Falcon and Pearson 1983), the shift in demand from starchy staples to livestock products may cause the income elasticity of total food demand measured in resource requirements to rise over some range. As shown by Gouel and Guimbard (2017), the elasticity of demand for starchy staples is generally low, even for low-income consumers, while the elasticity

---

[9] https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=about

of demand for livestock products is around 0.5, or higher, for low- to middle-income households. The income elasticities used by Baldos and Hertel (2012, p 12) show a similar pattern, with the income elasticities of demand for livestock products generally two or more times as high as for crops in low- and middle-income countries. These elasticities are consistent with increasing income elasticities of demand for total food as the animal-product share of consumption rises over this range.

Considerable care is needed in interpreting estimates of the growth of total food demand. If the focus is on the consumer, as in Gouel and Guimbard (2017), where food is measured in calorie equivalents of food consumed, the weight on livestock products is likely to be much smaller than—as in this paper—when the focus is on the resource cost of food consumed and livestock products receive a much larger weight.

Figure 4 plots the income elasticity of food demand implied by equation (1) with respect to PPP GDP per capita for our 134 sample countries. It presents the arc elasticity defined as the change in the log of CE consumption divided by the change in the log of GDP between 2009 and 2050. Specifically,

$$\varepsilon = \frac{Ln(\widehat{Cons}_{2050}) - Ln(\widehat{Cons}_{2009})}{Ln(GDP_{2050}) - Ln(GDP_{2009})}$$

where $Ln(\widehat{Cons}_{2050})$ and $(\widehat{Cons}_{2009})$ are the logs of predicted per capita CE consumption computed using equation (1) for 2050 and 2009, while $Ln(GDP_{2050})$ and $Ln(GDP_{2009})$ are the logs of per capita GDP for the same years taken from the SSP database.

A striking feature of this graph is the inverted-U shape of the aggregate income elasticity of demand for total food as income rises. At very low levels of income, where the dominant feature of dietary transformation is shifts from coarse grains and root crops to fine grains such as rice or wheat (Timmer *et al.* 1983, p29), we estimate this income elasticity to be relatively low at around 0.2; it rises as income increases to middle-income levels; and peaks at around 0.42 at a PPP GDP of around $10,000; and then decreases as per capita income continues to grow. Evaluated at projected income levels in 2030, income elasticities in populous countries, such as India and Indonesia, are around their peak levels. While the elasticity is beginning to fall in key middle-income countries such as China and Turkey by 2030, this decline is relatively gradual, and income elasticities remain far above their levels in high-income countries. The elasticities for many SSA

countries would still be on the rise in 2030. At higher income levels, the shift into livestock products is complete and the tendency for all income elasticities of demand for food to decline identified by Timmer *et al.* (1983, p57) results in elasticities of 0.1 or lower in high-income countries such as the United States.

This relationship between income elasticities and income levels suggests that income growth in middle-income countries—where food demand has begun its shift towards the animal products that are much more demanding in terms of resource requirements—may be particularly important for food demand growth measured in resource requirements rather than calories.

The last row of Table 1 reports the estimated CE consumption changes between 2009 and 2050. Using the middle-ground GDP and population projections from the IIASA SSP, per capita CE consumption in 2050 was computed using 2050 GDP projections at the country level, multiplied by 2050 population projections and added up to the global level to compute global food demand in 2050. Global CE food consumption is projected to grow at an average rate of 1.72 percent per year between 2009 and 2050, more than doubling food demand (up 102 percent) by 2050. Our estimate is much larger than the 70 percent increase in food demand projected by FAO (2009) and 69 percent projected by Pardey *et al.* (2014). But it is in line with Tilman *et al.* (2011) who projected a food demand increase of 100 to 110 percent between 2005 and 2050, considering the caloric and protein content of crops used for human foods and livestock/fish feeds.

Decomposing the projected food demand growth rate, we see an increase in the growth rate of per capita consumption—to 1.03 percent per year—and a sharp decline in the population growth rate, to 0.68 percent per year on average. Overall, Table 1 reveals an increasingly important role of per capita income growth relative to population growth in contributing to global food demand growth. Between 2009 and 2050, about 60 percent of projected food demand growth comes from per capita demand growth, as against 24 percent in the 1980s, 34 percent in the 1990s and 39 percent in the early 2000s. Baldos and Hertel (2016, p31), using an indicator of food market pressure that includes developments on both the demand and supply sides, also find an increase in the importance of income relative to population growth, concluding that income growth will, for the first time in history, rival population growth as a source of demand for food.

Appendix Table A1 reports the twenty countries which contributed the most to the actual CE food demand increases for each of the past three decades, along with the projected top twenty

between 2009 and 2050. Throughout the period, large developing countries such as China, India and Brazil have played an important role in the global increase in food demand. In particular, China accounted for 35 percent, 53 percent and 31 percent of global CE food demand increases in the 1980s, 1990s and 2000s while its share is estimated to decrease to around 17 percent between 2009 and 2050. By contrast, large developing countries such as India[10] and Nigeria may increase the shares of their contribution to food demand toward the middle of the century. While several high-income countries were among the list in the 1980s, namely the United States, Japan, Spain, Italy and France, only the United States is projected to remain in the 2009-2050 list, primarily because of population growth. The number of countries from SA and SSA which made the list doubled from four (India, Pakistan, Bangladesh, Nigeria) in the 1980s to eight in the 2009-2050 list, adding Ethiopia, Tanzania, Sudan and Uganda.

Quantifying Convergence and Its Impact on Food Demand

As noted in the introduction, neoclassical growth theory predicts that the differences in per capita incomes across countries would tend to diminish over time. Baumol (1986) pointed out that higher economic growth rates should be expected in lower-income countries because technological advances flow from leaders to followers, allowing the countries that start with lower incomes to grow more rapidly than the leading countries. In economic terms, countries inside the production possibility frontier can improve their technology both by adopting new technologies and moving towards the best-practice frontier, while leading economies can only do so by developing new technologies.

Baldwin (2016) argues that the revolution in information and communication technology, starting around 1990, triggered the beginning of a New Globalization and associated Great Convergence. Rapidly falling communication and organization costs encouraged firms in developed nations to move labor-intensive stages of production to low-wage nations. The fragmentation of production and outsourcing created new opportunities for developing countries to industrialize by joining global value chains. Many developing countries, including China and

---

[10] Some caution is needed in assessing the role of India in increasing food demand since India has not experienced as much food consumption increase as its high economic growth predicts. See Annex 2.1 in Alexandratos and Bruinsma (2012) for discussion.

India, have grown much more rapidly in the past few decades relative to their own past, and to the developed countries. Accelerated growth in developing countries has resulted in a dramatic fall in the global GDP share of the Group of Seven (G7) countries, from almost two-thirds in 1990 to less than half today (Figure 23, Baldwin 2016). Partly benefiting from a boom in commodity exports known as the 'commodity super-cycle', which was fueled by emerging economies' demands (Baldwin 2016), SSA economies finally started to grow in the late 1990s and many of them have now reached Middle Income Country status as defined by the World Bank (Devarajan and Fengler 2013).

To investigate whether developing countries have been experiencing higher per capita economic growth relative to higher income countries, we regress per capita annual GDP growth rates (Δlny_i) for country i on country i's initial log GDP (lny_i) relative to the country at the technological frontier (lny_{US}) which is assumed to be the United States (lny_i - lny_{US}).

$$\Delta lny_i = \alpha + \beta \, (lny_i - lny_{US}) \tag{2}$$

Table 2. Estimated rates of unconditional convergence, %

	1980-1991	1992-2000	2001-2009	2009-2050 (proj.[a])
ß	0.28	0.25	-0.43**	-0.85***
	(1.19)	(1.34)	(-2.33)	(-17.20)
No. of Obs.	115	134	134	134

Source: Authors' calculations. The United States is used as the frontier economy.
Notes: *t-statistics* are in parentheses.
[a] GDP Projection data for the year 2050 are for SSP2 (Leimbach *et al.* 2017).

The results in Table 2 show that the coefficients on the convergence terms for the final two decades of the last millennium are positive—implying unconditional divergence, rather than convergence—but not statistically significant. In contrast, the convergence term for 2001-2009 is negative and significant at the 2 percent level, suggesting countries' incomes started to converge in the first decade of the new millennium. The estimated rate of convergence of -0.43 percentage points in this period is, however, still only a quarter of the estimate of -1.57 percentage points for unconditional convergence among OECD members estimated by Dowrick and Nguyen (equation 1, 1989, p1018). The last column of Table 2 reveals that the SSP2 GDP projections for the middle of the century embody an assumption of much more rapid convergence (-0.85 percentage points) than in the 2001-2009 period.

To estimate the extent to which the income convergence embodied in SSP2 would affect growth in food demand, we perform a counterfactual simulation of uniform per capita growth in all countries at the rate that would result in world income being the same in 2050 as under SSP2. World GDP, per capita GDP and population are specified as growing at 3.1 percent, 2.4 percent and 0.68 percent per year respectively in both scenarios. Figure 5 compares the food demand increases normalizing food demand in 2009 at 100 to facilitate the comparison. The results are decomposed by region with the ten countries that contribute most to the difference broken out individually.

The result reveals a striking difference in food demand changes coming from the different income growth patterns, as the resulting difference in income distribution in 2050 would lead to a larger CE food demand increase with the convergent SSP2 scenario (102 percent) relative to the non-convergent uniform scenario (78 percent). The accompanying table shows that developing countries as a group dominate the increase in food demand. Out of a 102 percent food demand increase, 95 percent is attributable to developing countries in the SSP2 scenario, while 70 percent of the 78 percent increase in food demand under the uniform growth scenario comes from them. India, followed by China, Indonesia and Nigeria, are the largest contributors to the difference in the two scenarios, suggesting that whether these populous middle-income countries converge matters greatly for global food demand. As shown in Figure 4, the large impact of income convergence for middle-income countries is partly attributable to their relatively high-income elasticities of food demand due to greater agricultural resource use needed for dietary upgrading.

Figure 5 shows that high-income countries as a group would contribute modestly to global food demand increases (6.9 percent in SSP2 and 7.9 percent in the uniform scenario) partly due to slower population growth. While the counterfactual uniform scenario involves shifting world income from developing to high-income countries in 2050, the resulting increase in food demand in high-income countries is small (1.0 percentage point) due to the low income elasticities in these economies. Consistent with Cirera and Masset (2010), our results show that a decrease in between-country income inequality resulting from convergence increases aggregate food demand, given the same level of aggregate income.

Convergence and Correlations in Forecasting Food Demand Growth

The analysis in the previous section is undertaken in levels, which avoids any approximation errors, but does not allow us to understand why the results are so different between the uniform and convergent scenarios or to decompose them between the effect of per capita food demand growth and that of population growth. To understand the sources of the much higher growth in food demand under the convergent SSP2 scenario, we turn to a share-weighted log-difference approach.

We define per capita food demand growth under the SSP2 scenario, q^{sp} as:

$$q^{sp} = \sum S_i . \beta_i . y_i \tag{3}$$

where S_i is the share of country i in global food demand, β_i is the income elasticity for country i, and y_i is the rate of per capita economic growth in country i.

If the β and y variables are independent,

$$\sum S_i . \beta_i . y_i = \beta . y \tag{4}$$

where $\beta = \sum S_i . \beta_i$ and $y = \sum S_i . y_i$

If β and y are not independent, then we can use a second-order Taylor Series approximation around $\beta . y$ to obtain:

$$q^{sp} = \beta . y + \sum S_i (\beta_i - \beta)(y_i - y) \tag{5}$$

This equation makes clear that correlations between growth rates and income elasticities could affect food demand growth.

Another potentially important difference between the convergent growth scenario and the uniform growth scenario arises from the different weights involved in aggregating income and food demand. When we calculate the growth of global income, we are implicitly weighting by GDP shares, rather than by the food shares S_i. In the uniform growth scenario, the uniform growth rate is $y^u = \sum W_i . y_i$ where W_i is the GDP weight of country i. The estimated food demand using this approach is therefore $q^u = \beta [\sum W_i . y_i]$.

