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IFPRI Discussion Paper 00740

December 2007

Genetically Modified Food and International Trade

The Case of India, Bangladesh, Indonesia, and the Philippines

Guillaume Gruère
Antoine Bouët
and
Simon Mevel

Environment and Production Technology Division
and
Markets, Trade and Institutions Division

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ABSTRACT

Genetically modified (GM) food crops have the potential to raise agricultural productivity in Asian countries, but they are also associated with the risk of market access losses in sensitive importing countries. We study the potential effects of introducing GM food crops in Bangladesh, India, Indonesia, and the Philippines in the presence of trade-related regulations of GM food in major importers. We focus on GM field crops (rice, wheat, maize, soybeans, and cotton) resistant to biotic and abiotic stresses, such as drought-resistant rice, and use a multi-country, multi-sector computable general equilibrium model. We build on previous international simulation models by improving the representation of the productivity shocks associated with GM crops, and by using an improved representation of the world market, accounting for the effects of GM food labeling policies in major importers and the possibility of segregation for non-GM products going toward sensitive importing countries.

The results of our simulations first show that the gains associated with the adoption of GM food crops largely exceed any type of potential trade losses these countries may incur. Adopting GM crops also allows net importing countries to greatly reduce their imports. Overall, we find that GM rice is bound to be the most advantageous crop for the four countries. Second, we find that segregation of non-GM crops can help reduce any potential trade loss for GM adopters, such as India, that want to keep export opportunities in sensitive countries, even with a 5 percent segregation cost. Lastly, we find that the opportunity cost of segregation is much larger for sensitive importing countries than for countries adopting new GM crops, which suggests that sensitive importers will have the incentive to invest in separate non-GM marketing channels if exporting countries like India decide to adopt GM food crops.

Keywords: genetically modified food, international trade, segregation, Asia

1. INTRODUCTION

In the last 11 years, the global production of genetically modified (GM) crops has increased dramatically. Yet more than 95 percent of the area devoted to GM crops is located in only four countries: the United States, Argentina, Canada, and China (James 2006). During the same period, a group of countries with consumer opposition to GM food, led by the European Union (EU) and Japan, have implemented stringent policies regulating the approval and import of GM crops and the marketing of GM food. In the context of increased international agricultural trade, the regulations of those importers and the lack of demand for GM food in those countries have likely limited the expansion of agricultural biotechnology to many developing countries.

For several years, a number of Asian countries have been actively developing programs of research on agricultural biotechnology, focusing on GM crops with potentially beneficial agronomic traits (Runge and Ryan 2004). Some of these countries have developed biosafety regulatory frameworks, but until now only a few have approved one or more GM crops. Recent studies have shown that the introduction of Bt cotton (GM cotton resistant to insects) in India and China has generated revenue gains for farmers overall (e.g., Pray et al. 2002; Bennett et al. 2004). But those two countries approved only the large-scale production of GM cotton, in part because unlike other GM crops, the main products of cotton are not used for food and thus are not subject to food safety approval, traceability, and labeling regulations or GM-free private standards in major importing countries. In particular, neither Japan nor the EU directly regulates textile products derived from GM cotton.

In fact, the fear of export loss is a major driver in the reluctance to use GM technology in developing countries (Paarlberg 2002; Gruere 2006). That fear may be driven by large traders in exporting countries afraid to lose market access. Following a detection of unapproved U.S. GM rice in EU and Japanese markets, prompting rapid import bans, Thailand and Vietnam, two of the largest rice exporters, announced that they would remain GM-free and would not approve any GM rice. Rice exporters in India have argued against field-testing of GM rice for similar reasons. But the fear is also patent in countries importing current or potential GM crops. In many cases such fears are largely exaggerated and based on misinformation or a poor knowledge of the global trade system by biotechnology governing bodies. Paarlberg (2006) shows that African countries have virtually no export to lose from adopting current GM crops. Smythe, Kerr, and Davey (2006) show that despite claims by GM crop opponents, major exporters that adopted GM crops in the 1990s have experienced no loss in export value or volume; rather, their exports have been diverted to other markets. Several ex ante simulation models have also shown that China or Sub-Saharan Africa are bound to gain largely from adopting GM food or feed crops even with bans in large importing nations (Huang et al. 2004; Anderson and Jackson 2005). Lastly, the fear is also based on the mistaken idea that segregating GM and non-GM crops is infeasible or prohibitively costly. In fact, virtually all large GM-food- or feed-producing countries (the United States, Canada, Argentina, Brazil, South Africa) produce alternative non-GM crops, and even organic crops for domestic and/or international markets.

In this context, many Asian countries that have invested in research and regulations on GM food crops are confronted with what they see as three possible alternatives: (1) allow the production of GM food crops with the risk of losing potential exports; (2) reject the commercialization of any GM food crop; or (3) produce both GM and non-GM crops separately at a marketing cost.

The purpose of this paper is to provide an integrated economic assessment of these three strategies focusing on India, Bangladesh, Indonesia, and the Philippines—four countries that the agricultural biotechnology and trade literature has largely ignored. More specifically, the paper has two main objectives. First, the study assesses the impacts of large importers' regulations (such as the EU and Japan) on the potential benefits of adopting particular GM crops in the four countries. Second, we evaluate the opportunity cost of GM/non-GM segregation for such crops under the external constraints previously defined. We focus on four major traded commodities—rice, wheat, maize, and soybeans—but we also include cotton and its derived cottonseed. For each crop, we select a set of biotic or abiotic stress resistance traits (such as insect resistance or drought resistance) according to the status of research, and the productivity and income potential they promise in these four countries.

We build on previous literature using computable general equilibrium models by improving the representation of trade policies and refining the assumptions on the productivity effects of biotechnology. First, we account for the "trade filter" effect of GM food marketing policies in GM-food-sensitive countries, which allow the importation of products for intermediate consumption (as exceptions to the labeling policies) but not products for final consumption. Second, we include the option of costly segregation of non-GM crops for export, and we model GM crop adoption as a factor-biased productivity shock based on disaggregated data on agricultural constraints. These assumptions help us to obtain robust estimates of the economic effects of adopting GM crops in Bangladesh, India, Indonesia, and the Philippines under current trade regulations, and they allow us to derive the opportunity cost of segregation of GM and non-GM crops.

The paper is organized as follows. In the next section we briefly review the literature on global trade modeling of GM food introduction. Then, we describe the methodology employed to derive productivity shifts with the adoption of particular GM crops in the four countries. In the fourth section we explain the specificities of our trade model and present our scenarios. The results of the simulations are presented in section 5 and discussed in section 6. We close the paper with a few policy conclusions.

2. PREVIOUS LITERATURE

Since 2000, many papers have used multi-country computable general equilibrium (CGE) models to simulate the introduction of GM crops under various international scenarios. In their review of the applied economic literature on GM crops in developing countries, Smale et al. (2006) found 14 articles following this approach and focusing on developing countries. Each paper uses a modified version of a CGE model based on the Global Trade Analysis Project (GTAP) database (Hertel 1997) that includes vertical and horizontal linkages in the economy to examine the effects of GM technology adoption on multiple sectors and regions. The papers and approaches differ in their assumptions about the productivity effects of the technology, in their assumptions about the rate of adoption, and according to the scenarios they depict concerning trade policies, consumer perceptions, and market assumptions. In this section, we do not provide a complete review of the literature; instead we concentrate our attention on some of the relevant CGE studies on GM crop adoption in developing nations, particularly those that focus on Asian countries.

First, at a global scale, Nielsen, Robinson, and Thierfelder (2001) studied the introduction of GM oilseeds and grains in seven regions. They modeled the technology with a 10 percent Hicks-neutral productivity shift of primary factors, with costless segregation of GM and non-GM food in all countries and consumer price sensitivity differences. They find that the total welfare (as measured in terms of absorption) would increase by $12 billion with the adoption of GM maize and oilseeds in selected countries, but it could be reduced by $1 billion if consumers had a preference for non-GM food. Nielsen and Anderson (2001) later used a 5 percent productivity shift with the adoption of GM grains and oilseeds and ran three scenarios: first, the adoption of GM crops with no trade constraints; second, a ban of GM crops in western Europe; and third, a shift in consumer preference away from GM crops in western Europe. They obtain a lower range of global welfare effects with $9.9 billion in the first scenario, $3.4 billion in the second with a trade ban, and $8.5 billion in the case of the preference shift. Although most of the relative welfare loss with trade restriction or demand change is attributed to Europe, these two studies demonstrate the importance of European policies on potential gains from GM crop technology.

Several papers focus on China. Anderson and Yao (2003) simulated the introduction of GM rice, cotton, maize, and oilseeds in a number of countries with or without China, using a 5 percent Hicks-neutral productivity shift. They also include a scenario that eliminates the Chinese voluntary export restraint on textile. The results show that China would largely benefit from introducing GM rice before any other crop, and that a voluntary export restraint removal would multiply by 20 the benefits from Bt cotton. Huang et al. (2004) analyzed the effects of GM cotton and GM rice introduction in China, based on regional farm-level survey data, adding labeling costs, loss of demand in export markets, and dynamic adoption, but without adoption of these crops in other countries. Their results show that China can continue to benefit from an extended adoption of Bt cotton, but that it would benefit even more from the introduction of GM rice, whose formal approval decision has been postponed by regulatory authorities in the last few years.

Other studies focus on Sub-Saharan Africa. Anderson and Jackson (2005) use a factor-biased productivity shift to look at the effect of GM coarse grains, oilseeds, wheat, and rice in Sub-Saharan Africa with and without trade restrictions. They show that Sub-Saharan Africa would gain as much with or without a GM ban in the EU, but that imposing a moratorium on GM imports and production in the EU would result in significant losses worldwide. Anderson, Valenzuela, and Jackson (2006) evaluate the effect of Bt cotton introduction in Sub-Saharan Africa with and without World Trade Organization trade reform and show that the effects of GM cotton adoption could exceed those of a trade reform for Sub-Saharan African countries.

Lastly, a few studies focus on the effect of GM rice introduction in multiple countries. Anderson, Jackson, and Nielsen (2004) provide an analysis of GM rice and golden rice (nutritionally enhanced) adoption in multiple countries, using factor-biased productivity shifts and running various trade scenarios. They show that golden rice could provide a much bigger boost to countries adopting it due to its assumed effect on overall labor productivity in all sectors. Focusing on productivity-enhancing traits, Hareau et al. (2005) evaluate the effects of three different GM rice events (Bt, herbicide tolerant, and drought tolerant) with factor-biased productivity shifts, accounting for intranational differences in land type, providing a convincing approach to productivity modeling. Their results show that if the benefits of the three technologies are similar overall, the distribution of benefits highly depend on the particular trait.

Table 1. Ranges of welfare effects ($ million/yr) experienced by India, China, and the world overall obtained by selected CGE studies of the introduction of GM crops

Crop	India		China, with adoption of GM crops	World
	India does not adopt, others do	India adopts, others do		
Maize and soybeans	0 to 3	1265 to 1277	804 to 839	-1287 to 9859
Cotton	-26 to -41	710 to 822	314 to 563	856 to 2610
Rice	-18 to -23	458 to 709	190 to 4155	-5452 to 4887
Golden rice	n.a.	2528	7209	17438
Maize, soybeans, rice and wheat	n.a.	654 to 669	832 to 841	-946 to 7506

Sources: Ranges of estimates obtained from a combination of Anderson and Yao (2003); Anderson and Jackson (2005); Anderson, Jackson, and Nielsen (2004); Anderson, Valenzuela, and Jackson (2006); Hareau et al. (2005); Elbehri and MacDonald (2004); Huang et al. (2004); and Nielsen and Anderson (2001).

Table 1 provides ranges of estimates of the welfare effects India, China, and the world overall would see under the adoption of GM crops, drawn from previous literature under various scenarios. The large variance in results is naturally due to the diversity of scenarios and assumptions, in particular regarding productivity shifts and international trade. Still, a few general lessons can be drawn from observing these results. First, India seems to be better off adopting GM crops than rejecting them when other countries adopt them. Second, apart from the specific study on golden rice, it is difficult to draw general lessons about the relative advantage of different GM crops. Third, the world can lose with GM food or feed crop adoption under certain scenarios.

In their review of the literature focusing on research methodologies, Smale et al. (2006) note that CGE studies of GM crop introduction have progressively improved over time with a better representation of productivity shifts, from Hicks-neutral productivity shifts based on relatively general assumptions to factor-biased productivity shifts based on specific trait and regional differences (e.g., Elbehri and McDonald 2004; Hareau et al. 2005; Huang et al. 2004), and more complex trade policy representation (e.g., van Meijl and van Tongeren 2004; Anderson et al. 2006). Overall the improvement of the assumptions on productivity shifts has translated into a relative diminution of the results in terms of global welfare effects for current GM crops.

