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Evaluating nutrition and health impacts of agricultural innovations

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Abstract

Agricultural innovations are seen as a key avenue to improve nutrition and health in smallholder farm households. But details of these agriculture-nutrition-health linkages are not yet well understood. While there is a broad literature on the adoption of agricultural technologies, most studies primarily focus on impacts in terms of productivity and income. Nutrition and health impacts have rarely been analyzed. In this article, we argue that future impact studies should include nutrition and health dimensions more explicitly. A conceptual framework is developed to clarify possible impact pathways. Different nutrition and health metrics are reviewed in terms of their strengths and weaknesses and criteria of choice for different study purposes. To evaluate impacts of particular innovations, the chosen metrics have to be compared between adopters and non-adopters, using a suitable sampling design. Approaches of how to deal with possible selection bias are discussed. Finally, selected empirical examples in which these metrics and methods were used in practice are reviewed.

Keywords: food security; health; nutrition; agriculture; impact assessment; smallholder farmers

JEL codes: I15, I32, O12, O33, Q12

Evaluating nutrition and health impacts of agricultural innovations

Introduction

Agricultural technologies and related innovations are seen as a key mechanism to contribute to sustainable food and nutrition security (Huang et al. 2002; Minten and Barrett 2008; Godfray et al. 2010). From a long-term, macro-level perspective, the important role of agricultural growth for improved nutrition and health is well documented (Fogel 2004; Headey 2013). The development and spread of agricultural technology has contributed to sizeable production and productivity gains, making food more affordable and reducing rates of undernourishment in the world. Especially the technology-induced productivity gains in Asia and Latin America since the 1960s, which are referred to as the 'green revolution', had a strong positive effect in terms of increasing food availability and reducing market prices (Evenson and Gollin 2003). There is also research that has analyzed the effects of changing absolute and relative food prices on calorie consumption and dietary quality (Ecker and Qaim 2011; Bouis et al. 2011; D'Souza and Jolliffe 2014). However, beyond such general relationships between agricultural productivity growth, prices, and food security, relatively little is known about the impact of agricultural innovations on nutrition and health at the micro level (Webb and Kennedy 2014). Smallholder farmers make up a large proportion of the world's undernourished people, so that a better understanding of how agricultural technologies and related innovations affect their nutrition is of crucial importance for effective research and policymaking.

In a recent meta-analysis, Masset et al. (2012) reviewed the available literature about the effects of agricultural interventions on child nutrition. They only found 23 studies that had evaluated nutrition impacts in a rigorous way, most of them referring to home garden interventions. Masset et al. (2012) confined their review to interventions that had the explicit goal of improving the nutritional status of children. When looking at research that evaluates nutrition impacts of agricultural innovations more generally, the available literature gets even thinner (Ruel and Alderman 2013; Webb and Kennedy 2014). While numerous studies have analyzed the effects of different agricultural technologies in a small farm context, most of this work has looked at impacts in terms of yields, cost of production, and income. Only very few studies have evaluated nutrition effects of agricultural technologies more explicitly (Hotz et al. 2012; Shiferaw et al. 2014; Qaim and Kouser 2013; Kabunga et al. 2014). This is surprising, given that one of the main goals of the international agricultural research system is to sustainably improve food security and nutrition.

Often, studies that find positive yield and income effects of agricultural technologies conclude that these technologies will also improve nutrition in smallholder farm households. However, while income growth is generally associated with improved nutrition, this effect is not always straightforward and may be influenced by many other factors. For instance, it matters a lot who within the household controls agricultural production and whether additional yields and incomes are really used to improve nutrition and health. This also depends on gender relations, which may change through the introduction of new technologies (von Braun and Kennedy 1994; Fischer and Qaim 2012). Furthermore, increasing the consumption of calories alone may reduce hunger but not necessarily improve dietary quality and diversity, which are important conditions to reduce micronutrient malnutrition. We argue that studies on the impacts of agricultural innovations should go beyond yield and income and analyze nutrition effects more explicitly. Using rigorous analysis to demonstrate positive nutrition and health effects among smallholder farmers could help to gain more political support for agricultural research investments. A better understanding of what types of innovations really work to improve nutrition in particular contexts and what bottlenecks need to be overcome to optimize impacts would also be useful to guide research priority-setting and institutional policy design.

The objective of this article is to encourage more research in this direction and review methods and approaches that can be used for practical studies on nutrition and health impacts of agricultural innovations. In the next section, we present a simple conceptual framework of possible impact pathways. After that we discuss metrics of nutrition and health that can be used as outcome variables in quantitative analysis. We also review issues of study design before providing an overview of selected empirical examples. The last section concludes.

Conceptual framework

Figure 1 provides a simple framework to analyze the impacts of agricultural innovations on nutrition and health. This framework focuses on smallholder farm households that adopt a particular innovation. This innovation may affect their nutrition and health through multiple pathways. In the following discussion, we will often use technologies as examples of innovations, but the same principles apply to institutional innovations as well. For instance, improved market access through novel forms of farmer collective action or marketing contracts may have important impacts on nutrition and health (Fischer and Qaim 2012; Chege et al. 2014), just as the adoption of a new crop variety has. It is also important to stress that all forms of technical and institutional innovations may cause nutrition and health effects, even if this is not their primary intention. As nutrition and health are basic needs, understanding both intended and unintended effects is important, especially when the focus is on vulnerable populations. This is why we argue that the inclusion of nutrition and health aspects should become standard in agricultural impact studies in a smallholder context.

Figure 1 shows potential impact pathways. A first possible pathway is that the innovation influences the food quantity produced. An example could be a higher yielding staple crop variety that helps to increase household calorie production (Shiferaw et al. 2014; Bezu et al. 2014). A second possible pathway is through changes in the quality of the food produced. For instance, the innovation may affect the protein composition of staple crops, such as quality-protein maize (Gunaratna et al. 2010), or the micronutrient content, such as biofortified crops (Bouis and Welch 2010). A third pathway is that the innovation affects the diversity of food produced in the farm. Cases in point are the introduction of legumes or horticultural crops into cereal production systems (Keding et al. 2012; Fanzo et al. 2013). When part of the farm harvest is used for home consumption, as is typical in smallholder systems, these changes in food production quantity, quality, and diversity will directly translate into changes in diets and nutrition at the household level (Jones et al. 2014). How this affects food intake and nutritional status of individuals depends on intra-household food distribution (Hoddinott 2012).

But farm households do not only produce food for home consumption. Even smallholders are engaged in market transactions to varying degrees, meaning that they also sell part of their harvest in the market. Many smallholders also produce non-food cash crops, such as tea, coffee, or cotton, to diversify their income sources. Agricultural innovations may affect the cash income generated from farm product sales. Moreover, especially technologies that change the demand for family labor may also affect the income from off-farm economic activities (Noltze et al. 2013). Hence, the cash income pathway must not be ignored. In general, cash income is positively associated with food consumption and nutrition, but gender roles, which may change through technology adoption, are an important determinant in this respect. Research has shown that men often take greater control of agricultural income with the adoption of new technologies and rising levels of commercialization (von Braun and Kennedy 1994). And men tend to spend less than women on dietary quality (Hoddinott and Haddad 1995; Fischer and Qaim 2012). Therefore, statements about the nutrition impacts of agricultural innovations should not be based on income measures alone.