Adding and subtracting food demand growth under the uniform growth scenario, q^u, and recalling that $\beta . y = \beta [\sum S_i . y_i]$, we obtain:

$$q^{sp} \approx q^u + \beta [\sum (S_i - W_i) . y_i] + \sum S_i (\beta_i - \beta)(y_i - y) \tag{6}$$

This shows that the difference in food demand growth between the SSP2 and the uniform growth scenarios can be decomposed into (i) the sum of the cross-products between growth rates and differentials between countries' income shares and food consumption shares $\beta[\sum (S_i - W_i).y_i]$, and (ii) the covariance between the income elasticities and the growth rates $\sum S_i(\beta_i - \beta)(y_i - y)$.

When income growth is convergent, term (i) is likely to be positive. This is because low-income countries tend to have higher shares of food demand in global food demand, relative to their income shares in global GDP, i. e., $S_i - W_i > 0$ and vice versa for high-income countries ($S_i - W_i < 0$). Thus, faster income growth in low-income countries relative to their high-income counterparts would contribute positively to this term.

With income convergence, component (ii) resulting from the correlation between income growth and income elasticities ($\sum S_i(\beta_i - \beta)(y_i - y)$) is also positive, because the income elasticities of demand in developing countries tend to be above average, ($\beta_i - \beta > 0$) and their income growth is also higher under convergence ($y_i - y > 0$). High-income countries also tend to contribute positively to the term, since their elasticities of demand and growth rates tend to be below average, $\beta_i - \beta < 0$ and $y_i - y < 0$ respectively. However, the inverted-U shaped pattern of income elasticities shown in Figure 4 reduces this component, because some of the lowest-income economies have lower elasticities than the average.

Introducing global population growth into equation (6) yields:

$$q^t = q^{sp} + n \tag{7}$$

where q^t is global growth in food demand and n is the food-share-weighted population growth rate.

The decomposition of food demand growth between 2009 and 2050 is summarized in Table 3. Total global food demand growth between 2009 and 2050 turns out to be 70 percent in log-difference terms under the SSP2 scenario and 58 percent under the uniform growth scenario. These results are consistent with the 102 percent increase in food demand in the SSP2 scenario in the previous section ($e^{0.70} - 1 \approx 1.02$) and 78 percent increase in the uniform scenario ($e^{0.58} - 1 \approx 0.78$). While food-weighted population is found to grow by 23 percent in log-difference terms for both scenarios, food-weighted per capita demand growth under SSP2 of 48 percent in log-difference terms is found to be much greater than that of 36 percent in log-difference terms under

the uniform growth scenario. The difference can be partly explained by the component coming from the correlation between income growth rates and the share differentials (7 percent in log-difference terms) and partly by the component resulting from the relationship between income growth and income elasticities (4.4 percent in log-difference terms).

The food-share-weighted decomposition of per capita demand growth and population growth in this section differs from that shown in Table 1. The latter decomposition was population-share-weighted for comparability with the existing literature, while the population growth rates in Table 3 are food-demand-share weighted to attribute correctly the impact of population growth on food demand. Dividing the 23 percent population impact in log-difference terms in Table 3 by the 41 years of the projection period reveals a lower estimate (0.56 percent per year) of the impact of population growth than in Table 1 (0.68 percent per year).

Table 3. Decomposition of Food Demand Growth 2009-2050:
SSP2 vs. Uniform Growth Scenarios

	SSP2 Scenario (%)	Uniform Scenario (%)
Food-weighted Per Capita Demand Growth	**48**	**36**
Of which $\beta[\sum (S_i - W_i).y_i]$	7.0	
Of which $\sum S_i(\beta_i - \beta)(y_i - y)$	4.4	
Food-weighted population growth	**23**	**23**
Total Global Food Demand Growth	**70**	**58**

Source: Authors' simulation results based on a sample of 134 countries.
Note: Percentage changes are based on log-differences.

Modeling Food Supply

While our primary focus in this paper is on economic convergence and food demand, an obvious question is how the increase in demand for food associated with convergence might be met, and what the implications for food prices might be. In this section, we develop a parsimonious representation of supply based on per capita GDP, land availability and labor supply. This model captures three important stylized facts—that agricultural output rises with a country's land endowment; that higher economy-wide productivity increases output; and that agricultural output increases by less than total output as the economy grows (Martin and Warr 1993).

How rising food demand is met will be heavily influenced by the availability of agricultural land and other natural resources. Between 1992 and 2012, the world's arable land (arable land and

land under permanent crops) increased slightly, from 1,523 million hectares to 1,562 million hectares (FAOSTAT). While arable land use declined in the high-income group and the ECA region, arable land use increased in SSA, LAC and EA (other than China) regions. Between 1992 and 2012, the EA, LAC and SSA regions added 25 million hectares, 38 million hectares and 57 million hectares of arable land respectively.[11] During the same period, however, arable land per capita declined in all regions due to a combination of population growth and higher productivity of the land in use.

Figure 6 shows the evolution of arable land, which declined from an average of 0.28 hectares per person globally in 1992/1993 to 0.22 hectares in 2011/2012. The last two columns of the table show the average per capita arable land endowment during the period 1992-2012 and the percentage decline to 2011/12. In the ECA region and the high-income countries as a group arable land per person declined by 15 percent and 21.5 percent between 1992 and 2012 respectively. The LAC and SSA regions have been relatively land-abundant with 0.32 ha and 0.30 ha of arable land endowment on average. However, with high population growth, the land endowment per capita in the SSA region declined by 20.2 percent over the same period. In the MENA and SA regions, with relatively high population growth, arable land per capita fell by 31.6 percent and 29.0 percent respectively. China was relatively land-scarce throughout the period with 0.1 ha of per capita arable land endowment on average, which declined by 19.2 percent during the same period.

While arable land per capita has declined, the world has been successful in producing more food per person on average, primarily because of agricultural productivity growth. However, some observers are concerned by a decline in yield growth in recent years. Figure 7 plots the evolution of cereal yield per hectare[12] by region. The figure reveals that cereal yields increased by about one-third between 1992/1993 and 2012/2013 on average, but that yield levels and growth rates vary widely across regions. The high-income countries as a group had high productivity throughout the period. Land productivity in China has reached the average level of the high-income country

---

[11] The expansion of arable land for the LAC and EA regions appears to have been motivated in large measure by opportunities for exports, for instance, of soybeans from South America and of oil palm from Southeast Asia. In contrast, land expansion in the SSA region has been driven largely by growing needs for food and employment (Alexandratos and Bruinsma 2012).

[12] Fukase and Martin (2014) show a generally positive relationship between income and land productivity and between income and labor productivity (Figure 7ab). Fuglie (2012) reports that agricultural production growth of 'developed' countries is primarily attributable to total factor productivity (TFP) growth while their agricultural input growth has been negative since the 1980s.

group, perhaps reflecting a high degree of fertilizer use, expansion of irrigated land, widespread use of multiple-cropping and the introduction of new seed varieties and other technological improvements. By contrast, cereal yields in the SSA region remain about one-fifth of those in high-income countries throughout the period. Overall, closing the 'yield gap' on currently cultivated areas appears to be one way of increasing global agricultural output in a sustainable manner (Foley *et al.* 2011). Some economists argue that the fragmentation and offshoring of production associated with the New Globalization (Baldwin 2016) may offer new opportunities for poor farmers to be integrated into the global production network.[13]

Fukase and Martin (2016) estimated the following simple food production model in cereal equivalents as a function of income and land endowment per capita using a large data set for 1980-2009:

$$z = 0.23 + 0.0039 \ x^{0.62} \cdot l^{0.32} \qquad\qquad (8)$$
$$[0.11] \quad [0.0043] \ [0.10] \ [0.037]^{14}$$

where z is CE production per capita, *x* is PPP GDP per capita in 2005 constant prices, *l* is hectares of agricultural land per capita.[15] The exponent on the income per capita term is positive as higher agricultural productivity, associated with the higher economy-wide productivity that increases income levels, raises agricultural production. The positive relationship between income and agricultural production is likely to reflect not only higher yields per hectare but also better infrastructure and marketing know-how associated with higher income. The exponent on the agricultural land is positive as land-abundant countries tend to produce and export land-intensive commodities such as agricultural products.

Using the parameter values from Equation (8), Figure 8 shows the estimated CE production curves evaluated at different land endowments of selected countries, namely, the United States (land abundant), Japan (land scarce) and China (relatively land scarce) together with the global CE consumption curve (adopted from Figure 10abc, Fukase and Martin 2014). The figure suggests

---

[13] For instance, by joining supermarket value chains, small farmers in Madagascar benefited from spillovers from the productivity of technology for rice (Minten, Randrianarison and Swinnen 2009).

[14] Standard errors are in brackets.

[15] Following Rask and Rask (2011), hectares of agricultural land per capita are defined as a sum of arable land, land in permanent crops, and one-third of land in permanent pasture.

that agricultural production per capita rises with income; that the shape of the production curve is concave, but the curvature is much flatter than that of the consumption curve, revealing close to a linear relationship between income and production; and that countries with higher land endowments tend to produce more food given the same level of income. The figure also suggests that land abundant countries such as the United States tend to produce more food than they consume and to be exporters of food at almost all income levels. In contrast, land-scarce countries such as Japan are likely to consume more food than they produce, being food importers throughout their income levels. For relatively land scarce countries such as China, the concavity of the consumption curve implies that their consumption growth may be faster than production growth for a wide range of income, which in turn may contribute to rising net imports.

Some scholars view the role of agricultural trade as a way of shifting agricultural resources such as land and water from resource-abundant to resource-scarce areas (e.g., Chapagain, Hoekstra and Savenije 2006; Fader, Gerten, Krause, Lucht and Cramer 2013; Qiang, Cheng, Kastner and Xie 2013 for China; and Wichelns 2001 for the Arab Republic of Egypt). For instance, calculating the 'virtual' land use (i.e., resource flows hidden in traded products) embodied in China's agricultural trade, Qiang *et al.* (2013) find that China's massive imports of land-intensive soybeans from land-abundant countries such as the United States and Brazil made China's domestic cropland areas available for staple foods. Headey (2016) reports that the global agricultural land distribution has shifted towards land-abundant developing countries between 1961 and 2012 (Figures 1-2) and suggests that there may be a continued shift in agricultural production towards land-abundant countries with a comparative advantage in land-intensive goods.

Projections to 2050

Using the intermediate PPP GDP[16] and population projections for 2030 and 2050 from the SSP database (SSP2) (Leimbach *et al*. 2017), we perform simulation exercises to estimate how CE consumption and production might evolve in the future. We use projections of arable land kindly provided by Jelle Bruinisma, which reflect the detailed estimates underlying Alexandratos and

---

[16] One caveat in our analyses is that we rely our GDP projections on the SSP database and do not consider the potential growth slowdown identified by recent research (e.g., Laborde and Martin 2016; World Bank October 2016 for SSA).

Bruinsma (2012). While there are significant variations in the accuracy of regional projections,[17] models of this type tend to perform better at the aggregate level (Hertel *et al*. 2016; McCalla and Revoredo 2001; and Schneider *et al.* 2011). We therefore focus on aggregate measures in this section. The CE food consumption and production in 2030 and 2050 are estimated using the projection data and the parameter values in equations (1) and (8) at the country level, multiplied by projected population to compute the national consumption and production, and added up to the global level.[18] Figure 9a shows the results of estimated CE production and CE consumption for the years 2009, 2030 and 2050 (our base scenario). Table 4 focuses on results for 2050 alone to save space.