In this paper, we build on previous analysis by proposing an incremental improvement in three regards. First, as explained in the next section, we provide regionally based productivity in the countries we focus on. Second, as explained in section 4, we provide a more complex representation of the international market regulations. Third, we combine our analysis for our countries of study with assumptions on other countries reflecting the observed effects derived in published papers.

At the same time, we focus on four countries—India, Bangladesh, Indonesia, and the Philippines—that have largely been excluded from previous reports. Only Hareau et al. (2006) studied the effects of GM rice in these and other Asian countries, taking into account land type and technology differences but excluding trade restrictions. Most other studies only aggregated developing nations of Asia into China, India, and the rest of Asia. We aim to provide additional insights into the possible effects of GM food in these four populous countries of Asia.

3. PRODUCTIVITY MODELING

Predicting the effect of a future technology is not trivial; it necessarily relies on a careful analysis of available information based on the current situation, and on the determination of plausible scenarios. In the setting of global trade modeling, one single parameter standing for a productivity shift of a country or region will represent a complex agro-economic process that implicitly should derive from the local agronomic constraints, the local agronomic practices, the local likelihood of adoption of the new technology (based on its availability, price, input markets, and extension systems), and the local adaptation of the new technology.

In this paper, we attempt to take one step forward in this direction by modeling GM technology introduction with factor-biased productivity shifts (including yield, chemical use, and labor effects) using spatially disaggregated estimates of technology potential and adoption rates combined into national aggregate effects of technology in India, Bangladesh, Indonesia, and the Philippines. We also use expert data to formulate scenarios of adoptions accounting for plausible differences across types of land. This overall process is intended to help reduce uncertainties and replace what may appear as arbitrary productivity shifts by more consistent and plausible ones. In this section, we explain the successive steps of the method used to derive our assumed productivity shifts in the four countries of study.

A) Collection of Expert and Secondary Data on Constraints and Technology Potential

We conducted a series of consultations and focus group meetings with scientific, agricultural, and regulatory experts in India and Bangladesh in July 2005 and Indonesia and the Philippines in September 2005 on the potential effects of biotechnology improvements to resist biotic and abiotic stresses. In total, 10 meetings were held in five cities in India (Delhi, Bombay, Bangalore, Hyderabad, and Calcutta), two meetings in two locations in Bangladesh (Dhaka and Mymensingh), four meetings in Indonesia (in Bogor, Java), and four meetings in the Philippines (in Luzon). In each such meeting we discussed the status of research, agricultural constraints for major crops of interest, the potential of biotechnology to address those constraints, and other issues related to regulatory approval and consumer acceptance of transgenic crops.1 We also asked the participants at these meetings to fill out questionnaires in order to elicit subjective estimates of potential yield and input effects of future new technologies (as done for rice in Evenson, Herdt, and Hossain 1996). In parallel, we obtained existing national and international studies of GM technology, productivity constraints, and technology potential publicly available for these and other countries.

1 We do not provide an analysis of the outcomes of the meetings in this paper, but we plan to provide more explanations in a longer report. The results of the consultations conducted in Bangladesh are summarized in Gruere et al. (2006).

B) Obtaining the Range of Potential Technology Yield Effects in Affected Areas[2]

The discussions in our meetings helped us decide to focus on four types of traits—insect resistance, virus/disease resistance, drought resistance, and salt tolerance applied specifically to rice, wheat, maize, and soybeans in each country. Each GM crop/trait combination is modeled based on its effect on yields and use of chemical inputs (mainly pesticides) and its assumed effect on labor. We would have liked to include the cost of seeds as a third factor, but we later realized that we did not have the proper data to incorporate it into the global model. Yet we can justify the exclusion of seed premiums by using exogenous partial adoption rates. As a consequence our results will be inclusive of the benefits of developers and not only producers.

In this subsection we describe more specifically the case of yield effects, for which we use triangular distribution of estimates, but our derivations of the input effects also follow the same general procedure. Combining expert estimates on constraints and productivity potential and secondary data on yield constraints, we derived expected yield effects in rainfed versus irrigated land in Bangladesh, Indonesia, and the Philippines and in each water basin region of India. Triangular distributions of yield constraints (or yield gap) and of the potential effects of using transgenic crops from the questionnaires and meetings are aggregated by taking the "minmin" and "maxmax" values and by averaging the most likely values (excluding clear outliers). We compute average ranges of potential effects by averaging over the most likely values of yield constraints (or yield gap) from different data sources, with the minimum and maximum values retained. The ratio of expected yield effects on yield constraints derived from experts' data is used as a proxy for the expected efficacy of the technology. This efficacy rate is multiplied by the yield gap associated with the constraint to obtain the range of most likely yield effects of the technology.

C) Affected Land and Production Type by Water Basin Projection

The resulting yield effect is multiplied by the production share for each subregion represented by a particular type of land (and water basin in India) in order to obtain a weighted average of the total yield effects for each country. To do so, we used 2015 projections of irrigated and rainfed areas by water basins in India and in each of the other three countries from a baseline simulation of the IMPACT-Water model developed at IFPRI. IMPACT-Water is a multi-market partial equilibrium model of agricultural production and trade at the water basin level that projects the evolution of land and agriculture. The combination of yield effect by subregion and share of each subregion in each country generates national average yield effects of each technology assuming a 100 percent adoption rate.

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2 In this section, we focus on our derivations of the yield effects. The derivations of the input effects were mostly based on a combination of primary and secondary data per crop/trait combination, but did not involve range calculations.

For the case of crops resistant to abiotic stresses—i.e., drought- and salt-tolerant crops—we also estimated the share of affected areas in each subregion in order to account for the fact that not all land is affected by drought or soil salinity constraints. To do so, we used categorical indicators of drought and salinity constraints by areas of production, type of land, and water basin based on a satellite imagery and agricultural study developed by the spatial team of IFPRI.[3] The measure of drought is based on the annual variation (around a three-decade average) of the length of growing period computed for each of the 30 years from 1961 through 1990 (Fischer et al. 2002). The soil salinity index is based on a Fertility Capability Classification approach (Smith et al. 1998; Sánchez, Couto, and Buol 1982) applied to the mapping units of the Food and Agriculture Organization (FAO) Soil Map of the World. (FAO 1995). The results allowed dividing the land into 10 types of categories of risk based on the share of saline land in each spatial unit.

By filtering these indicators with production area in each spatial unit, we obtained the share of affected areas in each subregion. We then built categorical yield responses to the risk of drought or salinity. For instance, in the case of drought, the IFPRI spatial team was able to classify delimited areas of land in four categories: no risk, low risk, medium risk, and high risk. We attributed probability of risk for each category (using a linear approximation) to obtain expected damage or expected yield potential due to drought in a particular subregion. The output is a weighted average of damage in each subregion representing the national effect of abiotic-stress-resistant crops with a 100 percent adoption rate among producers affected.

D) Adoption: Expert Data and Secondary Data on High-Yield Varieties Adoption

There are two ways to model adoption: it can be done endogenously or exogenously. To our knowledge, all previous simulation models used exogenous adoption rates. In this study, we also use exogenous rates, but we vary the initial adoption rates according to the type of land and subregion. In particular, we assume that producers in rainfed areas will not have the same adoption rate as producers in irrigated areas. Generally speaking, producers in irrigated areas tend to have better access to new technologies, but at the same time, rainfed producers may benefit more from certain technologies.

In addition, regional differences matter, and in a country like India certain states tend to be the first to provide and adopt new technologies and have a higher proportion of technology adopters. To account for that fact, we correct the production share of each Indian region by a proportional factor linked to historical data on the adoption of high-yielding varieties of each crop obtained from IndiaStat. Instead of assuming that a GM crop will be adopted in all regions the same way, we let certain regions be

3 The detailed mapping methodology, using an entropy approach to spatial disaggregation, is explained in detail in You and Wood (2006). Abiotic stress indicators were developed by Liang You, Stan Wood, and Cynthia Rossi, following a methodology explained in detail in IFPRI (2005) for India and Bangladesh.

relatively larger adopters of the crop. The adoption rate in each subregion is then multiplied by each yield and area factor to obtain a total expected yield effect of the technology in 2010, 2015, and 2020.

E) Obtaining Land Type Aggregate Effect and National Effects

The aggregate national effect of the technology is computed with the following formula:

$\sum_l \left(\sum_w \alpha_{lt} \beta_w \sigma_{lw} y_{lw} . \lambda_{lw} \right)$ where *l* stands for type of land (irrigated or rainfed), *w* for the water basin, and *t* for time; *α* is the exogenous adoption rate per type of land (for abiotic stress it represents the adoption among producers affected) and period; *β* is the proportional spatial correction of adoption rate based on observed rates of adoption of high-yielding varieties in each water basin; *σ* is the share of production of the crop in the subregion; *y* is the yield effect in each subregion; and *λ* is the share of production under rainfed or irrigated conditions affected by a specific abiotic stress. Ten water basins are used to represent India, while the three other countries are represented by one unit each, and therefore only disaggregated according to the type of land and time.

F) Assumptions for the Major Technologies in the Countries of Interest

Table 2. Absolute productivity effects and initial adoption assumed for Bangladesh

Bangladesh	% Yield effects			% Input effects		% Initial adoption		
Technology	Min	ML	Max	Chemicals	Labor	IR	RF	Total
DR rice	0.13	1.13	4.89	0	0	7.8	34.4	9.76
ST rice	0.39	0.57	0.81	0	0	2.96	1.9	2.88
Bt rice	0.39	0.82	1.17	-14.62	-2.56	40	20	36.56
DR wheat	0.25	0.83	1.52	0	0	8	27.4	14.75
Bt maize	0	1.38	2.50	-10	-1.88	0	25	25
DR maize	0	1.75	5.25	0	0	0	7	7
VR maize	0	2.25	5.25	-6	-1.13	0	15	15

Source: Authors.
Notes: ML = most likely, DR = drought resistant, ST = salt tolerant, VR = virus or disease resistant, IR = irrigated land, RF = rainfed land.

Table 3. Absolute productivity effects and initial adoption assumed for India

India	% Yield effects			% Input effects		% Initial adoption		
Technology	Min	ML	Max	Chemicals	Labor	IR	RF	Total
DR rice	0.30	2.58	6.69	0	0	24.55	18.4	22.43
ST rice	0.37	1.97	3.76	0	0	9.95	4.06	7.91
Bt rice	0.30	1.03	2.13	-9.5	-2.31	60	10	27.6
VR rice	0.11	0.43	0.87	-0.97	-0.4	30	5	13.8
DR wheat	0.16	1.83	2.94	0	0	1.55	8.20	5.86
ST wheat	0.15	0.67	1.13	0	0	6.3	2.51	3.84
VR wheat	0.44	3.51	8.50	-1.47	-1.10	25	5	14.73
Bt maize	1.61	3.29	5.76	-1.46	-1.02	25	5	14.57
DR maize	0.34	2.20	3.06	0	0	1.79	15.42	8.92
VR maize	0.37	1.30	2.59	-0.37	-0.18	10	5	7.39
VR soybeans	0	0.83	4.58	-0.97	-0.68	15	8	9.66

Source*:* Authors.
Notes: ML = most likely, DR = drought resistant, ST = salt tolerant, VR = virus or disease resistant, IR = irrigated land, RF = rainfed land.

Table 4. Absolute productivity effects and initial adoption assumed for Indonesia

Indonesia	% Yield effects			% Input effects		% Initial adoption		
Technology	Min	ML	Max	Chemicals	Labor	IR	RF	Total
DR rice	0	0.46	1.27	0	0	4.5	36.4	7.75
Bt rice	0.49	1.23	2.46	-7.57	-4.34	50	20	43.38
VR rice	0.01	0.51	1.17	-1.70	-1.28	15	5	12.79
Bt maize	0.15	0.35	0.79	-3.00	-1.50	15	15	15
DR maize	0.10	2.15	4.24	0	0	2.3	34.1	28.06
VR maize	0.03	0.06	0.12	0	-0.06	5	2	2.38
IR soybeans	3	8.25	18	-13.5	-1.25	0	30	30
DR soybeans	0.09	1.89	3.73	0	0	0	23	23.15
VR soybeans	0.6	5.48	18.0	-18	-3.00	0	30	30

Source: Authors.
Notes: ML = most likely, DR = drought resistant, IR = insect resistant, VR = virus or disease resistant, IR = irrigated land, RF = rainfed land.