The lower part of Figure 1 indicates the close relationship between nutrition and health. As is well known, undernutrition and micronutrient malnutrition are leading risk factors for impaired physical and mental development, infectious diseases, and premature deaths. There are also important interlinkages, as infectious diseases can influence nutrient absorption and intake requirements. Overnutrition is associated with several chronic diseases. Health issues can also result from food contamination with toxic substances, such as mycotoxins or pesticide residues (Wu et al. 2014). Such food contamination and the health consequences can also be affected through agricultural innovations. Beyond the food consumption and nutrition pathways, agricultural innovations can also impact health directly, either positively or negatively. For instance, technologies that alter the use of chemical pesticides influence occupational health hazards for farmers and farm workers (Pingali et al. 1994; Kouser and Qaim 2011). Innovations in smallholder livestock systems may change risks of zoonotic diseases and their spread (McDermott and Grace 2012). Here, we focus primarily on the food consumption and nutrition pathways, although some of the methods described below are also suitable for the analysis of other health outcomes.

Nutrition and health metrics

Impact assessment requires that we measure outcome variables of interest in a suitable form. This is not straightforward, because there are different approaches to measure nutrition and health. In the following, we summarize the most common approaches and discuss advantages and drawbacks.

Nutrition measures

A large number of different measures and indicators of food security and nutrition are available and have been discussed and compared in the recent literature (Barrett 2010; de Haen et al. 2011; Headey and Ecker 2013; Maxwell et al. 2014). The most important measures for use at the micro (household or individual) level can broadly be subdivided into four categories, namely (i) clinical measures, (ii) anthropometric measures, (iii) food consumption based measures, and (iv) subjective measures of food security. Clinical measures, for instance based on blood samples, are precise in terms of measuring the status for particular nutrients, but they are relatively costly to compile and do not provide a broader picture of dietary practices and nutrition. Clinical measures are typically used in epidemiological studies and randomized interventions with very specific nutrition objectives (e.g., Hotz et al. 2012). They are rarely used by social scientists working with observational survey data. The other three categories of measures are described in some greater detail in the following.

Anthropometric measures are indicators of nutritional status of individuals. While several anthropometric indicators are used for different purposes, the most commonly used all relate to the height and weight of individuals. For adults, the body mass index (BMI) is often calculated. For children, commonly used indicators are stunting (low height for age), underweight (low weight for age), wasting (low weight for height), and thresholds based on BMI-for-age Z-scores. While some debate exists about the correct reference population to use for calculating these indicators in different contexts, anthropometry is commonly accepted as a relatively precise approach to measure nutritional outcomes (de Haen et al. 2011). Anthropometric measures are not included in standard agricultural household surveys. They can be included, although this adds to the cost and time required for the survey. Taking height and weight measures is somewhat more intrusive than only interviewing and requires that the selected household members are present during the visit.

Beyond their relative precision, anthropometric indicators also have several other advantages. As they are individual based, effects for particular target groups (e.g., children) can be analyzed, without having to make crude assumptions about intra-household food distribution. Anthropometric indicators cannot only be used to assess problems of undernutrition, but also to analyze overnutrition and obesity, which is hardly possible with the other measures. Furthermore, as measures of nutritional outcome, anthropometric indicators capture people's health and well-being more comprehensively than measures that focus on food access alone. However, anthropometric indicators also have drawbacks for analyzing the impacts of agricultural innovations. Exactly because they look at nutritional outcomes, which are determined by several factors, anthropometric indicators cannot be used to analyze details of changes in people's diets and nutrient intakes, which may be of particular interest as intermediate effects of agricultural and food interventions. Without properly controlling for important other factors, including current and past health and sanitation conditions, effects of agricultural innovations on anthropometric indicators are difficult to establish in empirical studies (Babatunde and Qaim 2010; Masset et al. 2012).

Food consumption based measures build on food recall data collected during household surveys. Typical measures used in empirical studies include indicators of dietary diversity, such as food variety and dietary diversity scores (Ruel 2003; Headey and Ecker 2013), indicators related to the intake of calories and specific nutrients, which are calculated using food composition tables (Ecker and Qaim 2011), and calorie shares of particular food groups (Jensen and Miller 2010; Qaim and Kouser 2013). Food consumption modules are often included in living standard measurement surveys, although proper questionnaire design is important in order to make such data useful for nutritional analysis. First, information on food quantity consumed should be captured, not only data on food expenditures. Second, there should be sufficient disaggregation in terms of food groups and individual food items considered, adjusted to the local context. A disaggregation into 60 or more different food items is useful, especially when issues of micronutrient consumption shall be analyzed. Third, shorter recall periods tend to deliver more accurate data (de Haen et al. 2011). For nutritional analysis, 7-day recalls are preferred over 30-day recalls. For certain questions, 24-hour recalls are more suitable, although in that case two visits to the household are recommended to better capture day-to-day variation in food consumption.

Food consumption based measures are the most appropriate to analyze issues of dietary quality and nutrient adequacy from a broader perspective. However, they also have some drawbacks. In most surveys, data on food consumption are collected at the household level. Hence, issues of intra-household distribution cannot be analyzed, and statements about impacts on the nutrition of specific target groups (e.g., children, women) cannot be made without relying on crude assumptions. While it is possible to collect food intake data at the individual level, this is more complex and requires modules that are different from the typical food consumption questionnaires. Food consumption indicators are also not very precise measures of actual intakes, because food waste, losses, issues of bioavailability, and other sources of measurement error cannot be controlled for perfectly. Finally, it should be kept in mind that food consumption is subject to seasonality.

Subjective measures of food security involve asking the household head or other household members about their own assessment of access to food, perceived adequacy of consumption, exposure to risk, and coping strategies. Different questionnaire modules and indices have been developed and tested recently to capture household subjective views, such as simple dichotomous indicators, and somewhat more comprehensive ones including the household hunger scale (HHS) and the household food insecurity access scale (HFIAS) (Maxwell et al. 2014).

Subjective measures have advantages in terms of being relatively cheap to collect and capturing psychological aspects of hunger and nutrition, which other indicators do not. Moreover, through appropriate questions seasonality aspects can be analyzed to some extent. Mostly, subjective questions are asked at the household level, although asking different individuals within the same household is generally possible. Disadvantages include response biases that are more common with subjective assessments and lack of comparability across countries and regions. There is mixed evidence about the correlation of subjective measure of food security with more objective indicators of nutrition and health (Headey and Ecker 2013).

This discussion of different types of nutrition measures shows that there is no single indicator or class of measures that is superior in all dimensions. For empirical studies on nutritional impacts of agricultural innovations, the choice of the most appropriate indicator (or combination of indicators) should be made based on different criteria. Important criteria include the type of agricultural innovation, expected impacts and impact pathways, the specific target group in mind, the intended sample size and geographic coverage, the time frame, and the resources available to carry out the study, among others.

Health measures

When assessing the impact of agricultural innovations on health, we are usually interested in knowing by how much the innovation reduces or increases the prevalence or incidence of certain diseases or adverse health conditions. Prevalence is the proportion of a population suffering from a particular health condition at a given point in time, whereas incidence is a measure of new cases of the condition arising in a population over a certain period (e.g., one year). Both prevalence and incidence rates can be used as outcome variables for impact analysis; the choice depends on the type of innovation to be analyzed, the type of health condition, and the intended statement. For instance, for a technology that reduces the use of chemical pesticide sprays, the incidence rates of acute and chronic health issues associated with pesticide poisoning would be outcome measures of particular relevance (Pingali et al. 1994). Similarly, for irrigation projects looking at the impact on incidence rates of malaria and water-borne diseases could be of interest (McDermott and Grace 2012).

Here, we are particularly interested in diseases and health conditions associated with malnutrition. Anthropometric nutrition indicators, such as stunting and wasting, already capture certain health dimensions, as discussed above. In addition, nutritional deficiencies are associated with certain infectious diseases, child mortality, mental impairment, and other adverse functional outcomes. For all these conditions, prevalence or incidence rates can be used for impact analyses. To be able to better compare across health outcomes of different severity, comprehensive measures such as the cost-of-illness or the loss of so-called disability-adjusted life years (DALYs) are sometimes calculated.