Table 4. Supply and demand gap 2050

	Base		Pure Convergence		Strong Convergence		Sensitivity without China & India	
	SSP2	Uniform (3.1%)	Pure Convergence	Uniform (2.7%)	Dowrick & Nguyen	Uniform (3.8%)	SSP2 w/o China/ India	Uniform (2.5%)
	Figure 9a	Figure 9b	Figure 9c	Figure 9d	Figure 9e	Figure 9f	Figure 9g	Figure 9h
CE Consumption 2050 (mil. tons)	12858	11301	12035	10669	14886	12233	8234	7273
CE Production 2050 (mil. tons)	13497	12981	12287	11768	15970	15011	8500	8076
CE Consumption Change (%)	102	78	89	68	134	92	88	66
CE Production Change (%)	112	104	93	85	151	136	94	85
Supply & Demand Gap (in log-dif.)	4.8	13.9	2.1	9.8	7.0	20.5	3.2	10.5
Price Change (in log-dif.)	-4.1	-12.0	-1.8	-8.4	-6.0	-17.6	-2.7	-9.0
Net price change (in log-dif.)	7.9		6.6		11.6		6.3	

Source: Authors' simulation results.

The results for the SSP2 scenario show that CE production would increase by 112 percent while CE consumption would increase by 102 percent over the period 2009 to 2050. The gap of around 4.8 percent in log-difference terms between our supply and demand projections would imply modest downward pressure on prices. If we accept the estimates of the three relevant

---

[17] See Appendix Figures A1-A3 for a validation exercise to examine how the model could replicate the past by region.

[18] Since there is an overestimate of CE consumption and an underestimate of CE production in the initial year, we remove these residuals by adjusting them multiplicatively so that initial CE consumption and production match the actual 2009 CE consumption and production. We apply the same multiplicative terms for the years 2030 and 2050 so that this adjustment preserves the percentage changes. There exists a slight gap between actual CE consumption and production in 2009 (about 0.9 percent) due to the missing countries in our sample. We adjust initial supply and demand at the mid-point of the actual supply and demand gap.

elasticities of response[19] from Hertel *et al.* (2016), this gap would translate into a price decline of around 4.1 percent.

To measure the extent to which the convergent assumption embodied in the SSP2 scenario is affecting food demand, Figure 9b and the second column of Table 4 report the results of the counterfactual uniform growth scenario, taking global income to the same level in 2050 as the SSP2 scenario. This implies annual global GDP growth of 3.1 percent in both scenarios. The move to a uniform growth scenario causes a much larger decline in food demand growth (from 102 percent to 78 percent) than that in food supply (from 112 to 104 percent). The resulting gap between supply and demand of 13.9 percent in log-difference terms would lead to a price decline of 12.0 percent. Comparing the results between SSP2 and uniform growth scenarios, the net effect on prices of moving from the uniform scenario to the SSP2 scenario is to increase prices by 7.9 percentage points. The growth convergence inherent in the SSP2 scenario is therefore partly offsetting what would otherwise have been substantial downward pressure on world food prices.

The differential GDP growth rates embodied in SSP2 scenario may reflect features of the data set other than convergence. If, for instance, it reflected a bias towards more rapid growth in the middle-income countries with the highest income elasticities, it would generate more rapid growth in global demand than one with the highest growth rate among the countries with the lowest incomes. To focus more directly on the convergence issue, we construct an alternative scenario in which country growth rates relative to the United States are determined solely by the convergence rate estimated for the SSP2 projection ('Pure convergence' scenario). Specifically, each country's annual growth rate is computed as 1.2 - 0.85 $[lny_i - lny_{US}]$ where lny_i is the initial log GDP for country *i, lny_{US}* is the initial log GDP of the United States and 1.2 is the projected growth rate for the United States in SSP2. Since this scenario would lead to a lower world GDP growth of 2.7 percent, in parallel to the base comparison, we construct a uniform scenario in which the world economies grow at the uniform rate of 2.7 percent. The results are shown in Figures 9cd and in Columns 3-4 in Table 4. Similar to the SSP2 scenario, the impact of convergence is larger on the

---

[19] The demand and supply elasticities implied in the global agricultural models tend to vary substantially (Table 3, Hertel *et al.* 2016). The emulator elasticities are: for food demand (-0.29), for the response of output due to substitution between land and other inputs (0.51), and for land supply (0.36). Together they imply a flexibility of price response to a proportional gap between supply and demand in the order of 0.86 $[\frac{1}{1.16} \approx 0.86]$. Thus, the gap of around 4.8 percent in log-difference terms between our supply and demand projections implies a price decline of about 4.1 percent.

demand side relative to the supply side, albeit to a lesser degree. The net effect of the convergence is to increase prices by 6.6 percentage points, or slightly less than the SSP2 scenario.

We also consider higher rates of convergence, such as might occur with higher rates of economic integration between rich and poor countries (Chapter 10, Baldwin 2016). Figures 9ef and Columns 5-6 of Table 4 explore what would happen if growth rates were to converge as rapidly as among the OECD countries between 1950 and 1985 (Dowrick and Nguyen 1989) ('Strong convergence' scenario). This scenario would result in an average annual world GDP growth rate of 3.8 percent. The increase in food demand of 134 percent under the strong convergence scenario is substantially larger than that under the comparable uniform growth scenario (92 percent). A much greater impact of convergence in demand than in supply would result in the net impact on prices of 11.6 percentage points, which is nearly 50 percent higher relative to the SSP2 scenario.

A question arises whether our results might be driven mainly by the outperformance of two populous Asian giants, namely China and India. We repeat a simulation assuming the economies converge at the same rate as that embodied in SSP2, but excluding China and India from our sample (Figures 9gh and the last two columns of Table 4). The qualitative results are essentially unchanged and our results appear to be robust regardless of the inclusion of China and India.

Overall, we find a robust pattern that the impact of income convergence on world food demand is substantially larger than the impact on supply. As a result, income convergence is likely to contribute to upward pressure on food prices. However, in all our scenarios, the pressure on food demand caused by convergence appears to be manageable, partially offsetting a baseline trend towards falling world food prices to 2050.

Conclusions

Using a simple econometric model focusing on the key drivers (income growth, population growth, dietary change, productivity growth and land endowment), this paper explores world food demand and supply towards the middle of the century. We focus on analyzing the implications of income convergence in influencing global food demand. We aggregate food into a single commodity measured by resource-based cereal equivalents (CE) (Rask and Rask 2011; Yotopoulos 1985), which allow us to evaluate the differential growth rates of consumption and production of food at different levels of income. Because of the much higher costs of producing livestock products, this

resource-cost-based measure of food demand is much more responsive to income growth than alternative measures based on final calories consumed.

Using the GDP and population projections from the SSP2 data set, we find that CE food demand would roughly double, increasing by 102 percent between 2009 and 2050. The decomposition of demand growth into per capita demand growth and population growth reveals that per capita growth plays an increasingly important role in raising food demand. This trend contrasts with the historical pattern in which population growth dominated consumption per capita growth in influencing food demand growth. It makes the relative importance of phenomena such as income convergence or divergence much greater than would have been the case in earlier decades.

The implications of income convergence for food demand seems timely, given the apparent reversal of fortunes in moving from the Great Divergence (Pritchett 1997) to the Great Convergence which started around 1990 (Baldwin 2016). We find that the coefficient for unconditional income convergence in our sample countries was not significant in the 1980s or 1990s, but became significant in the first decade of the 2000s, when developing countries grew, on average, much more rapidly than the developed countries. We also find that the rate of income convergence using the middle-ground GDP projections from the SSP database (SSP2) between 2009 and 2050 is about twice as rapid as the last decade, although still about half the rate estimated by Dowrick and Nguyen (1989) for the OECD countries in their post-war golden age of 1950-1985.

A series of simulation results reveal that the impact of convergence on food demand increase can be substantial. The rise in demand of our base scenario (102 percent), which embodies the assumption of income convergence from SSP2, is about one-third greater than that under the counterfactual non-convergent growth scenario (78 percent). The regional decomposition shows that developing countries as a group dominate the increase in food demand and that their income convergence does matter. We find that convergence by middle-income countries, especially such populous countries as India, China, Indonesia and Nigeria, is particularly important for global food demand. This is partly due to the inverted-U shaped pattern of income elasticities for aggregate food demand, with middle-income countries experiencing the largest income elasticities due to their dietary upgrading towards more resource demanding products.

24

On the supply side, our base projection suggests that food production would increase by 112 percent, slightly faster than the CE consumption increase of 102 percent. The impact of convergence on the supply side is much more muted than on the demand side, suggesting that convergence—if it continues to occur— will contribute to upward pressure on world food prices. Using the key elasticity values from Hertel *et al*. (2016), we see the pattern of deviations from uniform growth in the SSP2 scenario pushing up food prices by nearly 8 percentage points. Such increases are relative to a baseline which, like Baldos and Hertel (2016), involves falling real food prices, so meeting this demand appears to be manageable if agricultural productivity growth continues in line with historical patterns.

Finally, while our minimalist approach turns out to be useful in highlighting the interplay of key drivers of food demand, supply and prices, our model is subject to a number of limitations. In particular, our price baseline is based on an assumption that agricultural productivity will continue to rise steadily in line with past growth. Negative productivity shocks coming from, for instance, climate change, reductions in agricultural research investment and environmental degradation, would negatively affect food production capacities. On the other hand, good policies and actions at different levels, perhaps those envisioned in the SDGs such as responsible consumption and production, climate action and sustainable management of land and water, may counter-balance likely negative impacts on production.

References

Alexandratos, N., & Bruinsma, J. (2012). *World agriculture towards 2030/2050: the 2012 revision*. ESA Working Paper, 12-03.

Anderson, K., & Nelgen, S. (2013). Updated national and global estimates of distortions to agricultural incentives, 1955 to 2011. Washington DC: World Bank.

Atkin, D. (2013). Trade, tastes and nutrition in India. *American Economic Review*, *103*(5), 1629-63.

Baldos, U., & Hertel, T. (2012). SIMPLE: a Simplified International Model of agricultural Prices, land use and the environment. GTAP Working Paper, 70, Purdue University.

Baldwin, R. (2016). *The Great Convergence*. Cambridge: Harvard University Press.

Baumol, W. (1986). Productivity growth, convergence, and welfare: What the long-run data show. *American Economic Review, 76*, 1072- 85.

Ben-David, D. (1994). Convergence clubs and diverging economies. CEPR Working paper, 922, London.

Ben-David, D. (1993). Income disparity among countries and the effects of freer trade. In L. L. Pastinetti & R. M. Solow (Eds.), *Economic Growth and the Structure of Long Term Development*. London: Palgrave Macmillan, 45-64.

Chapagain, A. K., Hoekstra, A. Y., & Savenije, H. H. G. (2006). Water saving through international trade of agricultural products. *Hydrology and Earth System Sciences Discussions*, *10*(3), 455-468.

Cirera, X., & Masset, E. (2010), Income distribution trends and future food demand. *Philosophical Transactions of the Royal Society, B* 365, 2821-34. doi:10.1098/rstb.2010.0164.

Dervis, K. (2012). World economy, convergence, interdependence, and divergence. *Money*, *15*. http://www.imf.org/external/pubs/ft/fandd/2012/09/dervis.htm

Devarajan, S., & Fengler, W. (2013). Africa's economic boom: Why the pessimists and the optimists are both right. *Foreign Affairs*, *92*(3), 68-81.

Dowrick, S., & Nguyen, D. T. (1989). OECD comparative economic growth 1950-85: Catch-up and convergence. *American Economic Review, 79*(5), 1010-30.

Fader, M., Gerten, D., Krause, M., Lucht, W., & Cramer, W. (2013). Spatial decoupling of agricultural production and consumption: Quantifying dependences of countries on food imports due to domestic land and water constraints. *Environmental Research Letters*, *8*(1), 014046.

FAO. (2009). *How to Feed the World 2050*. Rome: Food and Agriculture Organization of the United Nations.