Table 5. Absolute productivity effects and initial adoption assumed for the Philippines

Philippines	% Yield effects			% Input effects		% Initial adoption		
Technology	Min	ML	Max	Chemicals	Labor	IR	RF	Total
DR rice	0.08	1.36	3.72	0	0	3.8	33.6	13.11
Bt rice	0	0.68	1.01	-20.50	-3.20	40	15	32.02
VR rice	0	0.61	1.23	-10.01	-1.52	20	5	15.21

Source: Authors.
Notes: ML = most likely, DR = drought resistant, VR = virus or disease resistant, IR = irrigated land, RF = rainfed land.

The assumptions derived from this process for the four countries of study are presented in absolute terms at the national level in tables 2, 3, 4, and 5. The tables present the assumed effects of each technology projected in 2015, as these are the ones used as reference for the simulation model.4 The parameters presented in the tables include minimum, most likely, and maximum value of the total yield effect, the total chemical effects, and the total labor effects at the national level under the initial adoption

4 We also derived the effects and adoption for each crop in 2010 and 2020, but we did not use them in the simulations presented in this paper. We may decide to use them later within a dynamic modeling approach.

rate presented in the last three columns.5 For instance, the introduction of Bt maize (insect resistant) in Bangladesh (fifth row of Table 2) at an adoption rate of 25 percent only in rainfed areas would result in a most likely 1.38 percent yield increase, a 10 percent reduction of chemicals, and a 1.88 percent labor reduction in maize at the national level. The introduction of drought-resistant rice in India (first row of Table 3) at an initial adoption rate of 22.43 percent, corresponding to 24.55 percent of irrigated land and 18.4 percent of rainfed land, in 2015 would most likely result in a 2.58 percent increase in total rice production in India.

The results show that certain crops are more promising than others, and that all crops will likely not be adopted at the same proportional rate in each country or under each type of land. Drought-resistant crops are not designed to increase existing yield levels, but rather to help crops survive under drought conditions, acting like crop insurance. But at the aggregate level, they will provide a boost in average yields, therefore acting as yield-enhancing technologies for growers affected by drought. Because of the lack of relevant data, we assumed that crops resistant to abiotic stresses do not affect labor and chemical use, while crops resistant to biotic stresses generate labor and chemical productivity increases. Bangladesh has lower initial adoption rates in certain crops because we presume that the technology will take a longer time to spread than in India and other countries.

To translate these data into usable inputs into the multi-market CGE model, we computed the aggregated *relative* productive effects of the composite GM crops. To do so, for each crop, we first summed the national productivity effects associated with each trait, and we divided these estimates by the sum of the adoption rates of each trait. For example, in the case of the most likely relative yield effects of rice in Bangladesh, we added the most likely absolute yield effects of the three traits used for rice (shown in the first three rows in Table 2) and divided it by the sum of the respective three total adoption rates (shown at the end of the same rows in Table 2). The ratio obtained is 2.52/49.2, which is equal to 5.12 percent.6

These relative parameters are presented in Table 6, but it is important to note that they are not all meaningful even if they are directly derived from estimated adoption and yield and input effects following the methodology described in this section. For example, it does not make sense to consider the effects of 100 percent national adoption of a drought-resistant variety when the productivity effects of such a variety will be effective in only 10 percent of the land. Moreover, these numbers would represent the effects of composite GM crops, which may be developed in the future but are not the main focus of current research programs.

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5 The total adoption rates are derived as weighted averages of irrigated and rainfed land based on the IMPACT-Water model.

6 The same method is used to derive relative input effects.

Table 6. Aggregate relative productivity factors and adoption rates of the composite GM crops for the countries of study used in the simulation model

Crop	Country	% Yield effects	% Input effects		Initial adoption
			Chemicals	Labor	
Rice	Bangladesh	5.12	-29.72	-5.2	49.2
	India	8.38	-14.59	-3.78	71.74
	Indonesia	3.44	-14.50	-8.79	63.92
	Philippines	4.39	-60	-7.82	60.34
Wheat	Bangladesh	5.63	0	0	14.75
	India	24.6	-6.02	-4.5	24.43
Maize	Bangladesh	10.55	-31.37	-5.9	51
	India	21.99	-5.93	-3.89	30.88
	Indonesia	5.63	-6.6	-3.43	45.44
Soybeans	India	8.59	-10.04	-7.04	9.66
	Indonesia	18.79	-37.88	-5.11	83

Source: Authors' computations.

For other countries and existing crops, the productivity shifts and adoption rates are derived from various farm-level and industry- or trade-level studies in each country. Our assumptions are shown in Table 7 with relative yields, input effects, and the initial adoption rates both under a first shock in the current GM-producing nations (noted I) and under a second, later shock, with larger adoption rates in a number of countries and a few added countries (noted II). For simplicity, and to isolate the effects of GM crops on certain countries, we assume that the adoption rates of countries that are already adopters in period I do not change in period II and we maintain the same productivity effects across periods. For maize, soybeans, and cotton, we use available ex post estimates, therefore only representing currently available traits that are pest resistant (maize, cotton), herbicide resistant (soybeans, maize, cotton), or both (maize, cotton) depending on the country. For rice, we assume that China will be a technology leader, but because of the lack of data, we only assume that China adopts Bt rice. For wheat, we assume that China and Argentina will use herbicide-resistant varieties.7

7 Some of the productivity assumptions shown in Table 7 (e.g., wheat and soybeans) are not completely comparable to the ones shown for our countries of study in Table 6 simply because the traits are not the same, and because the relative productivity effects shown in Table 6 represent composite (multi-trait) GM varieties rather than simple varieties.

Table 7. Relative productivity effects and initial adoption rates assumed for other countries

Crop	Country	% Yield effects	% Input effects		% Initial adoption	
			Chemicals	Labor	I	II
Rice	China IR	7.03	-65	-9.1	0	80
Wheat	China	7	0	-7.7	0	50
	Argentina	7	0	-7.7	0	50
Maize	USA	9	-1.5	-5	52	52
	Argentina IR	5	0	-5	40	40
	South Africa IR	32	0	-5	16	16
	Philippines IR	34	-52	-5	4	25
	Canada IR	5	0	-5	40	40
	EU (Spain) IR	6.3	0	-5	5	5
	Tanzania and Uganda IR	32	0	-5	0	25
Soybeans	Argentina HT	-0.3	-43.2	-7.7	98	98
	Brazil HT	-3	-3	-7.7	41	41
	USA HT	0	0	-5	87	87
	Canada HT	0	0	-5	50	50
Cotton	China IR	7	-67	-6.7	70	90
	USA IR+HT	11	-21	-2	81	81
	Australia HT	0	-21	-2	40	40
	India IR	34	-41	5	15	25
	Mexico IR	9.7	-77	-5	61	61
	Argentina IR	33.1	-46	-5	20	20
	Brazil IR	33.1	-46	-5	4	4
	South Africa IR	15.5	-23	-5	79	79
	Tanzania and Uganda IR	15.5	-23	-5	0	30

Sources: Authors' assumptions based on Elbehri and McDonald (2004); Qaim and Matuschke (2005); Marra, Pardey, and Alston (2002); and James (2005).
Notes: IR = insect resistant, HT = herbicide tolerant.

GM cotton is included because of its importance in developing countries and the fact that it is associated with increased cottonseed and cottonseed oil production, which are used for feed or food in a number of countries. Apart from current GM-adopting countries, we decided to add limited adoption of cotton and maize in Tanzania and Uganda as a supplementary experiment to our shock in Asia. Because these two countries do not export large volumes of either commodity we do not expect that they will influence the results of other countries too much, but we are interested in comparing their relative welfare changes with the ones in the countries of study.

4. TRADE MODELING AND SCENARIOS

The methodology we propose to apply in our study is based on a multi-country, applied general equilibrium framework. A modified version of the MIRAGE model (Bchir et al. 2002)8 is used to simulate a range of scenarios on the productivity effect, trade restrictions, and segregation options. This model is based on the GTAP 6.1 database, which represents the world as of 2001. For this application, we divide the economy into 21 regions, including GM-producing countries, sensitive importing countries, and other important countries, and 19 sectors, including the relevant production sectors, as well as the chemical sector. The MIRAGE model includes an updated representation of trade policies and unilateral, bilateral, and multilateral trade preferential agreements (using MacMap-HS6; 2001 data).

We first modify the MIRAGE model by dividing the five production sectors into GM and non-GM substitutes for all GM-adopting countries. Second, with this structure, the model is changed to allow for the use of specific productivity shocks only on GM products in each GM sector for each adopting country. The model is also modified to allow for the ban of GM and/or non-GM imports in selected countries only from GM-producing nations going toward final consumption to reflect the current effects of labeling policies (Gruere 2006). We also allow the model to block imports from GM-producing countries going toward both final and intermediate consumption for selected food crops in certain scenarios. Lastly, the model is changed to allow for the introduction of a segregation cost for non-GM crops going from GM-adopting countries to sensitive importing ones.

To calibrate the model, we use the assumed parameters provided in section 3 regarding the productivity shocks and the proposed initial adoption rates. However, because of the relative aggregated level of the GTAP database, we make four adjustments on the shocks and scenarios to the particular sectors we are interested in.

First, on the product side, we use proportional weights derived from FAOSTAT national production data in 2001 to reduce the adoption rates for maize taking into account its contribution to the GTAP coarse grains sector, for cotton to the GTAP plant-based fiber sector, and for soybeans and cottonseed to the GTAP oilseeds sector.

Second, we use a similar approach by reducing the productivity shock proportionally to account for the share of pesticide costs in the aggregated GTAP chemical sector for each GM crop concerned in each country. For cotton, this adjustment is done by weighing the share of pesticide costs in total chemical costs used in cotton production based on a survey of national production budgets (ICAC 2004). For all other GM crops, we use a two-step approach, first deriving the share of fertilizer in chemical use

8 The MIRAGE model was developed at the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) in Paris. Full description of the model is available at the CEPII website (www.cepii.fr).

from FAOSTAT 2001, and second by using general data on the share of insecticides in total pesticide use at the continental level (Yudelman, Ratta, and Nygaard 1998).

Third, for the case of countries adopting both GM cotton (and therefore cottonseed, an oilseed) and GM soybeans (another oilseed), we derive the productivity effect of a composite oilseed good. This is done by computing a weighted average of the respective productivity effects (yields, labor, chemical) of cotton and soybeans, using the expected share of GM cotton and GM soybeans in total oilseeds as respective weights.

Fourth, for scenarios allowing the segregation of non-GM maize and soybeans, we adjust the segregation cost imposed for non-GM crops going to sensitive importing regions by accounting for the share of imports of these two crops into the coarse grains and oilseed sectors in 2001, respectively (using FAOSTAT bilateral database 2001).

After this data adjustment, under each set of scenarios, the model is calibrated to incorporate the assumed productivity shocks in all selected GM-adopting nations. Then under each scenario, we run the model only once to simulate a comparative static shock, and we use a perfect competition representation of the economy for simplification. Further refinements of our simulations could include dynamics and imperfect competition modeling.

Table 8. GM-adopting countries and their producing GM sectors under each scenario set

Set of scenarios	Rice	Wheat	Maize	Cotton fibers	Oilseeds (soybeans and cottonseed)
A	-None-	-None-	Argentina, Canada, EU, Philippines, South Africa USA	Argentina, Australia, China, India, Mexico, South Africa USA	Argentina, Australia,[a] Brazil, Canada, China,[a] India,[a] Mexico,[a] South Africa,[a] USA
B	-None-	-None-	Argentina, Bangladesh, Canada, EU, India, Indonesia, Philippines, South Africa, Tanzania-Uganda, USA	Argentina, Australia, Bangladesh, China, India, Indonesia, Mexico, South Africa Tanzania-Uganda, USA	Argentina, Australia,[a] Bangladesh, Brazil, Canada, China,[a] India, Indonesia, Mexico,[a] South Africa,[a] Tanzania-Uganda,[a] USA
RICE	Bangladesh, China, India, Indonesia, Philippines	-None-	-None-	-None-	-None-
WHEAT	-None-	Argentina, Bangladesh, China, India	-None-	-None-	-None-

[a] Country producing only GM cottonseed and no GM soybeans as part of its oilseeds.