DALYs have become the standard tool to calculate the global burden of disease and risk factors. They have also been used in impact analyses for agricultural innovations such as biofortified crops (Stein et al. 2007; Stein et al. 2008). The number of DALYs lost is an index that combines the health loss through mortality and morbidity of relevant functional outcomes. It is calculated as the sum of the number of life years lost due to premature deaths and the number of years lived with disabilities, which are weighted according to the severity of the disabling conditions. DALYs can also be used for cost-effectiveness and cost-benefit analyses of nutrition and health interventions, including agricultural innovations (Qaim et al. 2007).

Design of impact studies

The basic idea of any empirical impact assessment is to compare the outcome variables of interest in the study population with and without the intervention, in our case the agricultural innovation. In the previous section, we have discussed suitable outcome variables that can be used to measure nutrition and health impacts. In this section, we summarize issues to be considered in broader study design.

A first important aspect to decide is the best timing for a study. Ex ante studies analyze potential impacts before the innovations are introduced. In this case, impacts are not observable, but they can be predicted or simulated when making appropriate assumptions. Ex ante studies are useful for research priority-setting and for identifying critical institutional and policy issues that still need to be addressed in order to achieve desirable outcomes. However, uncertainty about the suitability of the assumptions remains, so that results of ex ante studies need to be interpreted with some caution. Several ex ante studies were carried out to analyze the potential nutrition and health impacts of different biofortified crops (Qaim et al. 2007; Meenakshi et al. 2010).

Impact studies can also be carried out when a technology is ready to be released but before actual adoption occurred. In this situation, the technology can be assigned randomly to farm households, which allows rigorous impact assessment under relatively controlled conditions. Such randomized controlled trials (RCTs) are common for medical treatments; recently they have also gained popularity in agricultural and development economics. Hotz et al. (2012) carried out an RCT to analyze the impacts of orange sweet potato on vitamin A status in Uganda. While such randomized studies help to reduce typical biases in impact evaluation, their external validity is often limited, that is, the results are mostly context-specific. Nevertheless, RCTs constitute a very interesting tool for testing concrete hypotheses.

The most widely used approaches for the assessment of impacts of agricultural innovations are ex post studies with observational data (Qaim and Kouser 2013; Shiferaw et al. 2014; Bezu et al. 2014; Kabunga et al. 2014). These can be carried out in an early adoption phase, or also somewhat later when adoption rates are likely to be higher. The sampling frame needs to ensure that both adopters and non-adopters are surveyed, so that a comparison with and without the innovation can be made. However, such studies with observational data have to deal with selection bias, because the innovation is not randomly assigned. Hence, observed differences in outcome variables may be due to the innovation, but they may also be the result of other systematic differences between adopters and non-adopters. Special statistical and econometric techniques have to be used to reduce possible biases (Imbens and Wooldridge 2009).

Observed differences between adopters and non-adopters can be controlled through simple regression models or propensity score approaches. However, there may also be unobserved differences that require instrumental variable models for unbiased estimation. When panel data are available (e.g., a baseline survey before widespread adoption and a later follow-up), differencing techniques can be used that also help to reduce selection bias (Qaim and Kouser 2013; Bezu et al. 2014).

One additional remark is worth making in the context of analyzing nutrition impacts. As discussed above, nutrition measurement can be complex, and the different indicators may be subject to seasonality and several sources of measurement error. This is a problem when the objective is to make precise statements about the prevalence of undernutrition or specific nutrient deficiencies. However, in impact analysis the main idea is to compare the difference with and without the innovation. Usually, measurement errors occur for both adopters and non-adopters of the innovation, so that they cancel out in the comparison. Therefore, these types of inaccuracies in measurement are unlikely to affect the impact results systematically.

Selected empirical examples

In this section, we discuss selected examples of studies in which the tools discussed in previous sections were used for empirical analysis. These are studies on the nutrition and health impacts of tissue culture bananas, genetically modified cotton, and biofortified crops. These examples were chosen, because we have worked on them recently and the studies involve an interesting mix of different methodological approaches. We do not try to provide a complete overview of existing work in this direction (although the literature is relatively thin, as mentioned above). Nor do we claim that the technologies considered here cause nutrition and health impacts that are larger than those of other innovations.

Tissue culture bananas

In eastern and southern Africa, banana is primarily grown by smallholder farmers for home consumption and local markets. Due to pests, diseases, and poor crop management, banana yields in Africa have decreased over the last 30 years. Traditionally, bananas are vegetatively propagated using suckers. This practice fosters the transfer of pests and diseases, thus reducing potential yield from the beginning in newly established plantations. Tissue culture (TC) is an alternative form of plant propagation using in-vitro techniques in the laboratory to produce pathogen-free plantlets. TC bananas were shown to result in higher yields than traditional bananas under favorable conditions, but impacts in a smallholder context had not been analyzed until recently. In a recent study, we analyzed the impacts of TC adoption on household income and food security in Kenya (Kabunga et al. 2014). We used the household food insecurity access scale (HFIAS) as a subjective measure of food security.

The analysis builds on a survey of banana farm households that we carried out in the major banana-growing areas of central and eastern Kenya in 2009. We used stratified random sampling to select adopters and non-adopters of TC banana technology in the same environments. In total, 385 banana farmers, composed of 223 adopters and 162 non-adopters, were sampled. Sample households were diversified smallholders, most of them with farm sizes of less than 2 ha. In addition to banana, sample farms grew maize for home consumption and different horticultural crops. Many also had some livestock activities such as raising chicken and small ruminants, and some grew cash crops such as coffee on a small scale. Household heads were interviewed using a structured questionnaire specifically designed for this study. The questionnaire included a HFIAS module with 9 specific questions in which respondents were asked about their subjective assessment of food access over the last 30 days.

We used principal factor analysis to evaluate the HFIAS answers and construct two composite measures, namely a food insecurity and a severe food insecurity index. These indices are normally distributed across the sample with mean zero and standard deviation of one. Higher positive index values indicate higher levels of food insecurity. Noteworthy is that these indices represent relative food insecurity within the sample and are best used when comparing the extent to which one household differs from the other, a key principle in impact assessment.

Mean values for the two indices in the sample are shown in Figure 2, disaggregated by adopters and non-adopters of TC banana technology. Adopters have lower values than non-adopters, suggesting that they are more food-secure. Another way of looking at this is shown in Figure 3, where households are categorized into quartiles, rendering food-secure, mildly food-insecure, moderately food-insecure, and severely food-insecure households. The proportion of food-secure and mildly food-insecure households is higher among TC adopters, while the proportion of severely food-insecure households is higher among non-adopters. However, these comparisons do not control for other influencing factors and possible selection bias.

To estimate net effects of TC banana adoption, we estimated instrumental variable regression models where the individual adoption decision was instrumented with the technology adoption behavior of other households in the farmer's social network. Furthermore, a broad set of covariates was included in estimation to control for factors that may influence household food insecurity and welfare other than TC adoption. These covariates include farm, household, and contextual characteristics. In a first set of models, we used per capita farm and household income as dependent variables. The estimation results confirmed significantly positive impacts of TC adoption (Kabunga et al. 2014). In a second set of models, we used the food insecurity and severe food insecurity index as dependent variables. These results are summarized in Table 1. For correct interpretation, we remind that higher values of both indices indicate higher levels of food insecurity. Thus, negative coefficient estimates imply improvements (reductions in relative food insecurity) and vice versa.