Foley, J. A. *et al.* (2011). Solutions for a cultivated planet. *Nature*, *478*(7369), 337-342.

Fuglie, K. (2012). Productivity growth and technology capital in the global agricultural economy. In K. Fuglie, V. E. Ball, & S. L. Wang (Eds.), *Productivity Growth in Agriculture: an International Perspective*. CABI. 355-368.

Fukase, E., & Martin, W. (2016). Who will feed China in the 21st century? Income growth and food demand and supply in China. *Journal of Agricultural Economics*, *67*(1), 3-23.

Fukase, E., & Martin, W. (2014). Who will feed China in the 21st century? Income growth and food demand and supply in China. Policy Research Working Paper, 6926. Washington DC: World Bank.

Godfray, H. C. (2011). Food for thought. *Proceedings of the National Academy of Sciences, 108*(50), 19845-6.

Godfray, H. C. *et al*. (2010). Food security: the challenge of feeding 9 billion people. *Science*, *327*(5967), 812-818.

Gouel, C., & Guimbard, H. (2017). Nutrition transition and the structure of global food demand. IFPRI Discussion Paper, 1631. Washington DC: International Food Policy Research Institute.

Headey, D. D. (2016). The evolution of global farming land: Facts and interpretations. *Agricultural Economics*, *47*(S1), 185-196.

Hertel, T. (2011). The global supply and demand for agricultural land in 2050: a perfect storm in the making? *American Journal of Agricultural Economics, 93*(2), 259–275.

Hertel, T., & Baldos, U. (2016). *Global Change and the Challenges of Sustainably Feeding a Growing Planet*. Springer.

Hertel, T., Baldos, U., & van der Mensbrugghe, D. (2016). Predicting long-term food demand, cropland use and prices. *Annual Review of Resource Economics, 8*(1), 417-441.

Korotayev, A., Zinkina, J., Bogevolnov, J., & Malkov, A. (2011). Global unconditional convergence among larger economies after 1998? *Journal of Globalization Studies*, *2*(2), 246-280.

Laborde D., & Martin, W. (2016). Implications of slowing growth in emerging market economies for hunger and poverty in rural areas of developing countries. IFPRI Discussion Paper, 01554. Washington DC: International Food Policy Research Institute.

Lampe, M. *et al.* (2014). Why do global long-term scenarios for agriculture differ? An overview of the AgMIP global economic model intercomparison. *Agricultural Economics*, *45*(1), 3-20.

Leimbach, M., Kriegler, E., Roming, N., & Schwanitz, J. (2017). Future growth patterns of world regions–a GDP scenario approach. *Global Environmental Change, 42*, 215-225. DOI:10.1016/j.gloenvcha.2015.02.005.

Martin, W., & Warr, P. G. (1993). Explaining the relative decline of agriculture: a supply-side analysis for Indonesia. *The World Bank Economic Review*, *7*(3), 381-401.

McCalla, A. F., & Revoredo, C. L. (2001). Prospects for global food security: a critical appraisal of past projections and predictions. Food, Agriculture and the Environment Discussion Paper, 35. Washington DC: International Food Policy Research Institute.

Minten, B., Randrianarison, L., & Swinnen, J. F. (2009). Global retail chains and poor farmers: Evidence from Madagascar. *World Development*, *37*(11), 1728-1741.

Pardey, P., Beddow, J., Hurley, T., Beatty, T., & Eidman, V. (2014). A bounds analysis of world food futures: Global agriculture through to 2050. *Australian Journal of Agricultural and Resource Economics*, *58*(4), 571- 589.

Pritchett, L. (1997). Divergence, big time. *Journal of Economic Perspectives, 11*(3), 3-17.

Qiang, W., Liu, A., Cheng, S., Kastner, T., & Xie, G. (2013). Agricultural trade and virtual land use: the case of China's crop trade. *Land Use Policy*, *33*, 141-150.

Rask, K., & Rask, N. (2011). Economic development and food production–consumption balance: a growing global challenge. *Food Policy, 36*(2), 186-96.

Rask, K., & Rask, N. (2004). Reaching turning points in economic transition: Adjustments to distortions in resource-based consumption of food. *Comparative Economic Studies, 46*(4), 542-69.

Rimmer, M., & Powell, A. (1996). An implicitly additive demand system. *Applied Economics, 28*, 1613-22.

Schneider *et al.* (2011). Impacts of population growth, economic development, and technical change on global food production and consumption. *Agricultural Systems*, *104*(2), 204-15.

Tilman, D., Balzer, C., Hill, J., & Befort, B. L. (2011). Global food demand and the sustainable intensification of agriculture. *Proceedings of the National Academy of Sciences*, *108*(50), 20260-4.

Timmer, C. P., Falcon, W., & Pearson, S. (1983). *Food Policy Analysis*. Baltimore: Johns Hopkins University Press.

United Nations. (2017). *World Population Prospects: The 2017 Revision*. New York: United Nations.

Valin, H. *et al.* (2014). The future of food demand: Understanding differences in global economic models. *Agricultural Economics*, *45*(1), 51-67.

Wichelns, D. (2001). The role of 'virtual water' in efforts to achieve food security and other national goals, with an example from Egypt. *Agricultural Water Management*, *49*(2), 131-151.

World Bank. (October 2016). *Africa's Pulse, No. 14*. Washington DC: World Bank.

World Bank. World Development Indicators (WDI). (Accessed December, 2015). Washington DC: World Bank.

Yotopoulos, P. (1985). Middle-income classes and food crises: the "new" food-feed competition. *Economic Development and Cultural Change*, *33*(3), 463-483.

Figure 1. Annual per capita GDP growth rates 1980-2013: 'High' income versus 'Developing' countries (%)
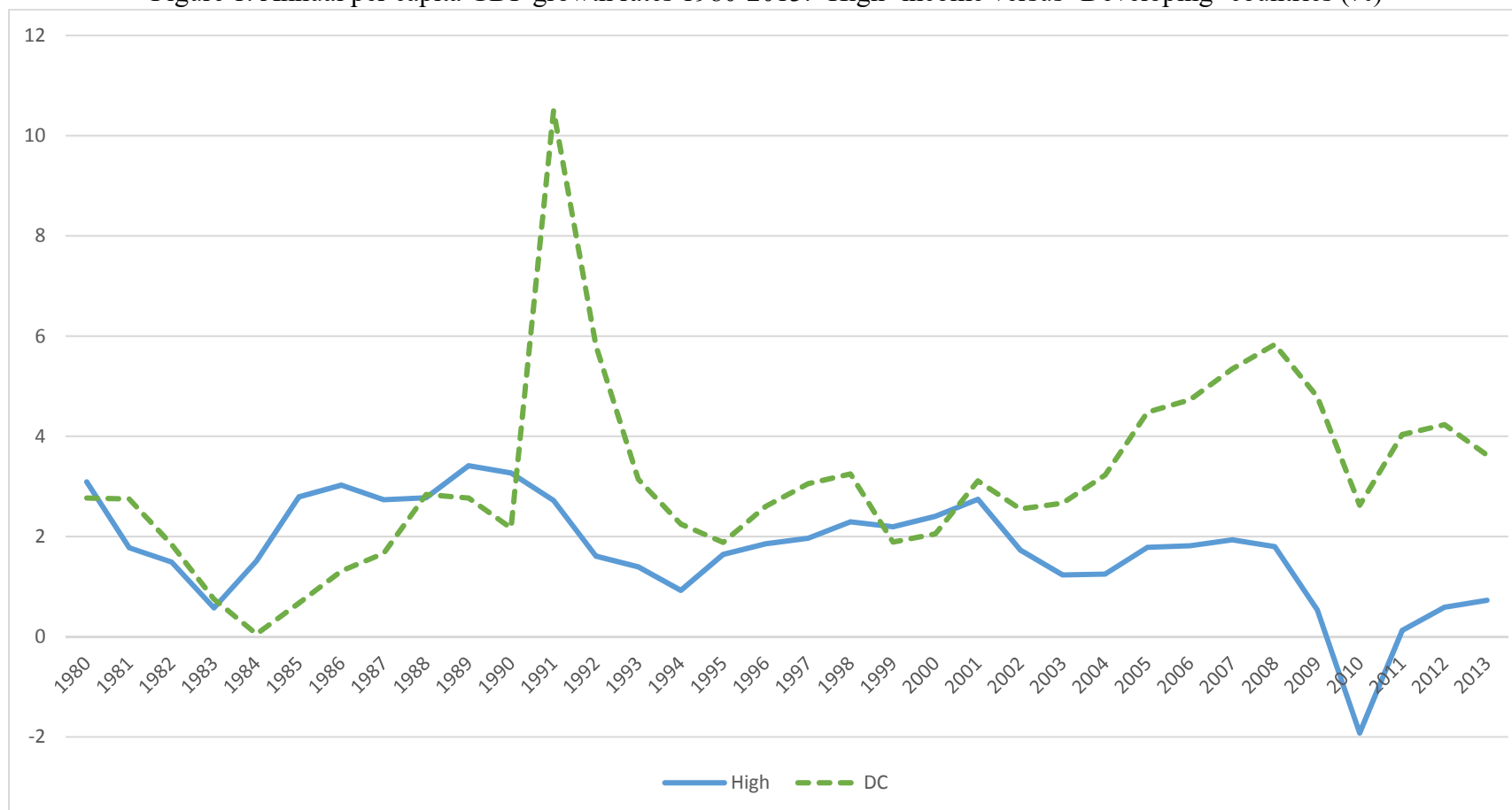
Source: The World Bank (2015)

Notes: The country classification is based on the status in 1992 (https://datahelpdesk.worldbank.org/knowledgebase/articles/906519).

The former Soviet Union and the other countries which belonged to the Council for Mutual Economic Assistance (COMECON) trading system are not included in the 1980s due to the unavailability of data.

Figure 2a. Changes in CE food consumption 1992-2009
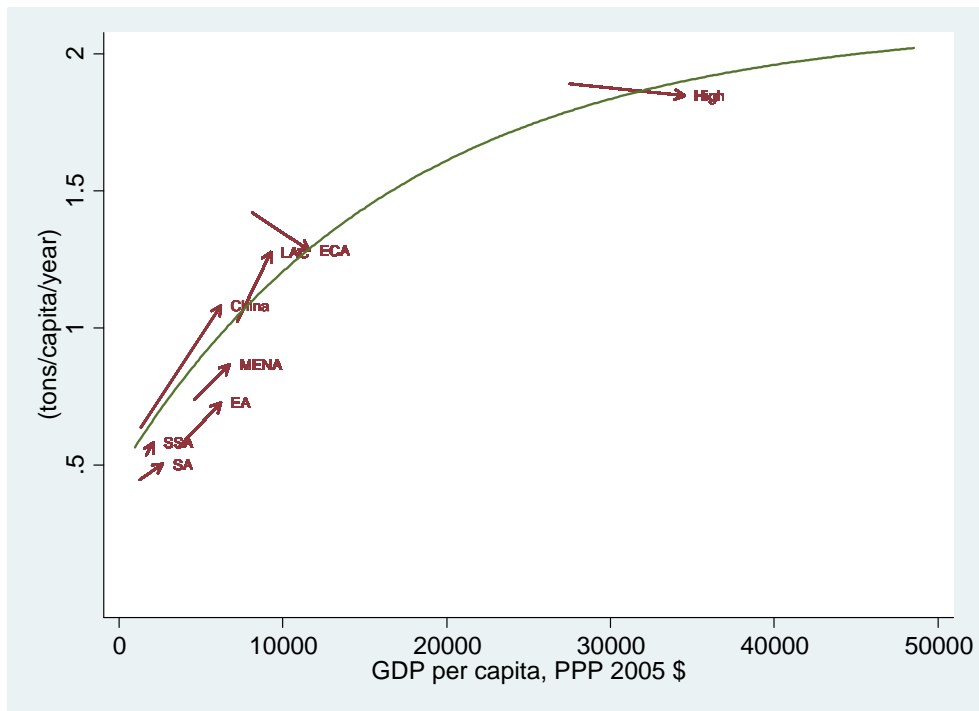
Sources: FAOSTAT and the World Development Indicators.