We define four distinct sets of scenarios as shown in Table 8. The first set, noted A, aims to represent 2005 GM-adopting nations and GM crops, namely maize, cotton, and oilseeds (soybeans and cottonseed),[9] and it is run as a benchmark to compare with other types of shocks, using initial adoption rates defined in the I column of Table 7. The second set, noted B, includes the same GM crops adopted in the same countries, at a higher initial adoption rate in some countries (e.g., cotton in India, maize in the Philippines). In addition, Bangladesh, India, Indonesia, and Tanzania and Uganda also adopt some of these GM crops. The initial adoption rates for these countries are defined in tables 2 through 5 and in the II column of Table 7. The third set, titled RICE, represents the case of the adoption of GM rice in the four countries of study and in China (using initial adoption rates defined in the relevant tables of section 3). In our consultation meetings, we found that local experts in the four Asian countries agreed that GM rice would enter their country only if China adopted it first. Lastly, the fourth set is named WHEAT and presents the introduction of GM wheat in Bangladesh, India, China, and Argentina, which are also assumed to be leaders in technology adoption. The initial adoption rates for rice and wheat are defined in tables 2 through 5 and in the II column of Table 7.

We deliberately separate the case of current GM crops from the case of largely noncommercialized GM food crops (rice and wheat) for two reasons. First, we want to singularize the effect of adopting GM rice and GM wheat, two major food crops, from the current crops that are mostly used for animal feed and nonfood products. Second, we apply specific scenarios to these two last cases reflecting potential complete rejection in sensitive importing countries in the short run (which will not happen for GM crops of set A and B that are all currently traded).

9 We do not include canola explicitly in our model due to the lack of sufficient data on its productivity effect in adopting countries.

Table 9. Features of each scenario for GM-adopting countries under each set of assumptions

Scenario number and title	Productivity shock on GM crops	Ban toward intermediate consumption in sensitive countries[a] of		Ban toward final consumption in sensitive countries[a] of		Segregation of non-GM product exported toward sensitive countries[a]
		Non-GM	GM	Non-GM	GM	
0. Base	No	No	No	No	No	No
1. Productivity shock	Yes	No	No	No	No	No
2a. Import ban, no segregation[b]	Yes	Yes	Yes	Yes	Yes	No
2b. Import filter, no segregation	Yes	No	No	Yes	Yes	No
3a.i. Import ban, costless segregation[b]	Yes	No	Yes	No	Yes	Yes
3a-ii. Import ban, 5% segregation costs[b]	Yes	No	Yes	No	Yes	Yes
3b-i. Import filter, costless segregation	Yes	No	No	No	Yes	Yes
3b-ii. Import filter, 5% cost segregation	Yes	No	No	No	Yes	Yes

[a] The sensitive countries are the European Union, Rest of Europe, Japan, South Korea, and Australia/New Zealand
[b] These scenarios are run for the RICE and WHEAT sets only.

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Each set of scenarios comprises five to eight individual scenarios, as shown in Table 9. Scenario 0 is run as a benchmark without GM production. We will not show its result, but it serves as a basis for the measured welfare changes in the other scenarios. Scenario 1 simulates a productivity shock associated with the adoption of GM crops and no trade restriction, that is, assuming all countries import and consume GM and non-GM crops with no differentiation.

Scenarios 2a and 2b include the same productivity shock with trade restrictions. Scenario 2a is run only for the RICE and WHEAT sets, and represents the short-run effect of the adoption of new GM varieties, namely, the import ban of GM and non-GM crops from the adopting countries in sensitive countries. Scenario 2b is run for all sets, and represents current trade restrictions on GM imports in sensitive countries. Current marketing regulations, private standards, and consumer reactions in these countries act as a trade filter. Products to be used for final consumption are not purchased or approved, but products for intermediate consumption (such as animal feed) can enter the market in sensitive countries because the corresponding final products are not necessarily subject to labeling requirements (e.g., meat in the EU, soy oil in Japan; for more on labeling, see Gruere and Rao 2007).

Lastly, scenarios 3a-i, 3a-ii, 3b-i, and 3b-ii allow for the segregation of non-GM products in GM-adopting countries to export to sensitive importing countries. The four scenarios are proposed to study the implication of segregation costs under trade ban or trade filter. 3a-i is run with costless segregation of non-GM but a ban of GM toward both final and intermediate consumption; 3a-ii is the same scenario with the addition of a 5 percent basic segregation cost.10 Similarly, scenario 3b-i represents the case of a trade filter in sensitive countries but costless segregation of non-GM toward the final consumption; 3b-ii adds a 5 percent segregation cost. As explained above, these costs have been adjusted according to differences in bilateral trade flows to account for the relative weight of concerned crops (e.g., maize) in aggregated sectors (coarse grains) imported by sensitive countries from GM-producing countries.

10 We choose to impose a 5 percent cost for two reasons: first, it corresponds to a median value in the literature on segregation cost (where estimates vary from a few percentage points to 10 to 15 percent); and second, it corresponds to the premium reported on the market for non-GM products. For instance, maize traders in South Africa reported in June 2007 that identity-preserved non-GM maize was sold for a 5 percent price premium compared with GM maize (personal conversation with GRAIN South Africa).

5. SIMULATION RESULTS

What can be expected from the adoption of a GM technology? As noted before, the adoption of a GM technology often implies an increase in yields (productivity of land) and in the productivity of labor, which are equivalent to an augmentation of endowments of these productive factors. Thus, if we consider the theory of growth in open economies, it can be concluded that in terms of national welfare, the overall impact of GM crop adoption is ambiguous, as it can be decomposed into three effects:

- *A technical gain effect*. The direct effect of technical progress or augmented endowment on welfare is positive as it entails an expansion of the production possibility frontier. Under constant terms of trade, this generates an increase in national welfare.

- *A term-of-trade effect*. In general (see, e.g., de Melo and Grether 1997), technical progress or augmented endowment in a single country (or not in all countries) leads to a deterioration of terms of trade unless this is a marked anti-trade growth, which reduces export supply. But in the case of a pro-trade growth (e.g., productivity gains in the specialized export market), export supply is increased and export prices are reduced.

- *A land supply effect*. In the MIRAGE model, the land supply is endogenous. Technical progress in a country, resulting in increased yields or augmented endowment of land, for example, implies that production techniques are more land intensive. As a consequence, the labor/land or capital/land ratios decrease, which leads to a decline in the marginal productivity of land and its real remuneration. The land supply is a function of this remuneration, and consequently it is reduced. This is true in particular in countries where land supply is relatively elastic such as Australia/New Zealand or Argentina.

The two first effects are traditional effects of the theory of international trade; the third one is specific to the MIRAGE model.

According to the theory of international trade, the second effect (terms of trade) can be negative and greater than the first effect; this is the famous case of "immiserizing growth," first illustrated by Bhagwati (1958).

We present the results in terms of welfare effects, defined as the equivalent variation (or real income) between each scenario and the base (0) for each set. Both absolute values in millions of dollars per year ($ million/year) and percentage (%) of total real income are shown for each region in each scenario. We also provide additional data on production, imports, and exports in the appendix (see tables A1, A2, A3, and A4) to explain the results obtained in some of the scenarios.

A) GM Maize, Oilseeds, and Cotton

Table 10 shows the results for set A. Rows representing GM-adopting nations are shaded in the table and their names are in boldface. This case represents the adoption of current GM crops, namely, soybeans, maize, and cotton. The global welfare gain with the adoption of these crops and without trade restrictions amounts to $4.4 billion, which lies within the ranges obtained in other studies presented in Table 1. The global welfare gain declines to \$2.7 billion with a trade filter applied in sensitive countries, but it rises back up to \$4.2 billion with costless segregation. With 5 percent segregation costs, the global welfare gain lies in between the costless segregation and trade restriction scenarios at \$3.7 billion. These results already bring forward three lessons: (1) trade restrictions and consumer resistance reduces the gain in global welfare by about \$1.7 billion; (2) the global opportunity cost of a non-GM segregation system for these crops is about \$1.4 billion; (3) the global welfare gain would be greater even with a 5 percent cost of segregation than with no segregation.

The adoption of GM crops consistently results in an increase in welfare in all adopting countries except Australia/New Zealand and Argentina. Australia and New Zealand partially adopt Bt cotton (at a relatively low level) and experience losses in terms of trade (see the previous second effect). Argentina experiences a significant loss, which can be explained partially by our productivity assumptions and by its loss in competitive edge in the vegetal oil sector in the global market. At the domestic level, Argentina experiences a degradation of the returns to land (see the previous land supply effect), accompanied by less production of oilseeds and therefore less vegetal oils, because we assume the yield effects of GM soybeans to be negative. At the international level, it also exports much less vegetal oils at a lower export price. The adoption of GM soybeans and cottonseed in many countries increases oilseed production, which reduces prices and contracts the international oilseed market. As a result, most countries reduce their exports of oilseeds and indirectly vegetal oils. At the same time, trade diversion occurs in the vegetal oil market, where Argentina loses market share to the United States, Brazil, and the Rest of Asia. Traditional importers of Argentinean oil such as India, by producing more cottonseed, also import much less oil.

The largest relative gains from GM crop adoption are experienced by India (+0.07 percent), followed by China and Mexico, because of the relative importance of the targeted crops in these countries. All adopters except Mexico and China experience a relative decline in the total welfare gain with trade restrictions. The exception of Mexico and China is related to the fact that they only adopt Bt cotton at a relatively high level and they import commodities at a reduced price (maize in Mexico, cotton in China) under trade restrictions. This has to be related to diverted trade: sensitive countries import less of these products and the export supply of these products is redirected to nonsensitive countries. The cotton sector is affected differently than the other two sectors with a trade filter, because these restrictions affect only products going toward final consumption and most cotton is used for intermediate consumption, and because no importer is regulating GM cotton imports. Simulation data (Table A.1) show that Mexico and China export less cotton under the second scenario but produce and import about the same amount. Costless segregation helps most GM-adopting countries, offsetting a large share of the relative losses with trade policies. Overall, the presence of a 5 percent segregation cost reduces their gains but still allows them to be better off than with no segregation.

Sensitive countries largely account for most of the relative decline in global welfare under trade restrictions, and are better off with costless segregation. Among the five regions, only Japan is worse off with costly segregation than with trade restrictions. This means that Japan would be better off only if the segregation costs for non-GM products stay under 5 percent. Europe and South Korea suffer apparent welfare losses under scenario 2b, due to the implementation of restrictive trade policies.[11]

11 However, these apparent market losses may not be actual welfare losses, as we do not account for the fact that consumers in these countries may prefer non-GM food and be willing to pay more to avoid GM food.

Table 10. Change in welfare effects ($ million/yr and %) under each scenario of set A: adoption of GM maize, soybeans, and/or cotton

Scenario set A Bold regions adopt GM maize, soybeans, and/or cotton	1. Productivity shock		2b. Import filter, no segregation		3b-i. Import filter, costless segregation		3b-ii. Import filter, 5% cost segregation	
Region	$ million	%	$ million	%	$ million	%	$ million	%
Australia and New Zealand	-50.344	-0.015	-52.728	-0.016	-49.286	-0.015	-46.446	-0.014
China	341.905	0.044	347.346	0.045	346.006	0.045	346.887	0.045
Japan	430.112	0.014	264.797	0.009	415.619	0.014	256.777	0.008
South Korea	353.145	0.122	-521.276	-0.180	200.850	0.069	50.076	0.017
Rest of Asia	136.167	0.024	148.412	0.026	136.944	0.024	139.517	0.025
Indonesia	40.679	0.041	42.957	0.044	41.027	0.042	41.105	0.042
Philippines	29.171	0.046	28.974	0.046	29.154	0.046	28.892	0.046
Bangladesh	-0.208	-0.001	-0.225	-0.001	-0.257	-0.001	-0.212	-0.001
India	254.173	0.068	249.856	0.067	254.652	0.068	252.632	0.068
Canada	41.054	0.008	38.621	0.007	41.677	0.008	43.370	0.008
United States	1856.187	0.022	1854.162	0.022	1859.333	0.022	1867.961	0.022
Mexico	332.332	0.069	335.539	0.070	332.712	0.069	333.291	0.069
Rest of Latin America	104.308	0.021	120.628	0.024	105.751	0.021	108.942	0.021
Argentina	-277.653	-0.122	-287.039	-0.127	-280.236	-0.124	-279.267	-0.123
Brazil	26.257	0.007	9.484	0.002	28.717	0.007	13.538	0.003
European Union	494.483	0.008	-113.287	-0.002	423.483	0.006	274.592	0.004
Rest of Europe	41.120	0.006	-7.286	-0.001	38.933	0.006	24.331	0.004
North Africa and Middle East	249.477	0.031	251.109	0.031	249.622	0.031	249.319	0.031
Rest of Sub-Saharan Africa	-2.965	-0.002	29.318	0.018	-1.306	-0.001	-0.498	0.000
South Africa	19.721	0.023	19.353	0.022	19.936	0.023	19.406	0.022
Tanzania and Uganda	0.460	0.003	0.725	0.005	0.469	0.003	0.404	0.003
World	**4419.583**	**0.018**	**2759.440**	**0.011**	**4193.798**	**0.017**	**3724.616**	**0.015**

Source: Authors' results from simulations.