The estimation results in Table 1 suggest that the adoption of TC bananas significantly improves household food security. TC adoption reduces food insecurity and severe food insecurity by 0.44 and 0.32 index points, respectively. Percentage interpretations relative to sample mean values are not possible, because the sample mean for both indices is zero by construction. However, given that the indices have a standard deviation of one, the estimated impacts are relatively large.

On the one hand, the favorable food security impacts of TC adoption can be explained by positive cash income effects. On the other hand, other pathways are also likely to play a role. First, banana is grown as a semi-subsistence crop. On average, in our sample 42% of the harvest is kept for household consumption. Hence, productivity growth through TC technology directly contributes to better food availability at the household level. Second, in the local context, banana is considered a security crop, which – in contrast to crops with seasonal production peaks – provides food and income more or less continuously throughout the year. TC technology further contributes to this security function and reduces actual and perceived household vulnerability to consumption shortfalls. Third, banana has traditionally been a woman's crop, so that – compared to typical cash crops – women have more control over production and income. We have no evidence that TC adoption has changed gender roles within households, although the data did not allow us to analyze this aspect in greater detail.

Genetically modified cotton

Cotton is grown by millions of smallholder farmers in Asia and Africa. As a non-food cash crop it does not contribute to subsistence consumption, but it is a major income source for the households and can therefore contribute to food and nutrition security through the cash income pathway. Cotton is plagued my several pests and diseases that can cause major crop losses, especially in the tropics and subtropics. To reduce crop losses, farmers in most cotton-growing regions also use substantial amounts of chemical pesticides. In the 1990s, genetically modified cotton with inbuilt resistance to major insect pests was developed. This cotton contains genes from *Bacillus thuringiensis* (Bt), which is why it is also called Bt cotton. Over the last 15 years, Bt cotton was commercialized and adopted in many parts of the world, including by smallholders in China, India, Pakistan, Burkina Faso, and several other developing countries.

Studies have shown that Bt cotton adoption reduces pesticide use and increases yields and incomes for smallholder farmers (Qaim 2009; Kathage and Qaim 2012). However, impacts on food security and nutrition had not been analyzed until recently. We addressed this research by analyzing nutrition effects for smallholder farm households in India (Qaim and Kouser 2013). Despite rapid economic growth, India is the country with the largest number of undernourished people worldwide. Bt cotton was first commercialized in India in 2002. By 2013, over 7 million farmers had adopted this technology on 95% of the country's total cotton area. For the analysis, we used comprehensive panel survey data and food consumption based measures to analyze effects of Bt adoption on calorie and nutrient consumption.

For the survey, we had randomly selected over 500 cotton-growing farm households in central and southern states of India. The sample households were surveyed repeatedly in four waves between 2002 and 2008. Using a structured questionnaire, households were interviewed about input-output details in cotton production, other economic activities, and their broader demographic and socioeconomic conditions. Sample households grew around 2 ha of cotton on average. Most of them were relatively poor; annual per capita incomes ranged between 300 and 500 US$.

The questionnaire also included a food consumption module, where household food consumption from all sources (purchases, own production, transfers etc.) was recorded over a 30-day recall period. This is a long recall period for nutritional analysis, but respondents found the questions relatively easy to answer, because grains, pulses, and other non-perishable foods are often purchased on a monthly basis. The household-level consumption data, together with local food composition tables, were used to calculate calorie consumption levels per adult equivalent (AE). Results show that Bt adopting households consumed significantly more calories than non-adopting households, and a smaller proportion of them was food insecure, defined as consumption below the safe minimum daily intake of 2300 kilocalories (kcal) per AE (Figure 4).

However, this simple comparison may suffer from selection bias. For instance, Bt adopting households may have larger farms, more favorable agroecological conditions, better education, or other characteristics that contribute to higher incomes and consumption, so that the calorie differences observed may not be due to Bt adoption alone. To control for such confounding factors, the panel structure of our data was of particular advantage. Since we had observed households in the sample before and after Bt adoption, we were able to use differencing techniques, namely panel regression models with household fixed effects. Differencing within households eliminates systematic, time-invariant differences that may exist between Bt technology adopters and non-adopters, so that they can no longer bias the impact estimates.

Results of these model estimates are shown in Table 2. Column (1) reveals that each ha of Bt cotton has increased total calorie consumption by 74 kcal per AE and day. This consumption effect results from higher cash incomes allowing more purchases of food. For the average adopting household with close to 2 ha of Bt cotton, the net effect is 145 kcal per AE, implying a 5% increase over mean calorie consumption in non-adopting households. Most of the calories consumed in rural India stem from cereals that are rich in carbohydrates but less nutritious in terms of protein and micronutrients. Yet the results in column (2) show that Bt adoption has also significantly increased the consumption of calories from non-staple foods such as pulses, fruits, vegetables, and animal products. This is a clear indication of improved dietary quality. Further computations with these estimates suggest that Bt cotton adoption has reduced food insecurity by 15-20% among cotton-growing farm households in India.

Beyond what we reported in Qaim and Kouser (2013), we also used the food recall data to calculate consumption levels of important micronutrients – such as iron, zinc, and vitamin A – in cotton-growing households. Furthermore, we estimated additional regression models to establish the net effects of Bt technology adoption on micronutrient consumption. These additional estimates are shown in columns (3) to (5) of Table 2. Bt adoption has significantly increased the consumption of all three micronutrients. For iron and zinc, the percentage increase is similar to that of calories. This is not surprising, because cereals and pulses that provide a large share of the calories are also the main sources of iron and zinc in the local diets. Interestingly, however, the percentage increase in vitamin A consumption is double as high. The most important sources of beta-carotene and vitamin A are higher-value foods such as vegetables, fruits, and animal products, the consumption of which was obviously increased over-proportionally through Bt cotton adoption. This underlines that income gains from cash crop production can be an important avenue for improvements in dietary diversity and quality.

While we did not further analyze the health effects resulting from these nutritional improvements in cotton-growing households, we analyzed the health effects resulting from reductions in chemical pesticide sprays. Bt adoption in India has lowered pesticide applications in cotton by 50%. Using our panel data we showed that this has reduced the incidence of acute farmer pesticide poisoning by several million cases per year (Kouser and Qaim 2011).

Biofortified crops

Biofortification is the breeding of staple crops for higher levels of micronutrients in order to reduce micronutrient malnutrition among the poor. The potential of this new technology is especially large in rural areas, where other existing micronutrient interventions are often less successful or more costly (Bouis and Welch 2010). Several initiatives to develop biofortified crops through conventional breeding and the use of genetic engineering were started recently, including the HarvestPlus Program and the Golden Rice Project. Most biofortified crops are still in the research and development pipeline, so that impacts on nutrition cannot yet be observed. However, a number of ex ante studies were carried out to analyze potential impacts of different biofortified crops in different countries (Qaim et al. 2007; Meenakshi et al. 2010; De Steur et al. 2012). Most of these studies used a disability-adjusted life years (DALYs) approach to quantify the potential health effects resulting from higher micronutrient intakes.

We carried out ex ante studies to assess the potential impacts of biofortified rice and wheat in India (Qaim et al. 2007; Stein et al. 2008), where deficiencies of iron, zinc, and vitamin A constitute serious public health problems. Rice and wheat biofortified with iron and zinc are developed by the HarvestPlus Program. Rice biofortified with provitamin A is developed by the Golden Rice Project. So far, biofortified varieties were not released in India, but they may become available to farmers and consumers in the next few years.

Data about food consumption and other important nutrition and health parameters required for the analysis were taken from nationally representative statistics. Based on these data, the number of DALYs lost due to iron, zinc, and vitamin A deficiency were calculated without biofortification. These measures of the current health burden of micronutrient malnutrition in India are shown in Figure 5. Iron deficiency causes an annual loss of 4.0 million DALYs, mostly due to impaired physical and mental development in children. Zinc deficiency cause a loss of 2.8 million DALYs due to stunting, child mortality, and infectious diseases. Vitamin A deficiency causes a loss of 2.3 million DALYs, primarily due to child mortality and to a lesser extent eyesight problems.