Figure 2b. Changes in calorie consumption 1992-2009
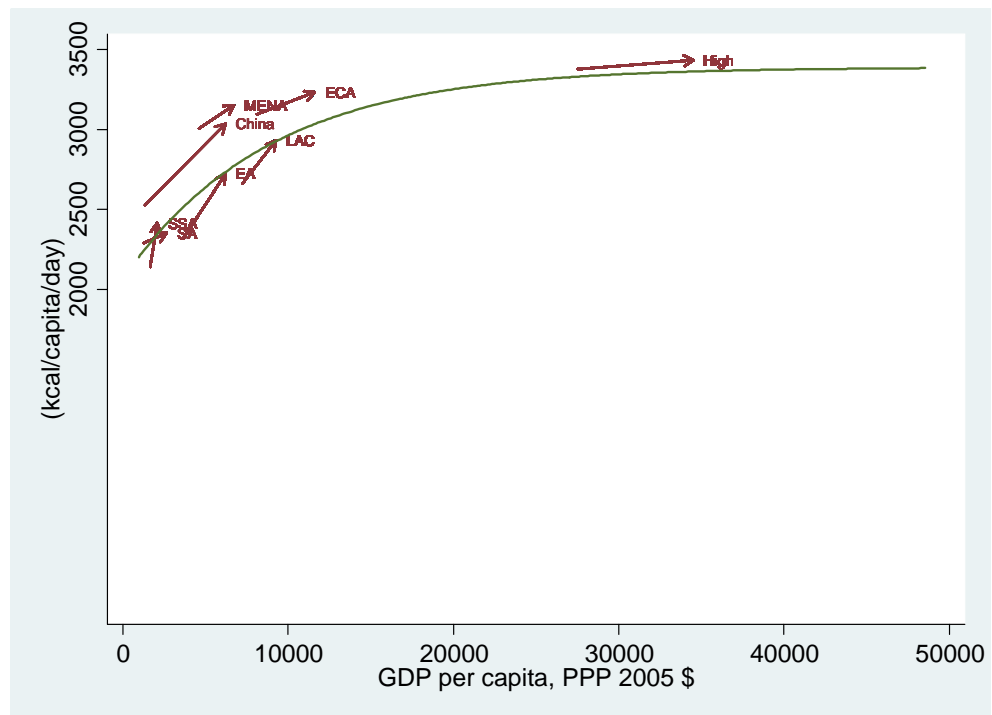
Sources: FAOSTAT and the World Development Indicators.

Figure 2c. Calorie vs. CE consumption 1992-2009
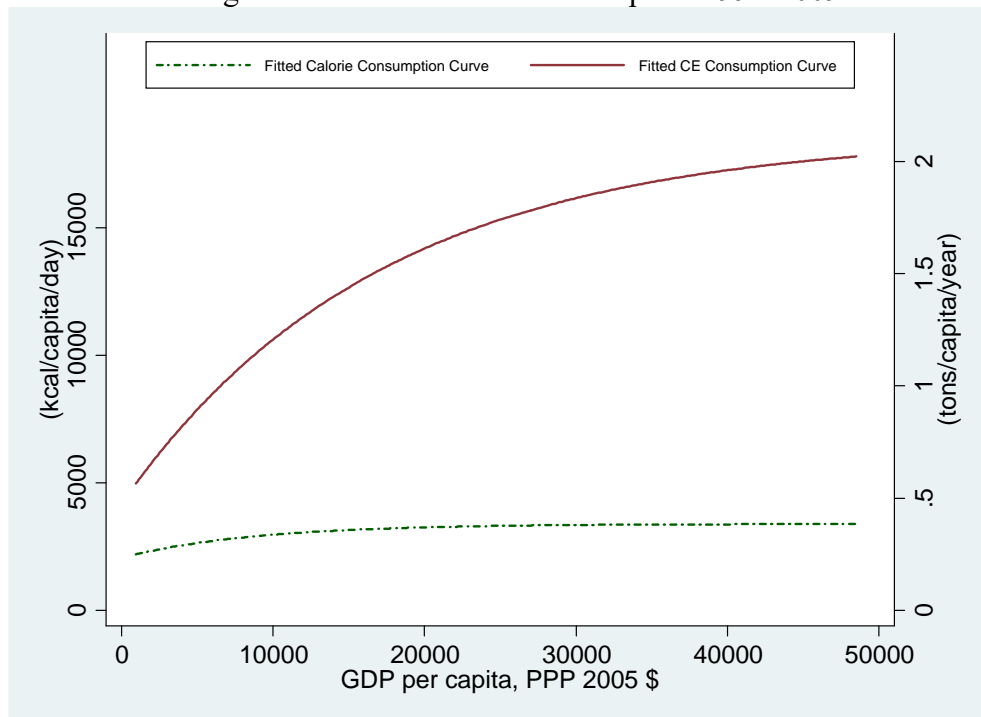
Note: Adopted following Fukase and Martin (2016).

Figure 3a. The annual growth rate of the global population (%)
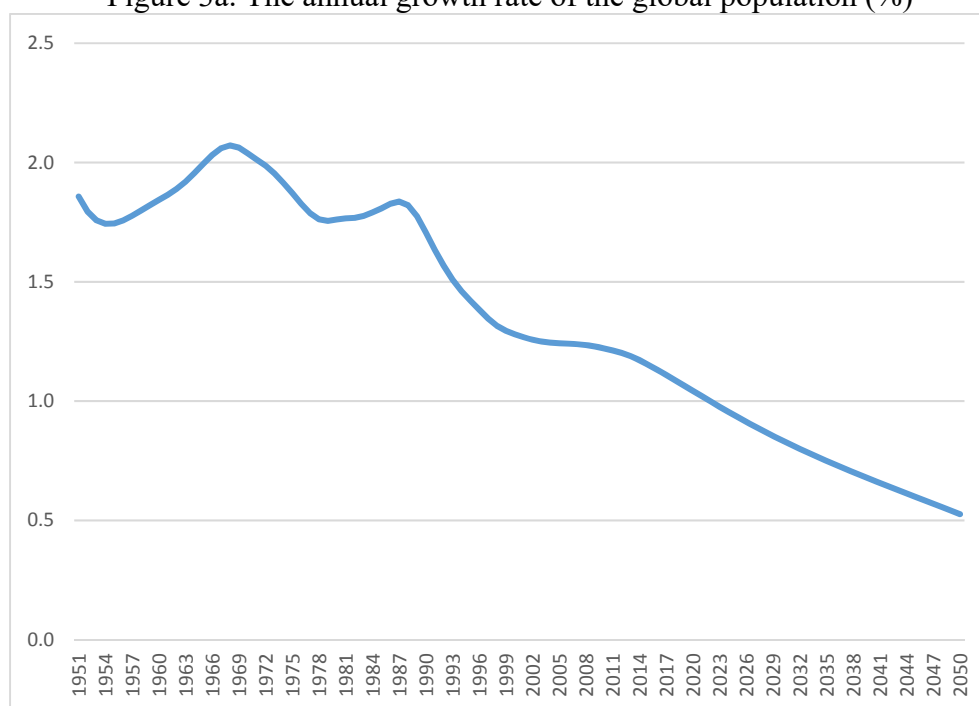
Notes: Medium Variant. Annual % changes are based on log-differences.

Figure 3b. Population by region 1992-2050 (million)
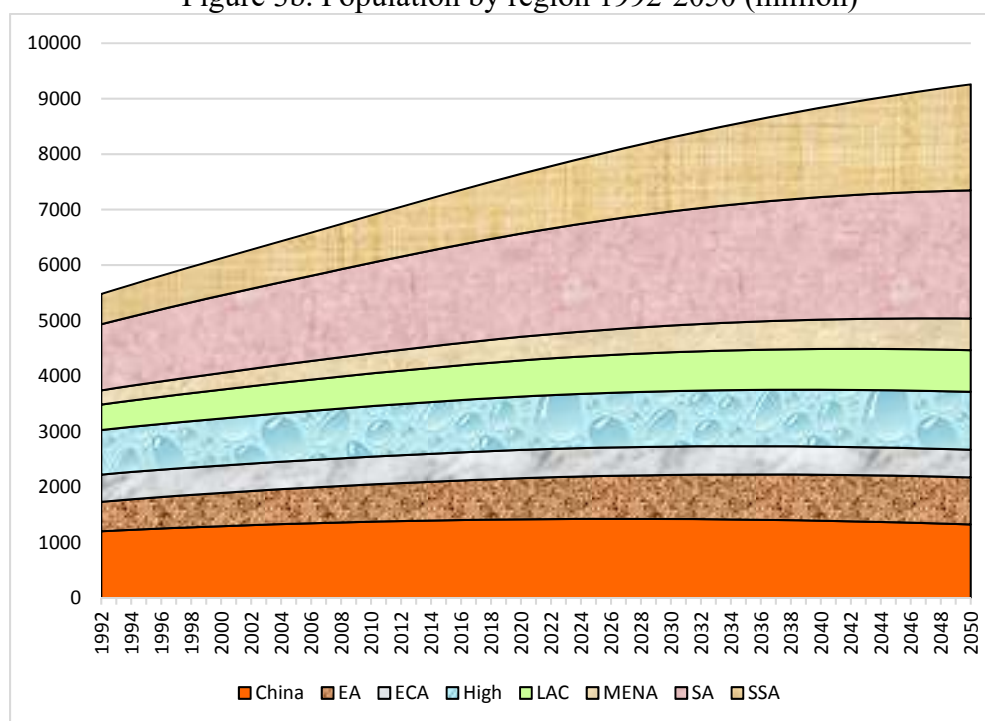
Source: FAOSTAT

Figure 3c. Contribution to population increase 2009-2050 by region (%)
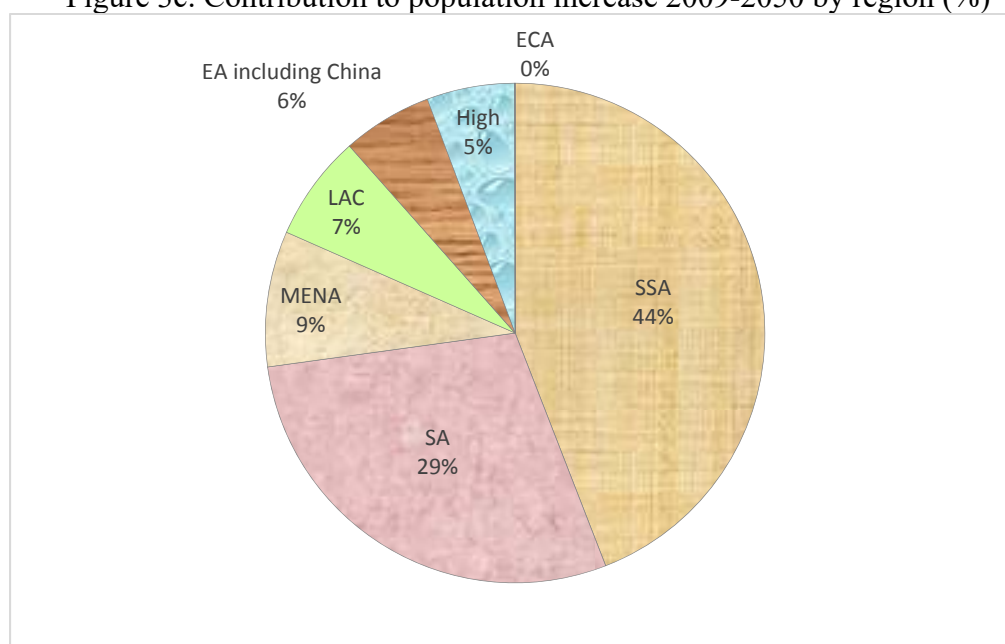
Source: FAOSTAT