Lastly, the results obtained in the region titled Rest of Sub-Saharan Africa are quite remarkable. In this region, which neither adopts nor restricts GM crop imports, the welfare effects vary largely across scenarios, from -\$3 million in scenario 1 to -\$1 million for the scenarios with segregation in sensitive countries, and reaching a maximum of +\$29 million in scenario 2b, with trade filtering and no segregation. This means that these countries benefit from the combination of GM maize, soybeans, and cotton with restrictive policies in Europe. As importers they benefit from the lower import prices they can obtain due to the excess surplus in other countries. This phenomenon is also true for other nonproducing and nonsensitive countries, such as Tanzania/Uganda, Indonesia, Rest of Latin America, Bangladesh, and North Africa/Middle East, who all share maximum gains under scenario 2b.

The welfare results for set B are presented in Table 11. In this case, more countries are producing GM crops and some of the adopting GM-producing countries also increase their rate of adoption. As a consequence, the gain in global welfare increases to \$5.1 billion. The global gain follows the same pattern as in set A, reaching the lowest level under scenario 2b with trade filtering and no segregation, and intermediate levels under scenarios 3b-i and 3b-ii. Applying a trade filter results in a relative reduction of gains of 32.5 percent, a difference smaller than the one obtained in set A (-37 percent). The largest relative gains with GM adoption (scenario 1) are derived in Tanzania/Uganda (+0.32 percent), then in India (+0.22 percent), and the Philippines (+0.19 percent). On the other hand, Argentina loses a little more, mainly because of the increased oilseed production in India, reducing its vegetal oils exports even more than under set A. China's relative gains also decline between set A and set B mostly due to a change in the competitiveness of its textile industry.

The four countries of study gain from GM adoption, but experience different relative changes in gains across scenarios. By adopting GM maize at a low rate, Bangladesh experiences a small gain, despite increasing its production of cereals. These gains do not vary significantly across scenarios, but as a net food importer Bangladesh is slightly better off under trade restrictions. India's extension of Bt cotton adoption, with adoption of GM maize and soybeans, increases its gains from \$254 million in set A to \$826 million in set B. Trade restrictions reduce these gains by only about \$4 million. India gains slightly more under scenario 3b-i (costless segregation) than under scenario 1, but the difference is insignificant in relative terms. India is still slightly better off with 5 percent segregation costs than with trade restriction. Indonesia adopts GM maize and soybeans, which results in gains reaching \$110 million, or 0.12 percent of total real income. Indonesia remains a net importer of coarse grains and oilseeds, which may explain why it gets slightly larger gains under the most restrictive scenario (2b) that result in lower import prices. But the difference is about \$1 million and less than 1 percent of the gains it obtains with the adoption of GM crops. Lastly, the Philippines extends its adoption of GM maize, and multiplies by four its welfare gains obtained under set A to reach \$120 million. Like Indonesia, the Philippines is not a net exporter of any of these crops, and imports a number of agricultural commodities. As a result the gains do not change much under the four scenarios.

Table 11. Change in welfare effects ($ million/yr and %) under each scenario of set B: extended adoption of GM maize, soybeans, and/or cotton

Scenario set B Same as set A plus Bangladesh, Indonesia, India, Philippines, and Tanzania/Uganda adopt GM maize, cotton, and/or soybeans	1. Productivity shock		2b. Import filter, no segregation		3b-i. Import filter, costless segregation		3b-ii. Import filter, 5% cost segregation	
Region	$ million	%	$ million	%	$ million	%	$ million	%
Australia and New Zealand	-53.062	-0.016	-55.449	-0.017	-51.994	-0.016	-49.154	-0.015
China	242.399	0.031	247.754	0.032	246.380	0.032	247.285	0.032
Japan	435.365	0.014	271.491	0.009	420.792	0.014	261.864	0.009
South Korea	360.583	0.125	-515.855	-0.178	208.357	0.072	57.709	0.020
Rest of Asia	143.124	0.025	155.671	0.027	143.888	0.025	146.457	0.026
Indonesia	113.213	0.115	114.480	0.116	113.553	0.115	113.639	0.115
Philippines	120.197	0.191	120.010	0.191	120.179	0.191	119.918	0.191
Bangladesh	1.008	0.003	1.015	0.003	0.959	0.003	1.004	0.003
India	825.588	0.221	821.383	0.220	826.075	0.222	824.106	0.221
Canada	39.428	0.007	37.009	0.007	40.051	0.007	41.738	0.008
United States	1848.543	0.022	1846.500	0.022	1851.711	0.022	1860.343	0.022
Mexico	333.683	0.070	336.899	0.070	334.060	0.070	334.641	0.070
Rest of Latin America	103.975	0.021	120.600	0.024	105.416	0.021	108.608	0.021
Argentina	-282.945	-0.125	-292.327	-0.129	-285.527	-0.126	-284.556	-0.125
Brazil	27.534	0.007	10.876	0.003	30.029	0.008	14.790	0.004
European Union	506.163	0.008	-106.192	-0.002	435.085	0.007	286.030	0.004
Rest of Europe	43.566	0.006	-5.092	-0.001	41.346	0.006	26.728	0.004
North Africa and Middle East	256.574	0.032	258.226	0.032	256.716	0.032	256.414	0.032
Rest of Sub-Saharan Africa	-2.877	-0.002	30.122	0.019	-1.217	-0.001	-0.420	0.000
South Africa	20.568	0.024	20.198	0.023	20.782	0.024	20.254	0.023
Tanzania and Uganda	44.558	0.322	44.262	0.319	44.558	0.322	44.523	0.321
World	**5127.184**	**0.021**	**3461.578**	**0.014**	**4901.200**	**0.020**	**4431.919**	**0.018**

Source: Authors' results from simulations.

The largest relative losses with trade restrictions are still borne by the sensitive importers, particularly South Korea. Under set A, South Korea was losing about $874 million with the introduction of trade restrictions (compared with scenario 1). Under set B it loses about the same amount, $875 million. The other sensitive regions experience small relative losses. Once again, Japan is slightly better off in a case with trade restrictions and no segregation than under cases of costly segregation, because even with the filter it is able to import the targeted products (that are mostly used for intermediate consumption) at a lower price than in these other scenarios.

Lastly, we find the same pattern as in set A for the non-GM-producing and nonsensitive region Rest of Sub-Saharan Africa (and to a lesser extent Rest of Latin America and Rest of Asia), with maximum gains under the most restrictive scenario (2b). In this case, Sub-Saharan African countries experience small losses ($1–$3 million) under all scenarios but 2b, under which they gain $30 million.

B) GM Rice Adoption

Table 12 shows the changes in welfare effects for set RICE. In this case, five countries adopt GM rice: China, India, Bangladesh, the Philippines, and Indonesia. Currently GM rice is being tested in China and India but has not been approved for cultivation in those two countries. The United States approved the use of herbicide-tolerant rice in 2006, but it is not cultivated because of fears of export losses. Iran has reportedly approved the cultivation of Bt rice, and it could be the only country producing GM rice at a small scale. We decided to neglect limited potential GM rice production in those two countries in order to isolate the shock with the adoption of GM rice in five Asian countries that are all relatively large producers and consumers of rice. In this set, we added scenario 2a, which corresponds to the short-run effect of GM rice adoption, i.e., a complete ban in sensitive countries. We also added scenarios 3a-i and 3a-ii, which are the equivalent of 3b-i and 3b-ii but with blocking of GM rice toward both final and intermediate consumption.

Table 12. Change in welfare effects ($ million/yr and % total) under each scenario with GM rice adoption in selected Asian countries

GM rice adopted in bold regions	1. Productivity shock		2a. Import ban, no segregation		2b. Import filter, no segregation		3a-i. Import ban, costless segregation		3a-ii. Import ban, 5% segregation cost		3b-i. Import filter, costless segregation		3b-ii. Import filter, 5% segregation cost	
Region	$ million	%	$ million	%	$ million	%	$ million	%	$ million	%	$ million	%	$ million	%
Australia and New Zealand	-5.543	-0.002	-4.311	-0.001	-6.075	-0.002	-4.954	-0.002	0.405	0.000	-5.799	-0.002	-0.545	0.000
China	4640.502	0.597	4617.579	0.594	4632.954	0.596	4627.666	0.596	4640.500	0.597	4636.040	0.597	4649.711	0.598
Japan	529.709	0.017	-292.492	-0.010	211.181	0.007	93.964	0.003	-131.621	-0.004	357.851	0.012	153.150	0.005
South Korea	191.106	0.066	-159.492	-0.055	165.182	0.057	21.943	0.008	-182.653	-0.063	177.587	0.061	-10.040	-0.004
Rest of Asia	-8.469	-0.002	-0.942	0.000	-5.830	-0.001	-6.432	-0.001	0.166	0.000	-7.474	-0.001	-1.285	0.000
Indonesia	1106.760	1.121	1102.298	1.116	1105.090	1.119	1105.502	1.119	1106.368	1.120	1106.210	1.120	1107.251	1.121
Philippines	638.752	1.017	637.598	1.015	638.458	1.016	638.240	1.016	638.041	1.016	638.619	1.017	638.466	1.016
Bangladesh	452.620	1.194	452.809	1.195	452.720	1.194	452.688	1.194	452.781	1.195	452.664	1.194	452.751	1.195
India	3258.806	0.874	3241.439	0.869	3252.751	0.872	3252.359	0.872	3250.822	0.872	3256.347	0.873	3255.455	0.873
Canada	10.288	0.002	10.886	0.002	10.547	0.002	10.539	0.002	16.322	0.003	10.406	0.002	16.171	0.003
United States	104.256	0.001	101.579	0.001	104.912	0.001	103.186	0.001	105.300	0.001	104.639	0.001	106.919	0.001
Mexico	6.097	0.001	5.180	0.001	5.877	0.001	5.661	0.001	8.742	0.002	5.987	0.001	9.105	0.002
Rest of Latin America	28.080	0.006	33.134	0.007	29.391	0.006	30.174	0.006	36.137	0.007	28.682	0.006	34.414	0.007
Argentina	-1.783	-0.001	-1.456	-0.001	-1.798	-0.001	-1.631	-0.001	-10.168	-0.005	-1.789	-0.001	-10.346	-0.005
Brazil	-0.814	0.000	-0.416	0.000	-0.714	0.000	-0.623	0.000	-30.130	-0.008	-0.764	0.000	-30.282	-0.008
European Union	350.235	0.005	-61.022	-0.001	194.811	0.003	165.029	0.003	-58.655	-0.001	276.452	0.004	67.100	0.001
Rest of Europe	38.648	0.006	14.850	0.002	27.266	0.004	26.207	0.004	7.794	0.001	32.631	0.005	14.721	0.002
North Africa and Middle East	105.535	0.013	106.017	0.013	106.496	0.013	105.398	0.013	105.340	0.013	105.899	0.013	105.857	0.013
Rest of Sub-Saharan Africa	74.142	0.046	73.451	0.045	74.408	0.046	73.691	0.046	74.676	0.046	74.235	0.046	75.264	0.047
South Africa	13.386	0.015	13.250	0.015	13.402	0.015	13.308	0.015	12.493	0.014	13.389	0.015	12.583	0.014
Tanzania and Uganda	1.587	0.012	1.565	0.011	1.600	0.012	1.568	0.011	1.538	0.011	1.591	0.012	1.563	0.011
World	**11533.902**	**0.047**	**9891.504**	**0.040**	**11012.627**	**0.045**	**10713.482**	**0.044**	**10044.200**	**0.041**	**11263.402**	**0.046**	**10647.985**	**0.043**

Source: Authors' results from simulations.

First, Table 12 shows that the global welfare gain with the adoption of GM rice is much larger than under the two previous sets, ranging from $9.9 billion to $11.5 billion per year. Trade restrictions in the form of an import ban in sensitive countries reduce the gain by 14 percent, less than in sets A and B. In other words the gain with GM rice adoption is about seven times larger than any potential loss experienced due to trade restrictions. Segregation at a 5 percent cost reduces the global gain by about 6 percent. Interestingly, segregation at a 5 percent cost also results in a lower global gain than a trade filter, which indicates that, provided rice is accepted in intermediate consumption, segregation would increase the global welfare gain if it does not cost too much.