In a next step, we generated scenarios of how this situation might change with the introduction of biofortified rice and wheat. Assumptions about technological parameters and future coverage of biofortified varieties were made based on expert interviews and existing data about the diffusion of agricultural technologies in India. Based on these data, two impact scenarios were constructed – one with more optimistic and the other with more pessimistic assumptions. For these scenarios with biofortification, the number of DALYs lost was recalculated. Because of the additional micronutrients contained in biofortified rice and wheat, health problems will be reduced, resulting in a lower number of DALYs lost, as also shown in Figure 5. Under optimistic assumptions, biofortified rice and wheat varieties could more than halve the health burden of micronutrient malnutrition in India. Even under pessimistic assumptions, the reduction is still significant, ranging between 9-19%.

These findings suggest that biofortification can be an effective way to reduce nutrition and health problems. The differences in impacts between the two scenarios are mainly due to the underlying assumptions on micronutrient contents in the grain and coverage rates of biofortified varieties. Since these parameters can still be influenced through further research and awareness policies, the results also demonstrate that public support is important for increasing the positive impacts.

We also carried out cost-effectiveness studies by calculating the cost per DALY saved through biofortification. On the cost side, we considered the cost of research, development, variety testing, and dissemination. For all three micronutrients considered, the cost per DALY saved was estimated below 20 US$, even under pessimistic assumptions, which underlines the high cost-effectiveness that biofortification could have (Qaim et al. 2007). Generally, health interventions are classified as cost-effective when their cost per DALY saved is lower than 200 US$.

Ex ante studies that were carried out for other biofortified crops and in other developing countries come to the same general conclusions: biofortification can be a very cost-effective strategy to address nutrition and health problems associated with micronutrient deficiencies among the rural poor (Meenakshi et al. 2010; De Steur et al. 2012). Ex post research on biofortification impacts is hardly available yet, but the first randomized intervention studies confirm that biofortification is effective in terms of improving micronutrient status (Hotz et al. 2012).

Conclusion

Issues of food and nutrition security and related health problems are ranking high on the policy agenda. This is good, because hunger and malnutrition are widespread in developing countries with insufficient progress over the last 20 years. Many of the undernourished people are smallholder farmers, so that agricultural innovations, both technical and institutional, could play a key role in terms of improving their nutrition and health. However, relatively little is known about the nutrition and health impacts of agricultural innovations at the micro level. While there is a large body of literature on the adoption and impacts of agricultural technologies, most studies look at yield and income effects, which is insufficient to draw conclusions about nutrition. We have argued that impact studies should be broadened to include nutrition and health effects. This is important not only for innovations that are aimed at improving nutrition, but also for other innovations that may unintendedly affect nutrition and health through resource reallocation, changing gender roles, or other unexpected pathways.

In this article, we have discussed methods and metrics that can be used for the analysis of nutrition and health impacts. All approaches have their strengths and weaknesses, so that the choice should be made case by case, depending on the concrete questions to be addressed. We have also reviewed selected empirical studies to demonstrate how the metrics and methods can be used in practice. The relatively few existing studies are instructive, but there is much scope for further conceptual and methodological improvement. Future studies should not only try to measure nutrition and health outcomes of innovations in a rigorous way, but also model impact mechanisms and pathways more explicitly (Chege et al. 2014). More research in this direction could help to better understand agriculture-nutrition-health linkages, which is an important precondition for designing effective interventions and policies.

References

Babatunde, R.O., Qaim, M. (2010). Impact of off-farm income on food security and nutrition in Nigeria. *Food Policy, 35*, 303-311.

Barrett, C. (2010). Measuring food insecurity. *Science, 327*, 825-828.

Bezu, S., Kassie, G.T., Shiferaw, B., Ricker-Gilbert, J. (2014). Impact of improved maize adoption on welfare off arm households in Malawi: a panel data analysis. *World Development, 59*, 120-131.

Bouis, H.E., Eozenou, P., Rahman, A. (2011). Food prices, household income, and resource allocation: socioeconomic perspectives on their effects on dietary quality and nutritional status. *Food and Nutrition Bulletin, 32*, S14-S23.

Bouis, H.E., Welch, R.M. (2010). Biofortification – a sustainable agricultural strategy for reducing micronutrient malnutrition in the global south. *Crop Science, 50*, S20-S32.

Chege, C.G.K., Andersson, C.I.M., Qaim, M. (2014). Impacts of supermarkets on farm household nutrition in Kenya. *GlobalFood Discussion Paper, 31*, University of Goettingen.

de Haen, H., Klasen, S., Qaim, M. (2011). What do we really know? Metrics for food insecurity and undernutrition. *Food Policy, 36*(6), 760-769.

De Steur, H., Gellynck, X., Van Der Straeten, D., Lambert, W., Blancquaert, D., Qaim, M. (2012). Potential impact and cost-effectiveness of multi-biofortified rice in China. *New Biotechnology, 29*(3), 432-442.

D'Souza, A., Jolliffe, D. (2014). Food insecurity in vulnerable populations: coping with food price shocks in Afghanistan. *American Journal of Agricultural Economics, 96*(3), 790-812.

Ecker, O., Qaim, M. (2011). Analyzing nutritional impacts of policies: an empirical study for Malawi. *World Development, 39*, 412-428.

Evenson, R.E., Gollin D. (2003). Assessing the impact of the green revolution, 1960-2000. *Science, 300*, 758-762.

Fanzo, J., Hunter, D., Borelli, T., Mattei, F., Eds. (2013). *Diversifying Food and Diets: Using Agricultural Diversity to Improve Nutrition and Health*. Earthscan/Routledge, London.

Fischer, E., Qaim, M. (2012). Gender, agricultural commercialization, and collective action in Kenya. *Food Security, 4*(3), 441-453.

Fogel, R.W. (2004). *The Escape from Hunger and Premature Death, 1700-2100: Europe, America, and the Third World*. Cambridge University Press, Cambridge.

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

Gunaratna, N.S., De Groote, H., Nestel, P., Pixley, K.V., McCabe, G.P. (2010). A meta-analysis of community-based studies on quality protein maize. *Food Policy, 35*(3), 202-210.

Headey, D. (2013). Developmental drivers of nutritional change: a cross-country analysis. *World Development, 42*, 76-44.

Headey, D., Ecker. O. (2013). Rethinking the measurement of food security: from first principles to best practice. *Food Security, 5*(3), 327-343.

Hoddinott, J. (2012). Agriculture, health, and nutrition: towards conceptualizing the linkages. In: Fan, S., Pandya-Lorch, R., Eds. *Reshaping Agriculture for Nutrition and Health*. International Food Policy Research Institute, Washington DC, pp. 13-20.

Hoddinott, J., Haddad, L. (1995). Does female income share influence household expenditures? Evidence from Cote D'Ivoire. *Oxford Bulletin of Economics and Statistics,* 57, 77-96.

Hotz, C., Loechl, C., Lubowa, A., Tumwine, J.K., Ndeezi, G., Masawi, A.N., Baingana, R., Carriquiry, A., de Brauw, A., Meenakshi, J.V., Gilligan, D.O. (2012). Introduction of beta-carotene-rich orange sweet potato in rural Uganda resulted in increased vitamin A intakes among children and women and improved vitamin A status among children. *Journal of Nutrition, 142*(10), 1871-1880.