Figure 4. GDP per capita and the income elasticity of food demand in 2030
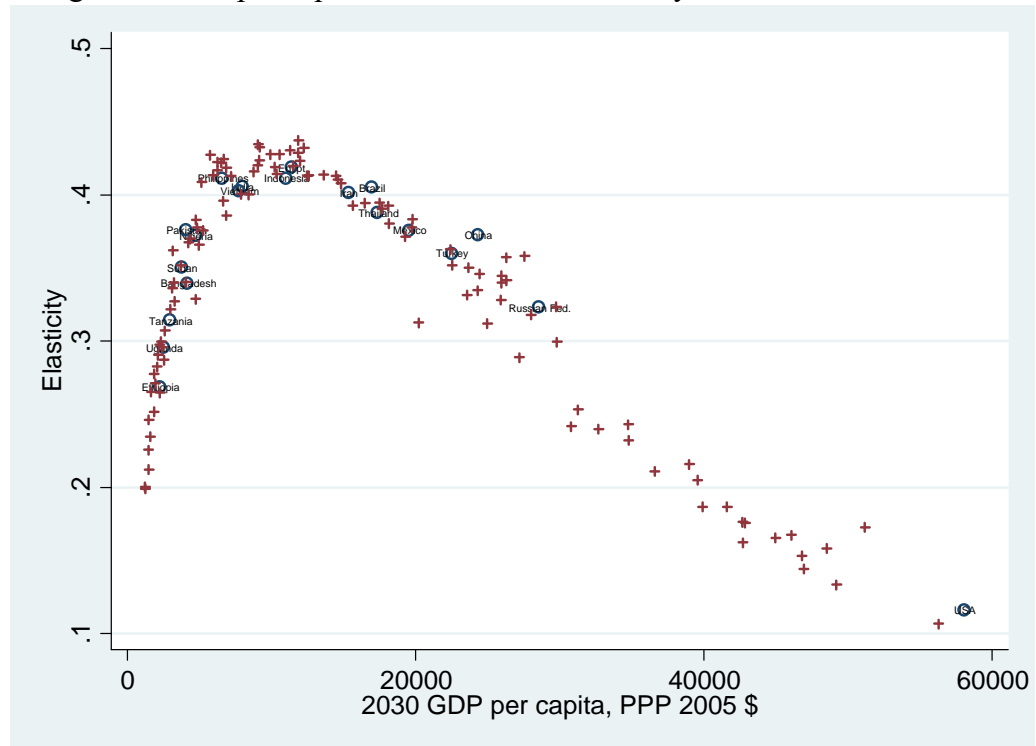
Source: Authors' calculations based on Equation (1) and the SSP2 projection data.

Figure 5. Contribution to CE consumption changes between 2009 and 2050:
SSP2 vs. Uniform scenarios (%)
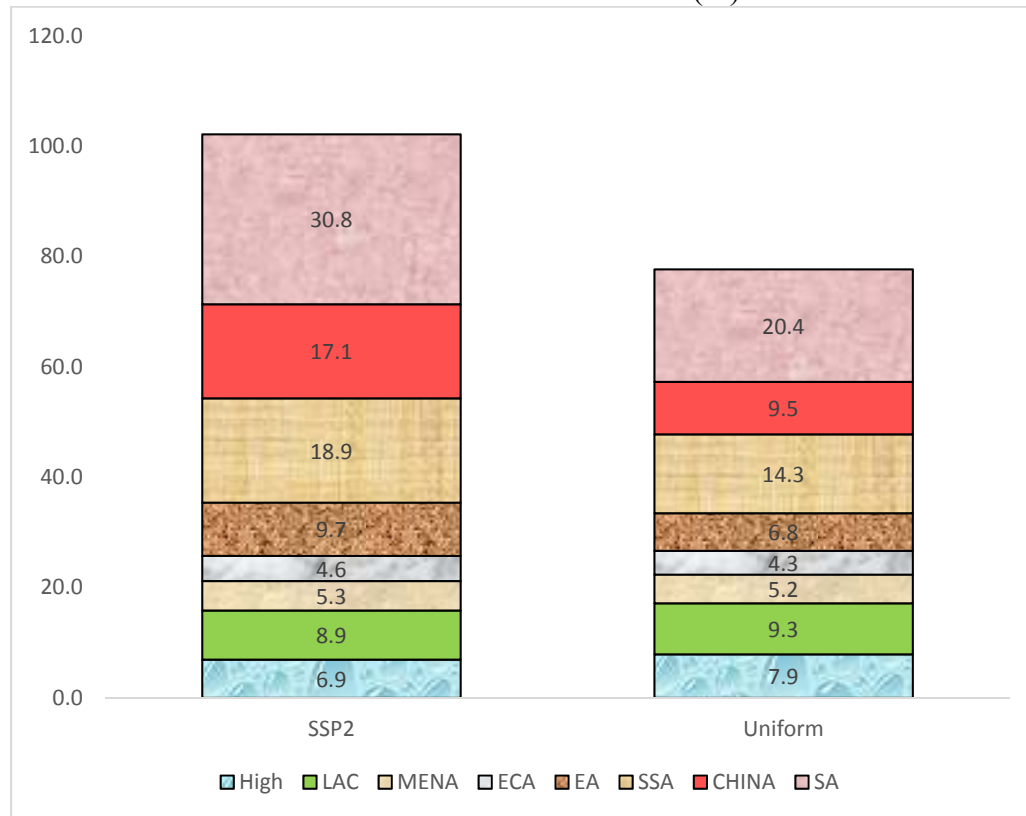
	SSP2 Change (%)	Uniform Change (%)	Difference (%)
Developing as a group	**95.3**	**69.8**	**25.4**
SA	30.8	20.4	10.4
Of which India	24.9	15.9	8.9
Of which Bangladesh	2.0	1.1	0.9
Of which Pakistan	3.2	2.8	0.4
China	17.1	9.5	7.5
SSA	18.9	14.3	4.6
Of which Nigeria	5.2	3.9	1.3
Of which Ethiopia	1.5	0.9	0.6
Of which Tanzania	1.2	0.8	0.3
EA	9.7	6.8	2.8
Of which: Indonesia	4.4	2.6	1.8
Of which: Vietnam	1.3	0.8	0.5
ECA	4.6	4.3	0.3
MENA	5.3	5.2	0.1
Of which: Egypt	2.0	1.7	0.3
LAC	8.9	9.3	-0.3
High-Income as a group	**6.9**	**7.9**	**-1.0**
Total	**102.2**	**77.7**	**24.4**

Source: Authors' simulation results based on a sample of 134 countries.
Note: CE food demand in 2009 is normalized to 100.

Figure 6. Evolution of per capita arable land by regions 1992-2012
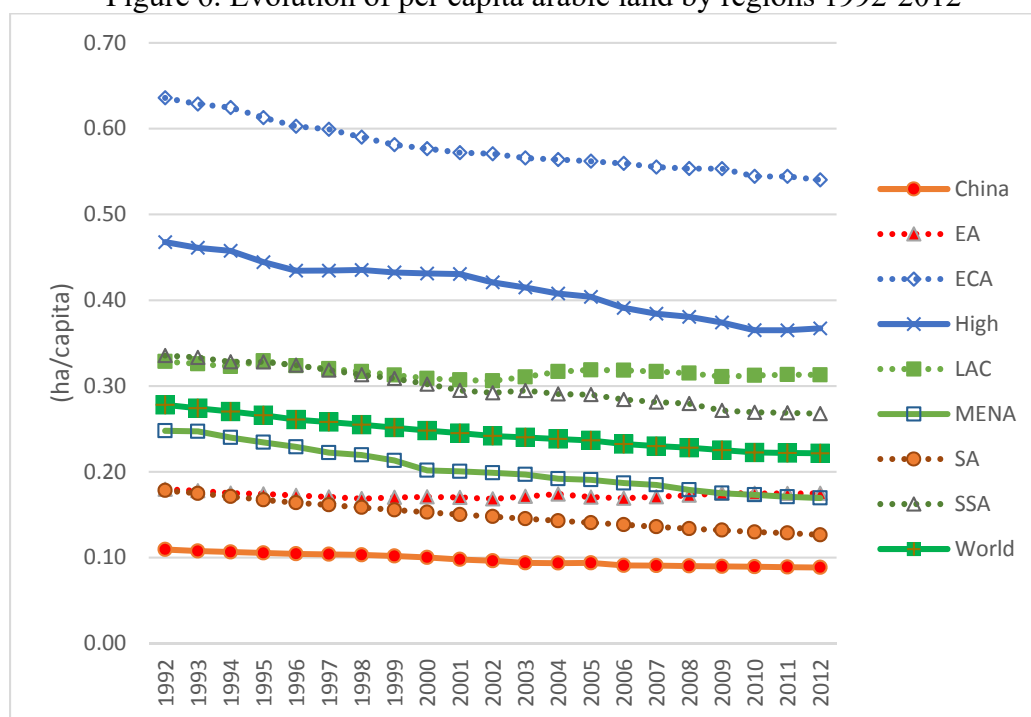
	1992-1997 av. (ha/capita)	1998-2002 av. (ha/capita)	2003-2007av. (ha/capita)	2008-2012av. (ha/capita)	1992-2012	
					Average (ha/capita)	Loss of land (%)
China	0.11	0.10	0.10	0.09	0.10	-19.2
EA	0.18	0.17	0.17	0.17	0.17	-2.6
ECA	0.62	0.59	0.57	0.56	0.58	-15.0
High	0.45	0.43	0.42	0.39	0.41	-21.5
LAC	0.33	0.31	0.31	0.32	0.32	-4.7
MENA	0.24	0.21	0.20	0.19	0.20	-31.6
SA	0.17	0.16	0.15	0.14	0.15	-29.0
SSA	0.33	0.30	0.29	0.27	0.30	-20.2
World	0.27	0.25	0.24	0.23	0.25	-20.3

Source: FAOSTAT.

36

Figure 7. Cereal yields per hectare by regions 1992-2012
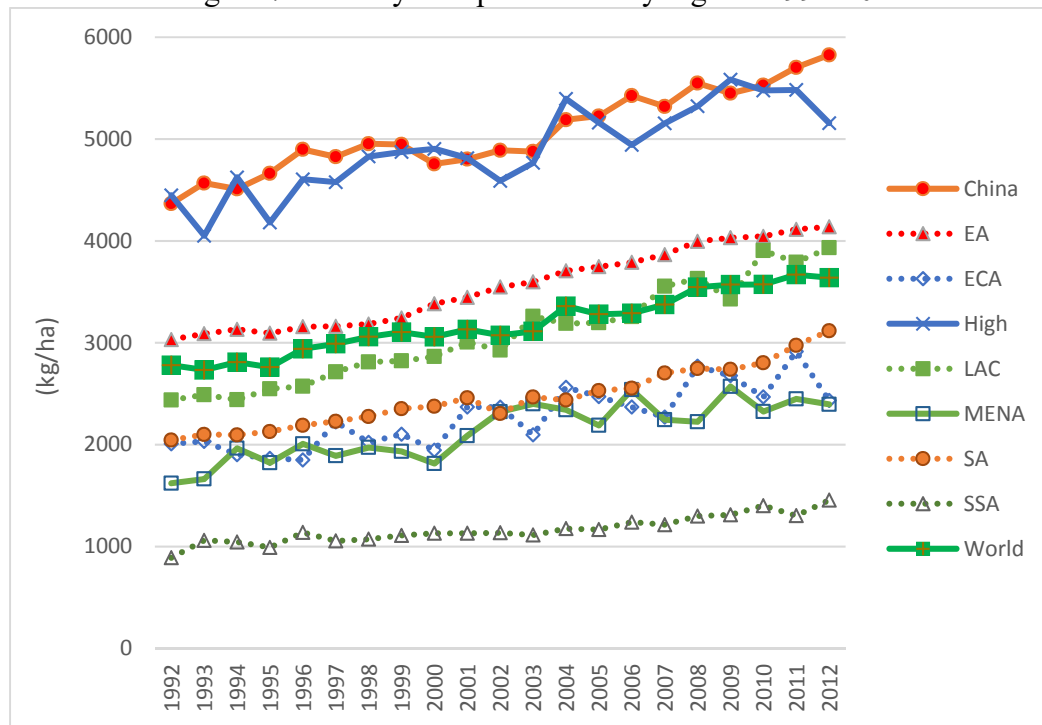
	1992-1997 av. (kg/ha)	1998-2002 av. (kg/ha)	2003-2007 av. (kg/ha)	2008-2012av. (kg/ha)	1992-2012	
					Average (kg/ha)	Yield Gains[a] (%)
China	4639	4870	5208	5611	5061	29.0
EA	3111	3361	3741	4065	3548	34.8
ECA	1980	2162	2354	2653	2273	32.4
High	4415	4802	5084	5405	4902	25.2
LAC	2534	2886	3291	3737	3084	56.7
MENA	1828	2026	2343	2393	2132	47.5
SA	2131	2354	2538	2876	2459	47.0
SSA	1030	1115	1182	1354	1163	41.4
World	2836	3085	3284	3600	3184	32.6

Source: World Development Indicators.