The major welfare gains occur in the five adopting countries. First, China, with a relatively large adoption rate, gains more than $4.6 billion per year (or 0.6 percent of total real income). This total is slightly larger than that obtained in Huang et al. (2004), because we do not explicitly reduce the gain from GM crops due to the price of seeds. Therefore the gain presented here includes the returns to the developers and adopting producers together. In the GTAP database used in this study, China's rice imports are just slightly inferior to its exports, making it a small net exporter. This may explain why an embargo on rice slightly reduces China's gain, a trade filter reduces it a little less, and the welfare gain with costless segregation is close to that in the first scenario. But at the same time, China obtains slightly higher gains with costly segregation in sensitive countries than under other scenarios.

India also obtains a large positive gain from adoption, exceeding $3.2 billion, or 0.87 percent of total welfare. But India is a net exporter of rice and therefore it gains less with trade restrictions and more with segregation. Interestingly, in opposition to the widespread belief that GM rice would result in extremely important losses for the economy, the net reduction in welfare gain with a complete ban of rice in sensitive countries amounts to only $17 million, representing only 0.5 percent of the total gain with GM rice adoption. This can be explained by the fact that India does not export as much to Europe (about 16 percent according to the original GTAP database) as it does to other regions, such as North Africa and the Middle East (47 percent) and other African countries (19 percent), and that trade diversion occurs with selective bans. Bilateral trade flows show that under scenario 2a, Indian rice is slightly diverted from Europe to South and North America and African countries. In total, under the trade ban, India produces 16 percent more than without GM rice, which is less than under other scenarios. It reduces total rice exports by 6 percent but still reduces its total rice imports by more than 50 percent (see Table A.3 in the appendix). Under scenario 2b, India's welfare is reduced by a much smaller amount. Segregation allows an increase in welfare by a few million dollars even at 5 percent costs.

Bangladesh obtains the largest relative gain with the adoption of GM rice, with an additional 1.2 percent gain in total welfare per year, which is equivalent to more than $450 million per year. Rice production increases by 7.5 percent under all scenarios, which allows the country to reduce rice imports by more than 27 percent. The trade ban results in a significant relative reduction in exports, but this loss is limited as the absolute value of its rice exports is small ($1 million in the GTAP database) compared with its imports ($74 million). As a net importer, Bangladesh is slightly better under the most restrictive trade scenarios, because they are associated with relatively lower import prices, particularly for non-GM rice.

Indonesia also obtains very significant gains from GM rice adoption, exceeding $1.1 billion per year, or 1.1 percent of total welfare. Indonesia is also a large net importer of rice. With GM rice, Indonesia increases its production by 20 percent and reduces its imports by 66 percent. A total trade ban in the short run has a small effect on Indonesia's welfare with a reduction of $4 million. Indonesia is slightly better off with a trade filter, and with segregation, but the differences are very small relative to the total gains.

The Philippines increases its welfare by 1 percent (or about $640 million) annually by adopting GM rice. Originally a net importer, the introduction of GM rice results in a production increase of about 17 to 19 percent under all scenarios, and reduces imports by more than half. The changes across scenarios are very small, resulting from production and import differences with price changes.

The relative loss experienced by sensitive importers from a total ban on rice coming from GM-adopting countries explains almost the entirety of the difference in global welfare across scenarios. In the group, Japan loses the most from a total ban and gains the most from a trade filter and costless segregation. Once again Japan's welfare rapidly declines with an increase in the segregation costs. Europe loses a small relative amount under the total ban but still gains under all other scenarios as a net importer of rice. Apart from that, we do not find the same result as in set A or set B for the Rest of Sub-Saharan Africa region. Although it gains more in absolute value than in sets A or B, the gains are very similar across scenarios.

C) GM Wheat

Lastly, Table 13 shows the results obtained with the WHEAT set, in which China, Argentina, India, and Bangladesh adopt GM wheat. The global gain is much less than with GM rice adoption, ranging between $1.6 billion and $2.3 billion annually. It is important to note that although Argentina, India, and China are relatively large producers of wheat, other countries of North America, Europe, or Oceania dominate the global wheat market. Global real income decreases only minimally with trade restrictions (2a or 2b) compared with the simple productivity shock (1), but reduces more significantly with the introduction of costs of segregation (3a-ii and 3b-ii). For comparison with previous scenarios, trade restrictions reduce welfare gains by 1.3 percent, while costly segregation reduces welfare gains by up to 30 percent. Most of the relative losses with costly segregation occur in sensitive countries, mostly Japan and South Korea, who have to pay more for imports of wheat. These same importers incur only relatively small reductions in welfare gains with trade bans because they are able to source their imported wheat from other countries, notably North America and Australia.

China increases its welfare by 0.09 percent (or $690 million) with GM wheat. The country increases its wheat production by 9 percent and reduces its imports by more than 40 percent. Trade restrictions do not affect its welfare gains significantly; however, adding a cost of segregation does increase China's total welfare gains, because it results in a small increase in exports to other countries (as shown in Table A.4). China exports about $42 million of wheat and imports 10 times more. The costly segregation scenario divides the market into GM (or mixed) and pure non-GM, and the non-GM export price to sensitive countries goes up significantly, while the GM price is slightly reduced, which could explain the observed gain.

Table 13. Change in welfare effects ($ million/yr and %) under each scenario with GM wheat adoption in selected Asian countries

GM wheat adopted in bold regions	1. Productivity shock		2a. Import ban, no segregation		2b. Import filter, no segregation		3a-i. Import ban, costless segregation		3a-ii. Import ban, 5% segregation cost		3b-i. Import filter, costless segregation		3b-ii. Import filter, 5% segregation cost	
Region	$ million	%	$ million	%	$ million	%	$ million	%	$ million	%	$ million	%	$ million	%
Australia and New Zealand	-21.171	-0.006	-15.979	-0.005	-21.168	-0.006	-19.967	-0.006	-14.365	-0.004	-21.170	-0.006	-15.683	-0.005
China	687.831	0.089	684.036	0.088	687.814	0.089	686.492	0.088	698.860	0.090	687.825	0.089	700.282	0.090
Japan	57.924	0.002	51.499	0.002	57.909	0.002	56.454	0.002	-175.323	-0.006	57.921	0.002	-173.753	-0.006
South Korea	15.359	0.005	-2.521	-0.001	15.341	0.005	10.894	0.004	-196.794	-0.068	15.354	0.005	-192.110	-0.066
Rest of Asia	14.773	0.003	13.795	0.002	14.773	0.003	14.498	0.003	20.953	0.004	14.773	0.003	21.251	0.004
Indonesia	4.298	0.004	4.010	0.004	4.298	0.004	4.219	0.004	5.310	0.005	4.298	0.004	5.396	0.006
Philippines	9.137	0.015	8.905	0.014	9.137	0.015	9.066	0.014	8.809	0.014	9.137	0.015	8.885	0.014
Bangladesh	10.373	0.027	10.556	0.028	10.376	0.027	10.389	0.027	10.502	0.028	10.374	0.027	10.485	0.028
India	945.243	0.254	940.520	0.252	945.192	0.254	944.655	0.253	942.633	0.253	945.235	0.254	943.277	0.253
Canada	-28.410	-0.005	-26.277	-0.005	-28.403	-0.005	-27.921	-0.005	-22.045	-0.004	-28.408	-0.005	-22.576	-0.004
United States	14.295	0.000	20.180	0.000	14.303	0.000	15.747	0.000	18.114	0.000	14.297	0.000	16.527	0.000
Mexico	2.482	0.001	2.045	0.000	2.480	0.001	2.376	0.001	5.418	0.001	2.481	0.001	5.531	0.001
Rest of Latin America	10.706	0.002	10.417	0.002	10.713	0.002	10.698	0.002	16.589	0.003	10.710	0.002	16.609	0.003
Argentina	215.369	0.095	212.716	0.094	215.229	0.095	214.158	0.094	205.847	0.091	215.309	0.095	206.997	0.091
Brazil	76.945	0.019	77.349	0.019	76.965	0.019	77.110	0.019	47.503	0.012	76.953	0.019	47.346	0.012
European Union	75.661	0.001	73.376	0.001	75.558	0.001	74.940	0.001	-146.386	-0.002	75.629	0.001	-145.686	-0.002
Rest of Europe	10.819	0.002	9.076	0.001	10.598	0.002	10.170	0.002	-8.411	-0.001	10.745	0.002	-7.841	-0.001
North Africa and Middle East	132.897	0.017	131.585	0.016	132.923	0.017	132.591	0.016	132.540	0.016	132.907	0.017	132.896	0.017
Rest of Sub-Saharan Africa	16.940	0.011	16.743	0.010	16.943	0.011	16.869	0.010	17.803	0.011	16.941	0.011	17.880	0.011
South Africa	9.201	0.011	9.234	0.011	9.204	0.011	9.226	0.011	8.399	0.010	9.202	0.011	8.376	0.010
Tanzania and Uganda	0.616	0.004	0.538	0.004	0.616	0.004	0.597	0.004	0.563	0.004	0.616	0.004	0.584	0.004
World	**2261.288**	**0.009**	**2231.802**	**0.009**	**2260.801**	**0.009**	**2253.260**	**0.009**	**1576.519**	**0.006**	**2261.127**	**0.009**	**1584.675**	**0.006**

Source: Authors' results from simulations.

Bangladesh is also a large importer of wheat, and only adopts GM wheat at a partial scale in this set of scenarios, for a small overall production, which is reflected by the small gains. Overall, Bangladesh produces 4 percent less wheat, imports a little less wheat, and exports less wheat. Thus, under our assumptions, Bangladesh absorbs less wheat overall and is not able to compete with India and the other GM wheat producers.

India is the main winner from GM wheat adoption, with gains of more than $940 million per year (or 0.25 percent of total real income). As a net exporter India gains more under scenarios 1 and 3a/3b and less with complete trade restriction under scenario 2a or 2b. Once again, the loss with a complete ban in sensitive countries is negligible ($5 million) compared with the gains with the adoption of GM wheat. Costless segregation does not make much difference with the trade filter scenario, which can be understood by the fact that virtually all wheat is used in intermediate consumption and not final consumption in importing sensitive countries. Costly segregation reduces the gain slightly but still allows India to be better off than under a complete ban. Argentina follows the same pattern as India with a smaller absolute gain with GM wheat.

6. DISCUSSION

The results of our multi-market CGE simulations vary across regions and scenarios, but they share a number of similarities that can help us draw a few general lessons. First, our simulations show once again that the adoption of GM crops can be translated into significant economic gains in the large majority of regions and in the presence or absence of trade restrictions in certain sensitive countries. Only a few regions experience net losses with the adoption of GM crops due to large changes in export-sensitive sectors. However, these rich countries have adopted restrictive policies in response to consumer concerns based on risk perceptions, lack of trust in safety authorities, and environmental or ethical reasons that can be translated into a consumer willingness to pay to avoid GM food products (not accounted here), so these real income losses might not be actual welfare losses. The results also show that adopting GM crops generates relatively larger gains for developing countries with rural economies. For example, the second set of simulations with current GM crops shows that Tanzania and Uganda would gain more relatively by adopting GM maize and cotton at a relatively low rate than any other country or region.

Second, our simulations show that although trade regulations can affect the gains from GM crops, the effect is relatively small compared with the gains under the adoption of GM crops. Applying a trade filter that allows only products for intermediate consumption to be imported, which reflects the regulatory situation faced by current GM crops, reduces the gains of exporting GM-adopting countries. Similarly a complete ban of rice or wheat from GM-producing countries by sensitive countries would result in lower gains for GM crop exporters. Yet, even with these barriers, most GM-adopting countries still gain from the adoption of GM crops, because the relative losses they experience with trade restriction are very small compared with the productivity gains experienced domestically, even with partial adoption. Table 14 shows the relative change in gains out of the total gain from GM crops under the most restrictive scenarios of each set. Even if globally the gains are reduced by up to 38 percent overall, we find that the gain reduction is closer to 1 percent in most cases for our countries of study and China, and does not exceed 6.7 percent of total gains. Interestingly, in certain cases trade restriction even results in a relative increase in gains for certain net importers or nonadopters.