Huang, J., Pray, C., & Rozelle, S. (2002). Enhancing the crops to feed the poor. *Nature, 418*, 678-684.

Imbens, G.W., Wooldridge, J.M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature, 47*, 5-86

Jensen, R.T., Miller, N.H. (2010) A revealed preference approach to measuring hunger and undernutrition. *NBER Working Paper, 16555*, National Bureau of Economic Research, Cambridge, MA.

Jones, A.D., Shrinivas, A., Bezner-Kerr, R. (2014). Farm production diversity is associated with greater household dietary diversity in Malawi: findings from nationally representative Data. *Food Policy* 46: 1-12.

Kabunga, N.S., Dubois, T., Qaim, M. (2014). Impact of tissue culture banana technology on farm household income and food security in Kenya. *Food Policy, 45*, 25-34.

Kathage, J., Qaim, M. (2012). Economic impacts and impact dynamics of Bt (*Bacillus thuringiensis*) cotton in India. *Proceedings of the National Academy of Sciences USA, 109*, 11652-11656.

Keding, G.B., Msuya, J.M., Maass, B.L., Krawinkel, M.B. (2012). Relating dietary diversity and food variety scores to vegetable production and socio-economic status of women in rural Tanzania. *Food Security, 4*, 129-140.

Kouser, S., Qaim, M. (2011). Impact of Bt cotton on pesticide poisoning in smallholder agriculture: a panel data analysis. *Ecological Economics, 70*, 2105-2113.

Masset, E., Haddad, L., Cornelius, A., Isaza-Castro, J. (2012). Effectiveness of agricultural interventions that aim to improve nutritional status of children: systematic review. *British Medical Journal, 344*, d8222.

Maxwell, D., Vaitla, B., Coates, J. (2014). How do indicators of household food security measure up? An empirical comparison from Ethiopia. *Food Policy, 47*, 107-116.

McDermott, J. Grace, D. (2012). Agriculture-associated diseases: adapting agriculture to improve human health. In: Fan, S., Pandya-Lorch, R., Eds. *Reshaping Agriculture for Nutrition and Health*. International Food Policy Research Institute, Washington DC, pp. 103-111.

Meenakshi, J.V., Johnson, N.L., Manyong, V.M., De Groote, H., Javelosa J., Yanggen, D.R., Naher, F., Gonzalez, C., Garcia, J., Meng, E. (2010). How cost-effective is biofortification in combating malnutrition? An ex ante assessment. *World Development, 38*(1), 64-75.

Minten, B., Barrett, C.B. (2008). Agricultural technology, productivity, and poverty in Madagascar. *World Development 36*(5), 797-822.

Noltze, M., Schwarze, S., Qaim, M. (2013). Impacts of natural resource management technologies on agricultural yield and household income: the system of rice intensification in Timor Leste. *Ecological Economics, 85*, 59-68.

Pingali, P.L., Marquez, C.B., Palis, F.G. (1994). Pesticides and Philippine rice farmer health: a medical and economic analysis. *American Journal of Agricultural Economics, 76*, 587–592.

Qaim, M., Kouser, S. (2013). Genetically modified crops and food security. *PLOS ONE, 8*(6), e64879.

Qaim, M. (2009). The economics of genetically modified crops. *Annual Review of Resource Economics, 1*, 665-693.

Qaim, M., Stein, A.J., Meenakshi, J.V. (2007). Economics of biofortification. *Agricultural Economics, 37*(s1), 119-133.

Ruel, M.T., Alderman, H. (2013). Nutrition-sensitive interventions and programmes: how can they help to accelerate progress in improving maternal and child nutrition? *Lancet, 382*, 536-551.

Ruel, M.T. (2003). Operationalizing dietary diversity: a review of measurement issues and research priorities. *Journal of Nutrition, 133*(11), 3911S-3926S.

Shiferaw, B., Kassie, M., Jaleta, M., Yirga, C. (2014). Adoption of improved wheat varieties and impacts on household food security in Ethiopia. *Food Policy, 44*, 272-284.

Stein, A.J., Meenakshi, J.V., Qaim, M., Nestel, P., Sachdev, H.P.S., Bhutta, Z.A. (2008). Potential impacts of iron biofortification in India. *Social Science & Medicine, 66*(8), 1797-1808.

Stein, A.J., Nestel, P. Meenakshi, J.V., Qaim, M., Sachdev, H.P.S., Bhutta, Z.A. (2007). Plant breeding to control zinc deficiency in India: how cost-effective is biofortification? *Public Health Nutrition, 10*(5), 492-501.

von Braun, J., Kennedy, E., Eds. (1994). *Agricultural Commercialization, Economic Development, and Nutrition*. Johns Hopkins University Press, Baltimore, MD.

Webb, P., Kennedy, E. (2014). Impacts of agriculture on nutrition: nature of the evidence and research gaps. *Food and Nutrition Bulletin, 35*(1), 126-132.

Wu, F., Groopman, J.D., Pestka, J.J. (2014). Public health impacts of foodborne mycotoxins. *Annual Review of Food Science and Technology, 5*, 351-372.

Figure 1. Impacts of agricultural innovations on nutrition and health in farm households