Note: [a] The first and last two years are averaged.

Figure 8. Relationship between CE production, income and land endowment
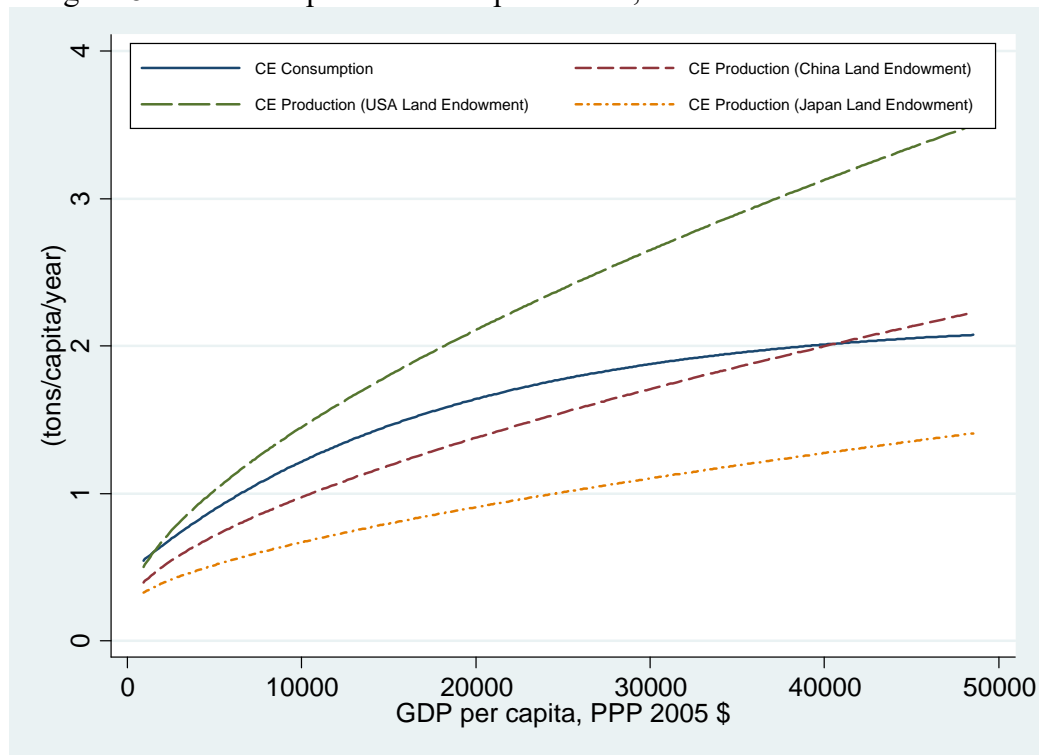
Source: Adopted from Fukase and Martin (Figures 10abc, 2014).
Notes: Following Rask and Rask (2011), agricultural land endowments are defined as the sum of arable land and one third of pasture. The land endowments for China, Japan and the United States used in this figure are 1980-2009 averages, which are 0.21 ha, 0.04 ha and 0.99 ha per person respectively.

Figure 9. Evolution of supply and demand for food 2009-2050

Figure 9a: SSP2

	2009	2030	2050
CE Cons	6360	9998	12858
CE Prod	6360	10155	13497

Figure 9b: Uniform (3.1%)

	2009	2030	2050
CE Cons	6360	8905	11301
CE Prod	6360	9383	12981

Figure 9c: Pure Convergence

	2009	2030	2050
CE Cons	6360	9043	12035
CE Prod	6360	9062	12287

Figure 9d: Uniform (2.7%)

	2009	2030	2050
CE Cons	6360	8629	10669
CE Prod	6360	8943	11768

Figure 9. (Continued)

Figure 9e: Strong Convergence

	2009	2030	2050
CE Cons	6360	10094	14886
CE Prod	6360	10120	15970

Figure 9f: Uniform (3.8%)

	2009	2030	2050
CE Cons	6360	9314	12233
CE Prod	6360	10068	15011

Figure 9g: Convergence without China India

	2009	2030	2050
CE Cons	4375	6173	8234
CE Prod	4375	6232	8500

Figure 9h: Uniform (2.5%) without China India

	2009	2030	2050
CE Cons	4375	5901	7273
CE Prod	4375	6137	8076

Source: Author's simulation results based on a sample of 134 countries.
.

Appendix Table A1. Top twenty countries contributing to CE food demand changes

	1980-1991 (Actual)					1992-2000 (Actual)		
	Country	Change (mil tons)	Share (%)	Cumulative (%)		Country	Change (mil tons)	Share (%)	Cumulative[20] (%)
1	China	305.2	35.3	35.3	1	China	435.2	53.3	53.3
2	India	120.2	13.9	49.2	2	India	71.2	8.7	62.0
3	Brazil	54.9	6.4	55.6	3	Brazil	70.1	8.6	70.5
4	United States	54.6	6.3	61.9	4	United States	62.8	7.7	78.2
5	Pakistan	30.3	3.5	65.4	5	Mexico	26.0	3.2	81.4
6	Japan	23.7	2.7	68.1	6	Pakistan	22.0	2.7	84.1
7	Indonesia	23.1	2.7	70.8	7	Nigeria	15.7	1.9	86.0
8	Mexico	22.1	2.6	73.4	8	Philippines	15.6	1.9	87.9
9	Spain	14.6	1.7	75.1	9	Egypt, Arab Rep.	15.0	1.8	89.8
10	Turkey	14.0	1.6	76.7	10	Vietnam	14.3	1.7	91.5
11	Iran, Islamic Rep.	13.8	1.6	78.3	11	Indonesia	13.7	1.7	93.2
12	Egypt, Arab Rep.	12.4	1.4	79.7	12	Bangladesh	12.0	1.5	94.6
13	Korea, Rep.	11.7	1.4	81.1	13	Korea, Rep.	10.6	1.3	95.9
14	Philippines	10.8	1.3	82.3	14	Japan	9.3	1.1	97.1
15	Bangladesh	10.5	1.2	83.5	15	Spain	9.0	1.1	98.2
16	Italy	10.4	1.2	84.7	16	Sudan	8.5	1.0	99.2
17	France	10.3	1.2	85.9	17	Colombia	8.0	1.0	100.2
18	Thailand	9.6	1.1	87.0	18	Canada	7.7	0.9	101.1
19	Nigeria	9.5	1.1	88.1	19	Argentina	6.9	0.8	102.0
20	Colombia	7.6	0.9	89.0	20	Iran, Islamic Rep.	6.5	0.8	102.8

	2001-2009 (Actual)					2009-2050 (Estimated)		
	Country	Change (mil tons)	Share (%)	Cumulative (%)		Country	Change (mil tons)	Share (%)	Cumulative (%)
1	China	271.2	30.9	30.9	1	India	1715.9	24.3	24.3
2	India	100.8	11.5	42.4	2	China	1176.6	16.7	41.0
3	Brazil	53.6	6.1	48.5	3	Nigeria	357.6	5.1	46.1
4	Vietnam	30.6	3.5	52.0	4	Indonesia	301.0	4.3	50.4
5	Indonesia	29.2	3.3	55.3	5	United States	241.0	3.4	53.8
6	United States	28.9	3.3	58.6	6	Pakistan	217.9	3.1	56.9
7	Pakistan	28.6	3.3	61.8	7	Brazil	178.5	2.5	59.4
8	Russian Federation	26.1	3.0	64.8	8	Bangladesh	140.1	2.0	61.4
9	Egypt, Arab Rep.	17.8	2.0	66.8	9	Egypt, Arab Rep.	139.8	2.0	63.4
10	Mexico	16.6	1.9	68.7	10	Mexico	133.8	1.9	65.3
11	Nigeria	16.6	1.9	70.6	11	Philippines	128.8	1.8	67.1
12	Philippines	15.5	1.8	72.4	12	Ethiopia	105.1	1.5	68.6
13	Iran, Islamic Rep.	15.4	1.7	74.1	13	Turkey	91.8	1.3	69.9
14	South Africa	13.2	1.5	75.7	14	Vietnam	91.2	1.3	71.2
15	Venezuela, RB	12.5	1.4	77.1	15	Tanzania	81.1	1.2	72.4
16	Bangladesh	12.1	1.4	78.5	16	Russian Federation	76.0	1.1	73.4
17	Ethiopia	10.3	1.2	79.6	17	Sudan	74.5	1.1	74.5
18	Colombia	9.6	1.1	80.7	18	Iran, Islamic Rep.	73.5	1.0	75.5
19	Turkey	8.8	1.0	81.7	19	Uganda	73.4	1.0	76.6
20	United Kingdom	8.8	1.0	82.7	20	Thailand	67.7	1.0	77.5

Source: Authors' calculations.

---

[20] The cumulative share exceeding 100 reflects the fact that some countries experienced CE food demand decrease. For instance, the CE food demand for Russian Federation decreased by 66 million tons during the period 1992-2000.

Appendix Figures A1-3: Does the model explain the past?

We examine how well our equations (1) and (8) predicted the actual changes in CE consumption and production over the period 1992-2009 for which we have detailed data. Columns 1 through 3 of the accompanying table in Figure A1 report actual CE consumption for the year 1992, that for the year 2009 and the resulting change in CE consumption between 1992 and 2009. The next three columns report predicted CE consumption for the years 1992, 2009 and the change between 1992 and 2009, using the coefficients reported in equation (1).

Overall, our model predicts past global CE consumption relatively well. The predicted CE consumption per capita and per year for 1992 is 0.92 tons, which is reasonably close to actual CE consumption of 0.88 tons, while that for the year 2009 is 1.07 tons (relative to the actual 0.98 tons). However, the model performance varies depending on the regions. The table attached to Figure A1 compares actual and predicted per capita CE consumption changes between 1992 and 2009 by regions. Our model estimates the changes in CE consumption reasonably well for China and the EA (other than China), MENA and SSA regions. However, in terms of the SA region, the actual CE consumption increase has been much smaller than their income level predicts. For the ECA region, the actual CE consumption in 1992 (1.4 tons) was much higher than their income level predicts in the aftermath of the dissolution of former Soviet Union (1.1 tons), but it decreased to 1.3 tons in 2009, at the level that our model predicts (1.3 tons). For the high-income countries as a group, while predicted and actual CE consumption were very close in 1992 to each other, at 1.8 tons and 1.9 tons respectively, our model does not predict the actual decline in their CE consumption mainly resulting from a dietary shift from CE intensive red meat (e.g., beef) to relatively feed efficient lean meat (e.g., chicken).