Table 14. Relative effect of trade restriction on total gains from GM crop adoption for selected countries in different sets of scenarios

Set Scenarios compared	Set A 1 vs. 2b	Set B 1 vs. 2b	Rice 1 vs. 2a	Wheat 1 vs. 2a
China	1.6%	2.2%	-0.5%	-0.6%
Bangladesh	n.a.	0.7%	0.0%	1.8%
India	-1.7%	-0.5%	-0.5%	-0.5%
Indonesia	n.a.	1.1%	-0.4%	-6.7%
Philippines	-0.7%	-0.2%	-0.2%	-2.5%
World	-37.6%	-32.5%	-14.2%	-1.3%

Source: Simulation results.
Note: n.a. = not adopting GM crops in this scenario.

Third, the use of segregation for non-GM crops can help offset some of the relative losses from trade restrictions. Differences between the trade scenario and the hypothetical case with costless segregation provide benchmark values for the opportunity cost of segregation, defined as the most a country could spend on segregation to avoid losing compared with trade restrictions with no segregation. Estimates of these opportunity costs are reported for selected countries in tables 15 and 16 in the cases of rice and wheat (as well as in Table A.6 in the appendix for set A and B crops).

Table 15. Opportunity cost ($ million/yr) of the segregation of non-GM rice for adopting and sensitive countries

Type of country	Country	Segregation of non-GM rice for final consumption only	Segregation of non-GM rice for final and intermediate consumption
GM producers			
	China	3.1	10.09
	India	3.6	10.92
	Indonesia	-1.9	3.2
	Bangladesh	-0.06	-0.12
	Philippines	0.16	0.64
Total GM producers		4.9	24.73
Sensitive countries			
	Australia/NZ	0.28	-0.64
	Japan	113.67	198.53
	South Korea	12.47	137.55
	EU	81.64	226.05
	Rest of Europe	5.37	11.36
Total sensitive countries		213.43	572.85
WORLD			
	Global	250.78	821.98

Source: Authors' derivations.

Table 16. Opportunity cost ($ million/yr) of the segregation of non-GM wheat for adopting and sensitive countries

Type of country	Country	Segregation of non-GM wheat for final consumption only	Segregation of non-GM wheat for final and intermediate consumption
GM producers			
	China	0.01	2.46
	India	0.04	4.14
	Bangladesh	0	-0.17
	Argentina	0.08	1.44
Total GM producers		**0.13**	**7.87**
Sensitive countries			
	Australia/NZ	0	-3.99
	Japan	0.01	4.96
	South Korea	0.01	13.42
	EU	0.07	1.56
	Rest of Europe	0.14	1.09
Total sensitive countries		**0.23**	**17.04**
WORLD			
Global		**0.33**	**21.46**

Source: Authors' derivations.

These results show that exporting GM-producing countries, such as India, have a positive but relatively limited opportunity cost of segregation. The results also show that most of the global benefits of segregation would occur in importing sensitive countries (as shown in tables 15, 16, and A6) rather than exporting GM-producing countries. This means that traders in sensitive countries will likely have a larger incentive to set up segregation systems in GM-adopting countries than the exporters in those latter countries themselves. Consequently, these results suggest that the adoption of new GM crops may not necessarily require high investment by traders willing to keep their market in sensitive countries. Because the immediate cost of bans will largely be borne by importers, they will have a clear incentive to invest in segregation.

More generally, by simulating costly segregation scenarios we show that in many cases, GM-crop-adopting countries will still gain from segregation even with a 5 percent cost (e.g., India for rice), while in other cases, such countries will gain only if the cost of segregation is lower (e.g., India for wheat). As expected, segregation for export is not a silver bullet to avoid trade losses—it all depends on the cost of doing so. Competitive transition economies (like India) that are already able to supply high-quality agricultural products (including niche market products) to sensitive importing countries should be able to take advantage of this option in an efficient way, particularly if the cost of entry is partially assumed by importers. Smaller developing countries may have less incentive and support to set up segregation systems, unless such setup is driven domestically by a strong niche market for non-GM products.

Fourth, the case of importing developing nations is different. With the examples of Bangladesh or Indonesia, we saw that large importers will not become net exporters with limited adoption of GM crops. Their opportunity cost of segregation is negligible and even negative in some cases, when segregation results in slight increases in import prices relative to no segregation. But thanks to the increase in production associated with GM crops, they can dramatically reduce their imports of agricultural commodities to feed their large populations. For such countries, the effect of trade restriction is limited to the changes in prices. They can be slightly better off overall under the most restrictive trade policies because the price of GM and especially non-GM products decreases under those scenarios compared with no trade restrictions. But these relative differences are minimal and most often negligible in comparison with the overall gains with the adoption of GM crops.

Fifth, the results obtained in countries of Sub-Saharan Africa, although not the focus of this paper, are quite interesting. The example of Tanzania and Uganda shows that the adoption of current GM crops would result in relatively higher gains than in any other countries. Our results also show that the rest of Sub-Saharan Africa is bound to gain significantly with the adoption of current GM crops elsewhere if there are trade restrictions in sensitive countries. This means that contrary to the general belief in many of these countries, trade restriction in sensitive countries can in fact be beneficial to them. Of course, these results are true only if these countries agree to import GM food products. Currently many of them do not regulate GM products, adopting an implicit position of don't ask/don't tell, while a few others do not allow imports of any GM product while waiting for their biosafety regulations to be implemented (Gruere 2006).

In general, our results are comparable to previous work, except in the case of GM rice. We obtain larger gains for GM rice than previous studies, whether in China or globally. It is not always easy to compare results with those of other studies, because the studies do not necessarily use comparable models. For instance, Huang et al. (2004) focus only on China, without including adoption in other countries, but they also use a more detailed representation of the rice sector and of the economy. We do not explicitly reduce the gains from GM crops due to the price of seeds. Therefore the gains presented here include the returns to the developers and adopting producers together. In contrast, Huang et al. (2004) include higher seed costs in their analysis, which may contribute to their lower welfare gains.12 At

12 We did not have the relevant data to make assumptions about the costs of seed in the total production cost in all adopting countries, so instead we justify our restriction by shocking them with exogenous small adoption rates.

the same time, our simulations include the adoption of GM rice in a larger number of countries, therefore resulting in larger global welfare effects than other studies. Lastly, because we impose factor-biased productivity shocks that can result in large efficiency gains in certain critical sectors, our results may be different from what one would get by the imposition of a Hicks-neutral 5 percent shock in all producing nations.

Table 17. Welfare gains in $ million per percentage point actual adoption of GM rice and wheat

Crop	Country	1	2a	2b	3a-i	3a-ii	3b-i	3b-ii
Rice								
	China	58.01	57.72	57.91	57.85	58.01	57.95	58.12
	Bangladesh	9.19	9.2	9.2	9.2	9.2	9.2	9.2
	India	45.42	45.18	45.34	45.34	45.31	45.39	45.38
	Indonesia	17.31	17.24	17.29	17.3	17.31	17.31	17.32
	Philippines	10.59	10.57	10.58	10.58	10.58	10.58	10.58
Wheat								
	China	13.76	13.68	13.76	13.73	13.97	13.76	14.01
	Bangladesh	0.70	0.72	0.70	0.70	0.71	0.70	0.71
	India	38.69	38.5	38.69	38.67	38.59	38.69	38.61
	Argentina	4.31	4.25	4.3	4.28	4.12	4.31	4.14

Source: Authors' derivations.

Despite the differences with previous studies, we believe that our results are plausible. Still, as in any simulation model, the results depend on the assumptions of the model and scenarios. One of the critical factors is the yield effect. To verify the validity of the results we ran two sets of additional simulations using the minimum and maximum values for yields in the four countries of study (tables 2 through 5). We do not present all the results, but the case of selected scenarios under set B is presented in the appendix in Table A.5. As expected, the welfare effects are consistently lower for GM-adopting countries with the minimum yield effect than with the most likely yield effect. The shock with a maximum yield effect also results in slightly higher welfare gains for GM-adopting countries and overall, which means that the immiserizing growth effect is not visible for adopting nations.

A second critical factor is the adoption rate. To provide a consistent idea of the welfare gains experienced by our countries of study in the case of GM rice and wheat, we divided the total annual gains by the adoption rates. The results are shown in millions of dollars per percentage of actual adoption in Table 17. In the case of rice, the gains range between $9 million and $60 million per percentage point depending on the country. India and China experience larger gains than the three other countries because the GM rice varieties they adopt provide larger relative gains in yields and because their rice sectors largely exceed the ones in other countries. Still, all these gains are significant. For instance, each percentage point of GM rice—as represented by the vector of traits defined in section 3—produced in

India will yield an estimated \$45 million per year. This is quite remarkable. In the case of wheat, India derives a much higher gain from GM wheat (\$38 million per percentage point) compared with other countries because of its higher productivity effect, and Bangladesh experiences only a really small gain compared with the other countries for the same reason and a much smaller wheat sector. These differences may also partially be the result of the repercussion of GM crop adoption on other factors and on overall efficiency.

7. CONCLUSIONS

The introduction of transgenic crops is perceived as a relative success by some, as revealed by their reported adoption by millions of farmers in countries across the world, but it is perceived as a relative failure by others, in part because of its limitation to a few countries, crops, and traits, and because of consumer concerns in a number of countries. One of the reasons for the limitation of transgenic, or genetically modified, crops to certain traits and countries is related to market sensitivity, international trade risks, and the fear of export losses.

In this paper we study the potential effects of introducing GM commodity crops in Bangladesh, India, Indonesia, and the Philippines—four Asian countries with large rural poor populations—in the presence of potential trade restrictions. We focus on GM field crops resistant to biotic and abiotic stresses that have not all been approved yet, such as drought-resistant rice, and use a multi-country, multi-sector computable general equilibrium model. We build on previous international simulation models by improving the representation of the productivity shocks with GM crops, taking into account regional or land type disparities, and by using an updated representation of the world market, accounting for the trade filter effects of labeling policies and the possibility of segregation for non-GM products going toward sensitive importing countries. Our scenarios of simulations also include current GM crop adopters and plausible leaders in the adoption of GM food crops.

The results of our simulations first show that the gains associated with the adoption of GM crop combinations largely exceed any type of potential trade losses. In most countries and scenarios, the gains with GM technology, even at partial adoption rates, exceed the losses with trade by a factor of 14 or more. Second, we find that segregation can help reduce any potential trade loss for GM adopters that want to keep export opportunities in sensitive countries, but its advantage will depend on the segregation cost. Our results also show that the opportunity cost of segregation is much larger for sensitive importing countries than for exporting countries adopting new GM crops. This suggests that importers will likely have the incentive to invest in segregation chains for non-GM supplies to mitigate their expected losses due to the introduction of GM crops in exporting countries.

Our results also show that GM rice is bound to be the most advantageous crop for the four countries of study. For instance, we find that a 1 percentage point increase in the adoption of GM rice in India, combining different traits in different regions, could result in gains exceeding $45 million per year, with or without trade blocks in sensitive countries. Provided it is adopted, GM rice would also result in large production increases that would significantly decrease rice imports in countries with dense populations, such as Bangladesh or Indonesia. More generally, the relative gains with GM crop adoption are much larger for developing nations than for developed nations.

Therefore, our results demonstrate that, as in other countries, fears of trade losses related to the use of GM food crops in these Asian countries are plainly overstated in the current regulatory situation. It is certain that trade barriers could multiply with the adoption of similar trade-distorting regulations in a larger set of countries. A number of developing countries are intending to introduce stringent labeling requirements that could result in additional trade losses. Moreover, the Biosafety Protocol almost adopted generalized information requirements for GM commodities that would have incurred high costs on global commodity trade especially for developing countries that are members of the Protocol (Gruere and Rosegrant 2008). But the possible restrictions would likely result in economic losses for those particular countries, without being compensated by real consumer satisfaction, especially in the poorest and more populous countries of Asia. Still, in the current regulatory environment where enforced regulations are concentrated in a few importers, Bangladesh, India, Indonesia, and the Philippines are bound to gain greatly from adopting GM commodity crops.

At the end of this study, one question remains: What explains the discrepancy between our and others' results showing the lack of real commercial risks and the fear of export losses in these various countries? Responding to this question would require delving into the political economy of biotechnology decision making in each of these countries, which is not the purpose of this study. Part of our team is conducting research on this particular issue, focusing on the role of various special interest groups, including traders, activists, and large importing companies in sensitive countries, in spreading the fear of commercial risks in different countries of Asia and Africa. As our results show, importers in sensitive countries would value segregation, but they would likely prefer to oppose the introduction of GM crops to avoid paying the cost of segregation. Our results further show that some importing nations of Sub-Saharan Africa would gain from the adoption of current GM crops in other countries if there are trade restrictions in sensitive countries, as they would benefit from trade diversion and lower import prices. Yet many of them reject imports partially because they lack proper regulations but also because they fear they would affect their exports to sensitive countries. More needs to be done to investigate these contradictions and the role of different political actors in spreading exaggerated and perhaps irrational fears.