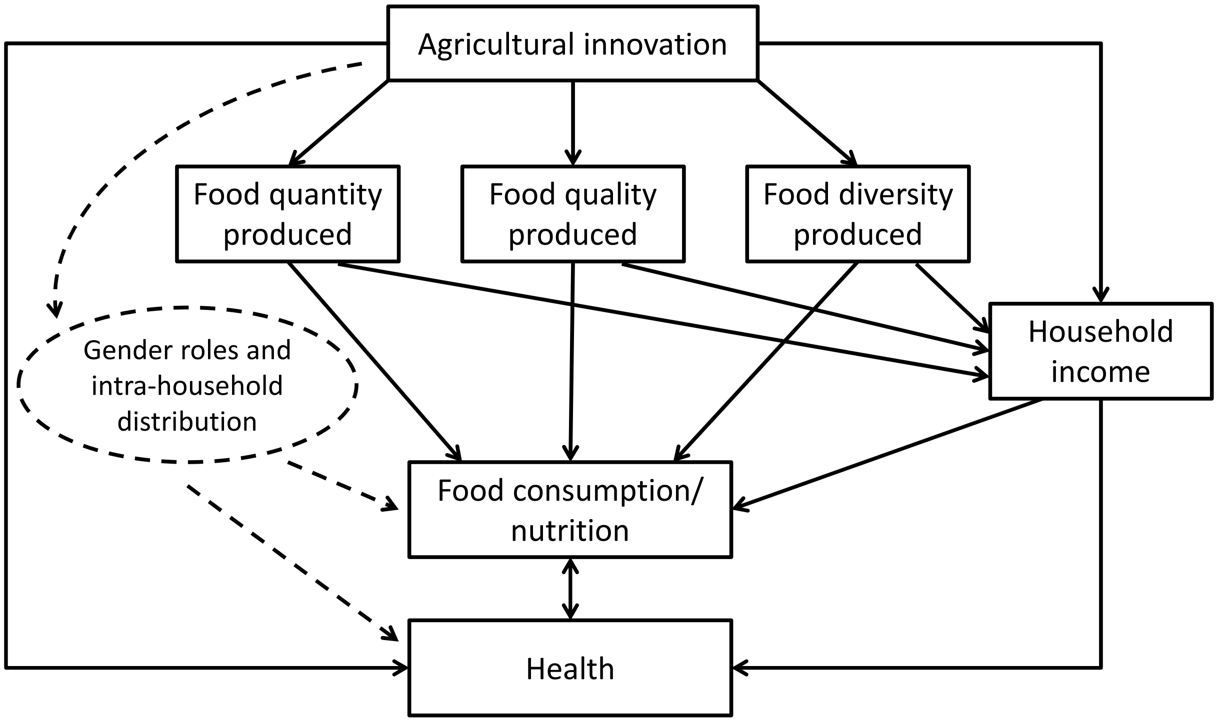
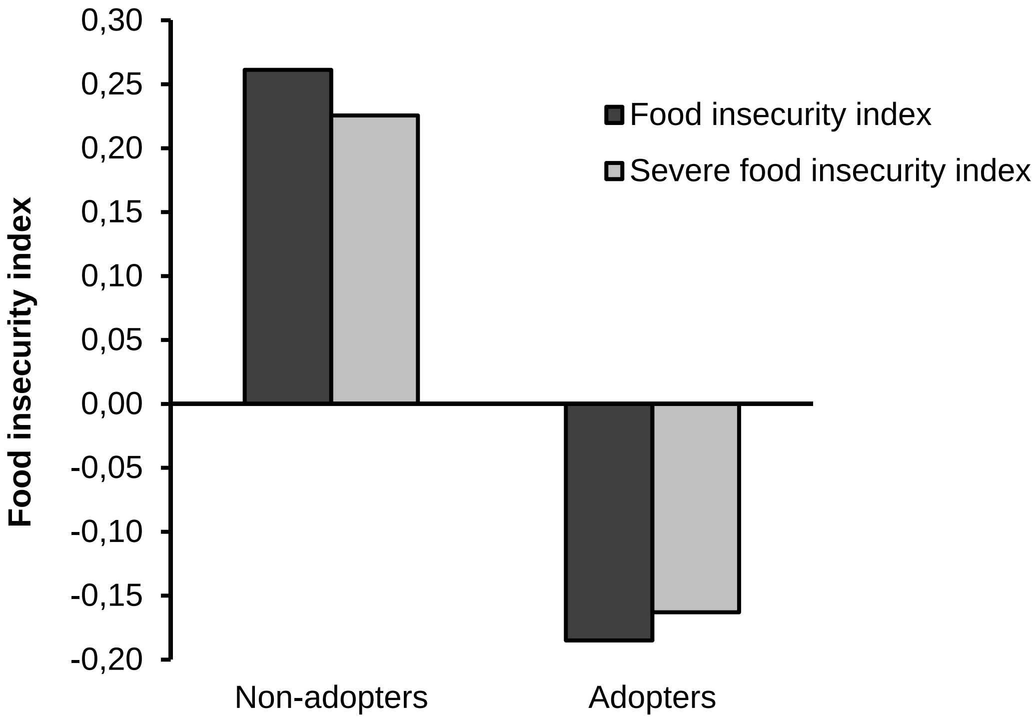
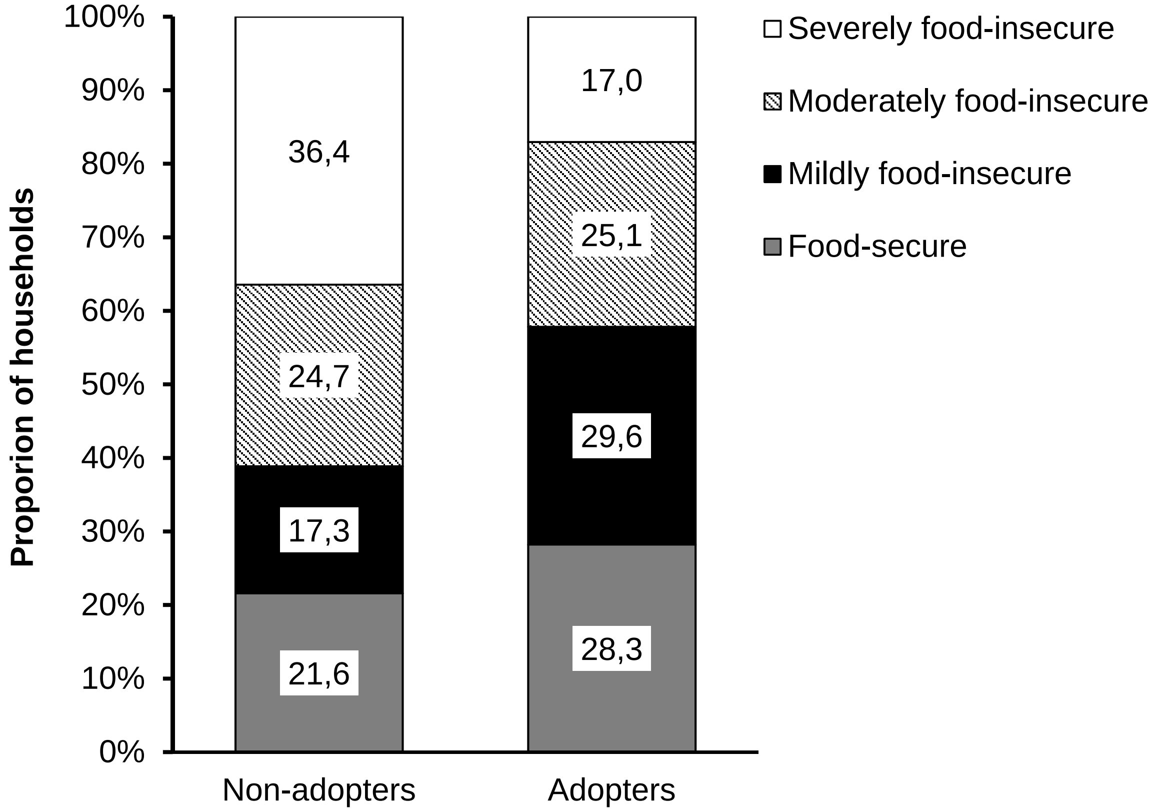


Figure 2. Relative food insecurity among adopters and non-adopters of TC banana technology



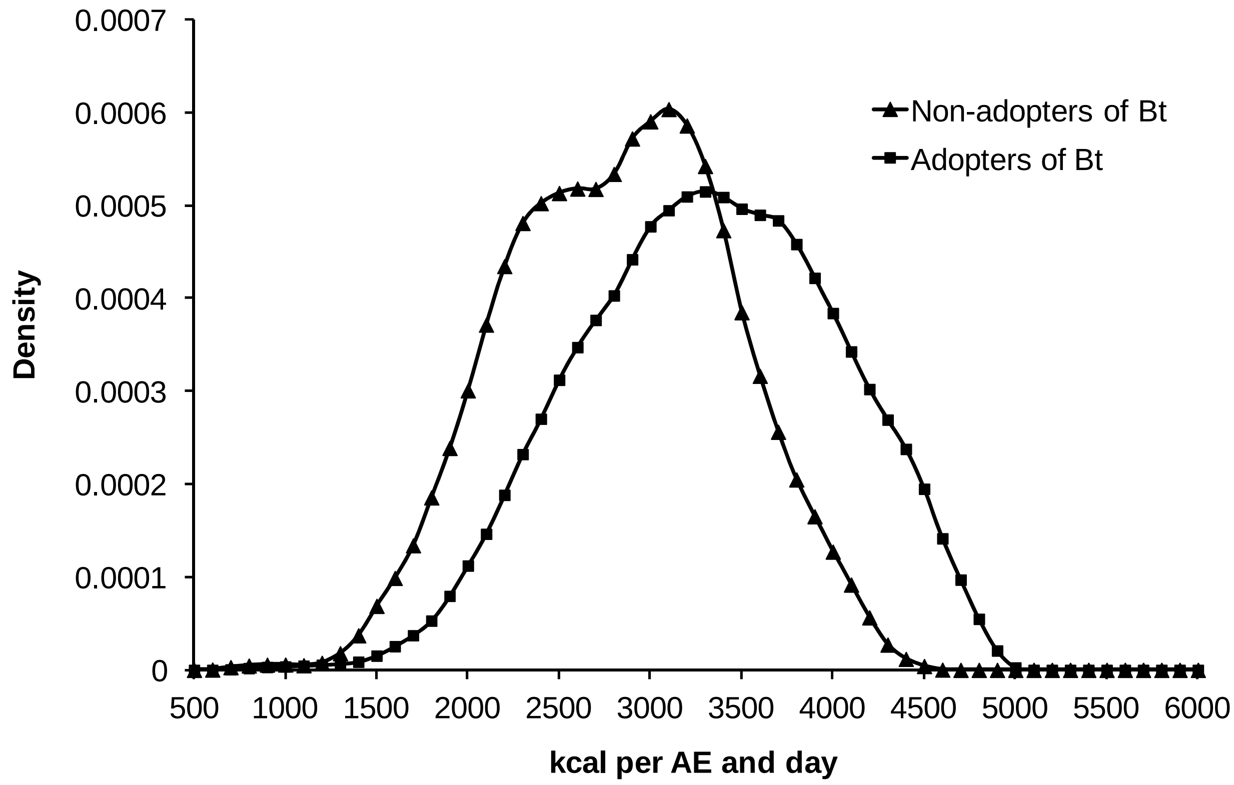
Source: Kabunga et al. (2014).