Figure A2 repeats the same calculation on the CE production side. The results show that equation (8) predicts CE production reasonably well, with predicted CE production of 0.82 tons (relative to the actual CE production of 0.89) for 1992 and 0.93 tons (relative to the actual 0.99 tons) respectively. Between 1992 and 2009, the LAC region increased its CE production much faster than its land endowment and income level predict, mainly driven by the high performance of Brazil. The EA region, mainly Southeast Asian countries, as well as China, also outperformed given their income levels and land endowments. CE production of ECA and high-income countries as a group decreased, perhaps reflecting the transition to a market-oriented system and a shift in diets to relatively CE efficient food respectively. Godfray *et al*. (2010) show that global production of chicken, and to a lesser extent, that of pigs has risen substantially since 1960, while the production of cattle and sheep has stagnated (Figure 1B, Godfray *et al*. 2010).

Using the estimated coefficients reported in equation (8), Figure A3 and the attached table decompose the change in CE production into the contribution of the change in agricultural land endowment and that of the change in productivity proxied by GDP. As agricultural land per capita decreased between 1992 and 2009, the contribution of land change to CE production per capita is negative. However, the much faster increase in productivity associated with GDP growth appears to have outweighed the negative impacts of reduced land endowment, resulting in an increase in CE production per capita. The qualitative result is consistent with the insight from the SIMPLE model (Hertel 2011; Hertel and Baldos 2016) which suggests a tradeoff between the intensive and extensive margins of agricultural supply, i.e., the need for cropland area expansion can be reduced, if yields can be increased at a sufficiently rapid pace to meet the demand.

Figure A1. Changes in CE consumption: actual vs estimated 1992-2009

	Actual CE Consumption (tons per capita per year)			Estimated CE Consumption (tons per capita per year)		
	1992	2009	Changes 1992-2009	1992	2009	Changes 1992-2009
China	0.6375	1.0822	0.4447	0.6269	1.0139	0.3871
EA	0.5658	0.7275	0.1617	0.8026	0.9524	0.1498
ECA	1.4209	1.2834	-0.1375	1.1193	1.2977	0.1784
High	1.8921	1.8475	-0.0446	1.8472	1.9583	0.1111
LAC	1.1182	1.3347	0.2166	1.0840	1.2061	0.1221
MENA	0.7374	0.8663	0.1289	0.8894	1.0358	0.1464
SA	0.4468	0.5047	0.0579	0.6194	0.7421	0.1227
SSA	0.5368	0.5812	0.0444	0.6478	0.6826	0.0348
Global	0.8820	0.9828	0.1009	0.9191	1.0707	0.1516
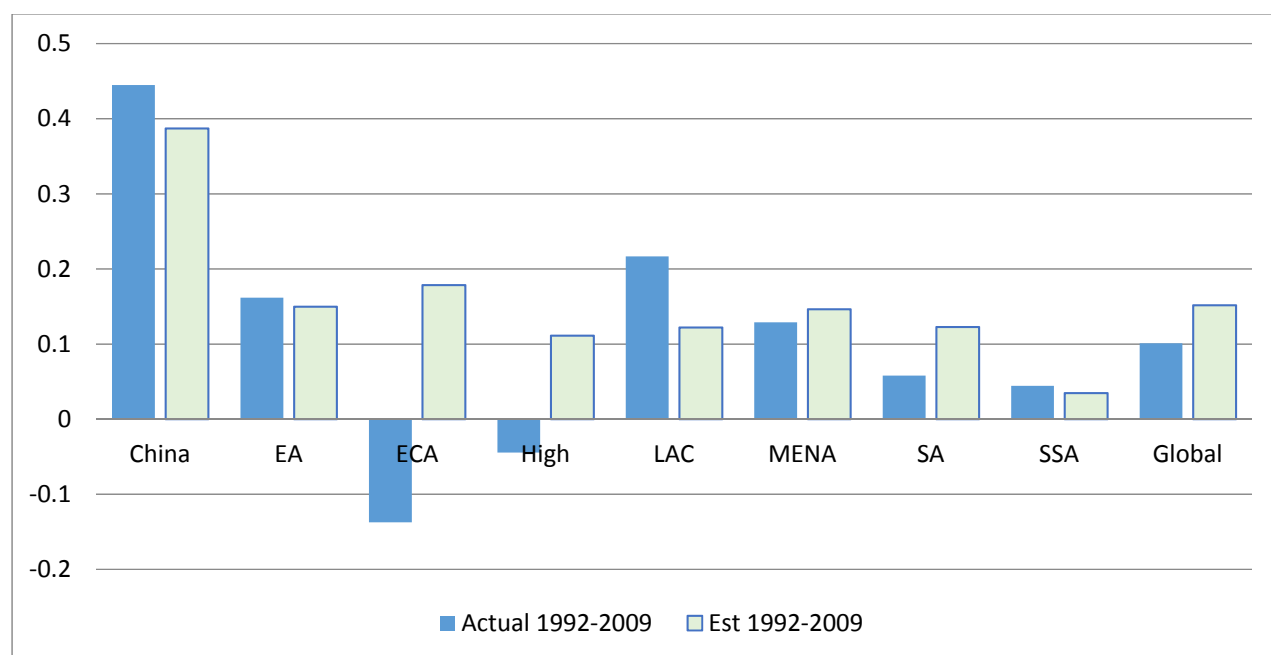
Source: Authors' calculations.

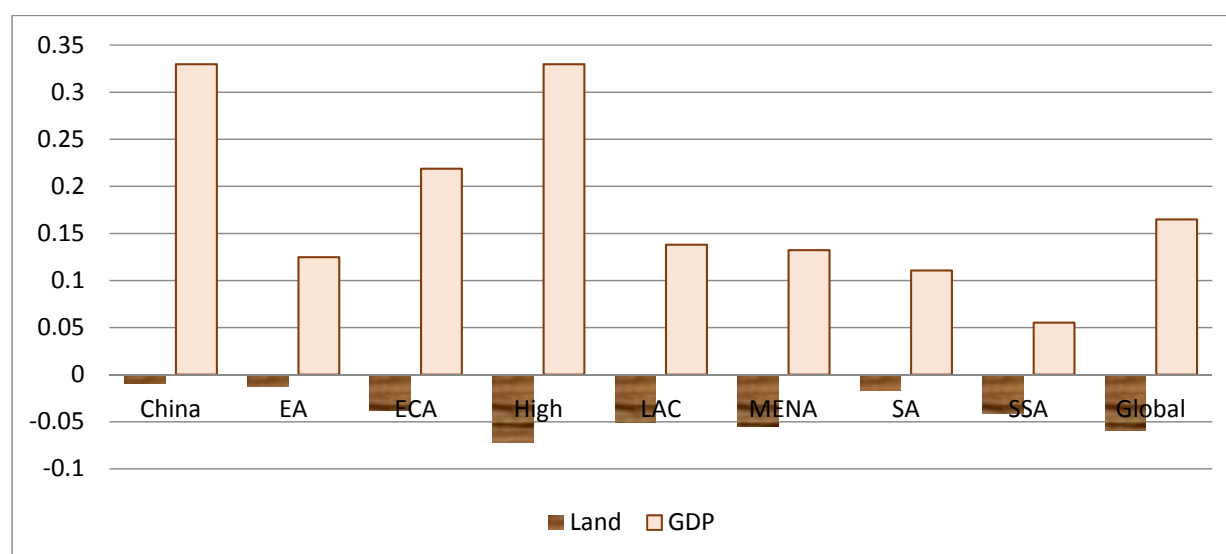Figure A2. Changes in CE production: actual vs estimated 1992-2009

	Actual CE Production (tons per capita per year)			Estimated CE Production (tons per capita per year)		
	1992	2009	Changes 1992-2009	1992	2009	Changes 1992-2009
China	0.6257	0.9899	0.3642	0.4374	0.7424	0.3050
EA	0.5866	0.8467	0.2601	0.5613	0.6722	0.1108
ECA	1.3617	1.2650	-0.0966	1.1703	1.3538	0.1835
High	2.0486	2.0086	-0.0400	1.9469	2.1424	0.1955
LAC	1.1934	1.5668	0.3733	1.0906	1.1767	0.0862
MENA	0.4980	0.6160	0.1180	0.7572	0.8290	0.0718
SA	0.4379	0.4954	0.0575	0.4168	0.5011	0.0843
SSA	0.4769	0.5061	0.0292	0.5598	0.5773	0.0175
Global	0.8885	0.9925	0.1040	0.8152	0.9349	0.1197
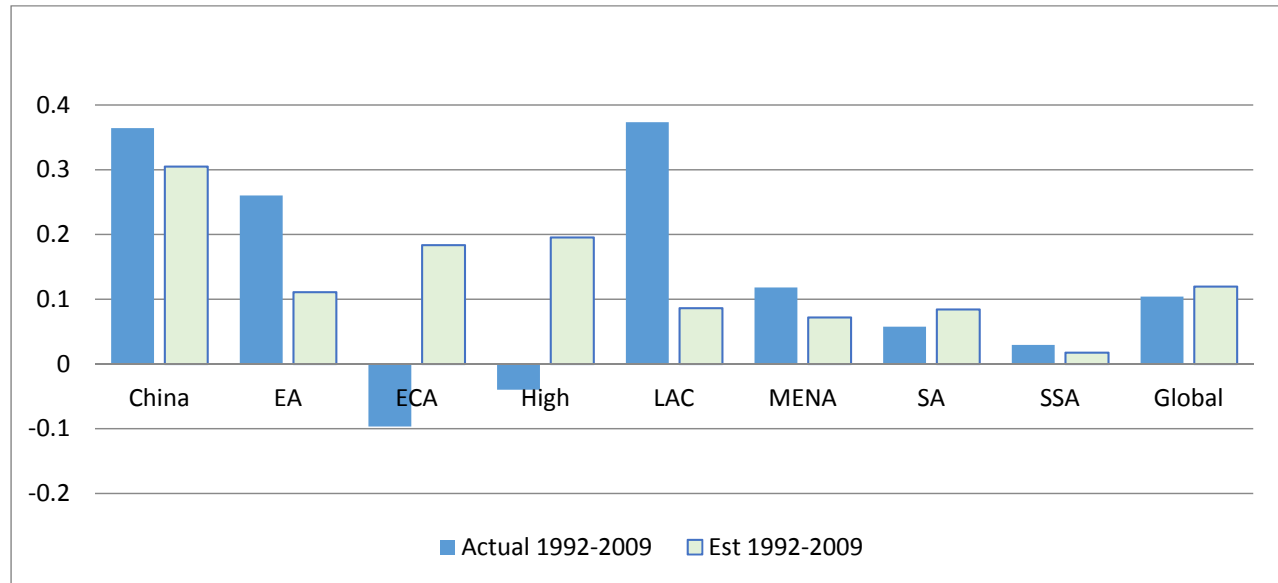
Source: Authors' calculations.

Figure A3. Estimated contribution of land and GDP changes to CE production change (tons)

	Contribution of Changes in Land (tons per capita per year)			Contribution of Changes in GDP (tons per capita per year)		
	1992	2009	Changes 1992-2009	1992	2009	Changes 1992-2009
China	0.4374	0.4278	-0.0095	0.4374	0.7670	0.3297
EA	0.5613	0.5489	-0.0125	0.5613	0.6862	0.1248
ECA	1.1703	1.1327	-0.0377	1.1703	1.3891	0.2188
High	1.9469	1.8747	-0.0722	1.9469	2.2766	0.3297
LAC	1.0906	1.0396	-0.0509	1.0906	1.2285	0.1380
MENA	0.7572	0.7019	-0.0554	0.7572	0.8895	0.1323
SA	0.4168	0.4003	-0.0165	0.4168	0.5275	0.1107
SSA	0.5598	0.5181	-0.0417	0.5598	0.6151	0.0553
Global	0.8152	0.7557	-0.0595	0.8152	0.9801	0.1649

Source: Authors' calculations.