Figure 3. Proportion of food-insecure households among adopters and non-adopters of TC banana technology



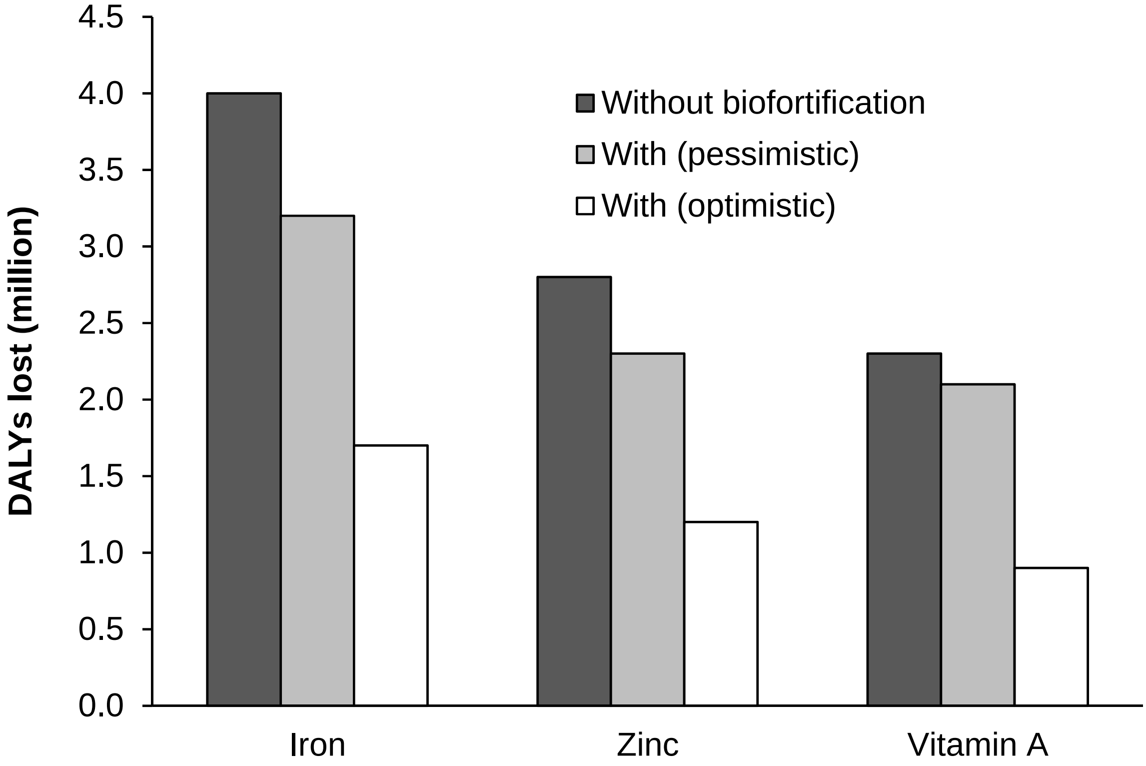
Source: Kabunga et al. (2014).

Figure 4. Distribution of household calorie consumption for adopters and non-adopters of Bt cotton technology



Source: Qaim and Kouser (2013).

Figure 5. DALYs lost in India due to micronutrient deficiencies with and without biofortification



Source: Own presentation based on Qaim et al. (2007).

Table 1. Estimated impacts of TC banana adoption on food insecurity

	Food insecurity index	Severe food insecurity index
TC banana adoption (dummy)	-0.437*** (0.127)	-0.316*** (0.102)
Education (years of schooling)	-0.032** (0.013)	-0.019 (0.013)
Age (years)	0.002 (0.004)	0.007* (0.004)
Household size (members)	0.072*** (0.024)	0.040 (0.028)
Assets (value)	-0.001*** (0.000)	-0.001*** (0.000)
Credit constraint (dummy)	0.675*** (0.093)	0.487*** (0.099)
Constant	-0.044 (0.362)	-0.354 (0.356)

Notes: Coefficient estimates of instrumental variable (treatment effects) models are shown with robust standard errors in parentheses. Not all covariates included in estimation are shown for brevity. Full results are provided in Kabunga et al. (2014). *, **, *** Significant at the 10%, 5%, and 1% level, respectively.

Table 2. Estimated impacts of Bt cotton adoption on calorie and nutrient consumption

	(1) Total calories (kcal/AE)	(2) Non-staple calories (kcal/AE)	(3) Iron (mg/AE)	(4) Zinc (mg/AE)	(5) Vitamin A (µg/AE)
Bt cotton adoption (ha)	73.71*** (21.40)	23.17** (10.05)	0.57*** (0.20)	0.30*** (0.10)	15.54** (6.16)
Farm size (ha)	-0.69 (7.80)	1.97 (3.56)	0.05 (0.08)	0.03 (0.04)	-0.03 (1.46)
Off-farm income ($)	0.05*** (0.02)	0.01* (0.007)	5.2E-4** (0.00)	2.4E-4** (0.00)	0.01 (0.01)
Household size (AE)	-89.46*** (14.43)	-29.33*** (6.89)	-0.68*** (0.15)	-0.36*** (0.07)	-21.40*** (2.81)
2004 (dummy) [a]	-5.98 (51.60)	-45.25* (25.33)	0.46 (0.50)	-0.08 (0.25)	-104.17*** (11.34)
2006 (dummy) [a]	30.09 (61.12)	-112.87*** (29.41)	-1.79*** (0.67)	-0.70** (0.33)	-77.17*** (15.92)
2008 (dummy) [a]	-74.59 (69.51)	-72.70** (30.20)	-2.00*** (0.75)	-1.38*** (0.36)	-33.14** (16.09)
Constant	3537.08*** (78.16)	843.23*** (41.42)	29.64*** (0.82)	15.89*** (0.41)	492.96*** (17.13)
Predictions of Bt effects for average adopting household					
Absolute change	145.19***	45.70**	1.12***	0.59***	30.61**
Change in percent	5.13***	7.15**	4.58***	4.51***	9.59**

Notes: Coefficient estimates of panel fixed effects models are shown with robust standard errors in parentheses. All dependent variables are expressed as daily consumption values per adult equivalent (AE). Estimates in columns (1) and (2) are from Qaim and Kouser (2013) [a] The reference year is 2002. *, **, *** Significant at the 10%, 5%, and 1% level, respectively.