Even if our simulations are based on improvements in assumptions and scenarios, they are still subject to a number of limitations. First, as with any ex ante simulation, the productivity effects are still largely uncertain and their level affects the results significantly. A sensitivity analysis on the yield factors for the countries of study showed that larger yield gains result in higher welfare gains ceteris paribus. More sensitivity analysis, particularly on the input factors in these and other countries, as well as on the segregation costs, would help provide a more complete picture of the range of possible effects of GM crops in the four countries of study.

Second, our simulation would gain by adopting a dynamic rather than a comparative static framework. Local expert meetings and elicitation provided some insight into the potential evolution of adoption in the countries of study. Accounting for the crop/trait-specific regulatory lag, extension lags, and adoption dynamics would help improve the plausibility of our results.

Third, despite our effort to reduce obvious biases linked to the overaggregation of the GTAP database with the use of proportional factors, our model would be better served with structural differentiation within the relevant sectors. For instance, we use the share of maize in coarse grains in the reference database for calibration, but the model would perform more consistently with a structural model dividing the coarse grains sector into maize and other crops under all scenarios. Similar improvement could be made in the chemical sector, used as input, within the oilseed sector, or within each country at the regional level. Ultimately, a structural representation accounting for product and regional specificities could help derive disaggregated benefits per product and strata of the population in a particular region.

More generally, it is necessary to keep in mind that the results of our global simulations, like the ones of other papers, do not account for the positive or negative effects of technology adoption on the environment and potential other externalities it may generate on other activities of the economy. On the one hand, the reduction of chemical inputs may provide benefits for farmers' health and/or the environment; on the other hand, pest resistance building may affect other types of agriculture, and potential gene flows could affect natural biodiversity in specific cases. Our implicit assumption throughout the paper is that the GM crops we focus on are released after assessment and approval by the biosafety regulatory authorities in the relevant countries, on the conclusion that their potential risks are negligible or at least manageable under particular practices. Naturally, any possible external costs incurred by adopters would have to be compared with the large expected income gains we found in the four Asian countries we focused on.

APPENDIX: ADDITIONAL TABLES

Table A.1. Percentage changes in production, export, and import volumes for selected set A scenarios in GM-adopting countries (numbers corresponding to GM-adopting region and sector are shown in bold)

Set A		Scenario	Australia / New Zealand	Canada	Mexico	United States	Argentina	Brazil	European Union	China	India	Philippines	South Africa
Production	*Coarse grains*	1	-3.3	**-4.5**	-6.0	**9.0**	**5.5**	-1.6	**-0.7**	-0.6	0.0	**1.1**	0.1
		2b	-3.5	**-4.5**	-6.0	**9.0**	**5.6**	-1.7	**-0.7**	-0.5	0.0	**1.1**	0.2
		3b-ii	-3.3	**-4.5**	-6.0	**9.0**	**5.5**	-1.6	**-0.7**	-0.6	0.0	**1.1**	0.1
	Cotton	1	**-3.3**	-22.5	**-28.3**	**20.8**	**4.8**	**-3.8**	-3.7	**-0.1**	**2.1**	-3.4	**33.0**
		2b	**-2.9**	-22.5	**-28.3**	**20.8**	**4.8**	**-3.7**	-3.7	**-0.1**	**2.1**	-3.6	**33.1**
		3b-ii	**-3.3**	-22.5	**-28.3**	**20.8**	**4.8**	**-3.8**	-3.7	**-0.1**	**2.1**	-3.4	**33.0**
	Oilseeds	1	**-7.5**	**-9.9**	**-7.2**	**17.8**	**-11.4**	**0.3**	-4.7	**0.4**	**0.4**	-6.6	-3.8
		2b	**-6.3**	**-9.9**	**-7.3**	**18.6**	**-11.3**	**0.9**	-5.4	**0.4**	**0.4**	-9.0	-2.9
		3b-ii	**-8.0**	**-10.0**	**-7.3**	**18.0**	**-11.4**	**0.4**	-4.8	**0.3**	**0.4**	-6.8	-3.8
Exports	*Coarse grains*	1	-4.8	**-10.2**	-6.1	**-16.6**	**-10.6**	-5.2	**-5.2**	-7.6	-5.0	**-3.9**	-12.4
		2b	0.1	**-10.7**	2.1	**-17.5**	**-11.8**	2.2	**-8.7**	-4.7	-0.8	**-7.4**	-14.0
		3b-ii	-4.7	**-10.1**	-6.1	**-16.1**	**-10.3**	-5.1	**-5.1**	-7.5	-5.0	**-3.8**	-12.0
	Cotton	1	**-11.0**	-23.8	**-7.2**	**-9.9**	**-6.4**	**-9.5**	-7.3	**-12.9**	**-1.0**	-11.4	**-22.8**
		2b	**-13.0**	-23.8	**-10.7**	**-10.9**	**-6.9**	**-10.5**	-7.0	**-16.2**	**-5.1**	-6.8	**-23.1**
		3b-ii	**-10.2**	-23.8	**-4.5**	**-8.6**	**-6.3**	**-9.4**	-7.3	**-9.9**	**-0.3**	-10.7	**-22.6**
	Oilseeds	1	**-10.7**	**-14.6**	**-6.4**	**-12.6**	**-9.2**	**-11.5**	-7.3	**-9.7**	**-12.2**	-7.8	-11.1
		2b	**-13.3**	**-16.2**	**-7.6**	**-15.7**	**-10.6**	**-17.1**	-8.0	**-18.8**	**-15.9**	8.4	-14.5
		3b-ii	**-9.0**	**-14.1**	**-5.7**	**-4.9**	**-5.1**	**-7.6**	-7.5	**-3.2**	**-10.1**	-6.9	-9.8
Imports	*Coarse grains*	1	-5.1	**-15.7**	-18.6	**-14.7**	**-13.3**	-5.2	**-3.0**	-0.9	-3.1	**-9.2**	-5.8
		2b	-7.1	**-15.6**	-18.5	**-14.8**	**-13.6**	-4.9	**13.4**	-1.0	-3.1	**-9.2**	-6.0
		3b-ii	-3.9	**-15.8**	-18.7	**-14.7**	**-13.4**	-5.3	**-1.9**	-0.9	-3.1	**-9.2**	-5.9
	Cotton	1	**-5.9**	-30.4	**-15.4**	**-27.3**	**-11.7**	**0.3**	-2.0	**-7.7**	**-11.1**	-9.6	**-6.4**
		2b	**-8.7**	-30.4	**-15.4**	**-27.5**	**-11.7**	**0.0**	-1.9	**-7.7**	**-11.1**	-9.5	**-6.5**
		3b-ii	**-4.1**	-30.7	**-15.8**	**-27.4**	**-11.7**	**0.2**	-1.7	**-7.8**	**-11.2**	-9.8	**-6.4**
	Oilseeds	1	**-10.9**	**-17.2**	**-23.7**	**-21.4**	**7.3**	**-4.1**	-8.2	**-10.5**	**-1.3**	-18.7	0.2
		2b	**-12.5**	**-17.2**	**-23.8**	**-22.2**	**6.3**	**-5.6**	-10.5	**-10.5**	**-3.0**	-18.9	-2.6
		3b-ii	**-11.3**	**-19.3**	**-25.2**	**-21.8**	**6.9**	**-4.1**	-1.3	**-11.6**	**-1.6**	-19.8	0.0

Table A.2. Percentage changes in production, export, and import volumes for selected set B scenarios in GM-adopting countries (numbers corresponding to GM-adopting region and sector are shown in bold)

Set A		Scenario	Australia / New Zealand	Canada	Mexico	United States	Argentina	Brazil	European Union	China	India	Philippines	South Africa
Production	*Coarse grains*	1	-3.3	**-4.5**	-6.0	**9.0**	**5.5**	-1.6	**-0.7**	-0.6	0.0	**1.1**	0.1
		2b	-3.5	**-4.5**	-6.0	**9.0**	**5.6**	-1.7	**-0.7**	-0.5	0.0	**1.1**	0.2
		3b-ii	-3.3	**-4.5**	-6.0	**9.0**	**5.5**	-1.6	**-0.7**	-0.6	0.0	**1.1**	0.1
	Cotton	1	**-3.3**	-22.5	**-28.3**	**20.8**	**4.8**	**-3.8**	-3.7	**-0.1**	**2.1**	-3.4	**33.0**
		2b	**-2.9**	-22.5	**-28.3**	**20.8**	**4.8**	**-3.7**	-3.7	**-0.1**	**2.1**	-3.6	**33.1**
		3b-ii	**-3.3**	-22.5	**-28.3**	**20.8**	**4.8**	**-3.8**	-3.7	**-0.1**	**2.1**	-3.4	**33.0**
	Oilseeds	1	**-7.5**	**-9.9**	**-7.2**	**17.8**	**-11.4**	**0.3**	-4.7	**0.4**	**0.4**	-6.6	-3.8
		2b	**-6.3**	**-9.9**	**-7.3**	**18.6**	**-11.3**	**0.9**	-5.4	**0.4**	**0.4**	-9.0	-2.9
		3b-ii	**-8.0**	**-10.0**	**-7.3**	**18.0**	**-11.4**	**0.4**	-4.8	**0.3**	**0.4**	-6.8	-3.8
Exports	*Coarse grains*	1	-4.8	**-10.2**	-6.1	**-16.6**	**-10.6**	-5.2	**-5.2**	-7.6	-5.0	**-3.9**	-12.4
		2b	0.1	**-10.7**	2.1	**-17.5**	**-11.8**	2.2	**-8.7**	-4.7	-0.8	**-7.4**	-14.0
		3b-ii	-4.7	**-10.1**	-6.1	**-16.1**	**-10.3**	-5.1	**-5.1**	-7.5	-5.0	**-3.8**	-12.0
	Cotton	1	**-11.0**	-23.8	**-7.2**	**-9.9**	**-6.4**	**-9.5**	-7.3	**-12.9**	**-1.0**	-11.4	**-22.8**
		2b	**-13.0**	-23.8	**-10.7**	**-10.9**	**-6.9**	**-10.5**	-7.0	**-16.2**	**-5.1**	-6.8	**-23.1**
		3b-ii	**-10.2**	-23.8	**-4.5**	**-8.6**	**-6.3**	**-9.4**	-7.3	**-9.9**	**-0.3**	-10.7	**-22.6**
	Oilseeds	1	**-10.7**	**-14.6**	**-6.4**	**-12.6**	**-9.2**	**-11.5**	-7.3	**-9.7**	**-12.2**	-7.8	-11.1
		2b	**-13.3**	**-16.2**	**-7.6**	**-15.7**	**-10.6**	**-17.1**	-8.0	**-18.8**	**-15.9**	8.4	-14.5
		3b-ii	**-9.0**	**-14.1**	**-5.7**	**-4.9**	**-5.1**	**-7.6**	-7.5	**-3.2**	**-10.1**	-6.9	-9.8
Imports	*Coarse grains*	1	-5.1	**-15.7**	-18.6	**-14.7**	**-13.3**	-5.2	**-3.0**	-0.9	-3.1	**-9.2**	-5.8
		2b	-7.1	**-15.6**	-18.5	**-14.8**	**-13.6**	-4.9	**13.4**	-1.0	-3.1	**-9.2**	-6.0
		3b-ii	-3.9	**-15.8**	-18.7	**-14.7**	**-13.4**	-5.3	**-1.9**	-0.9	-3.1	**-9.2**	-5.9
	Cotton	1	**-5.9**	-30.4	**-15.4**	**-27.3**	**-11.7**	**0.3**	-2.0	**-7.7**	**-11.1**	-9.6	**-6.4**
		2b	**-8.7**	-30.4	**-15.4**	**-27.5**	**-11.7**	**0.0**	-1.9	**-7.7**	**-11.1**	-9.5	**-6.5**
		3b-ii	**-4.1**	-30.7	**-15.8**	**-27.4**	**-11.7**	**0.2**	-1.7	**-7.8**	**-11.2**	-9.8	**-6.4**
	Oilseeds	1	**-10.9**	**-17.2**	**-23.7**	**-21.4**	**7.3**	**-4.1**	-8.2	**-10.5**	**-1.3**	-18.7	0.2
		2b	**-12.5**	**-17.2**	**-23.8**	**-22.2**	**6.3**	**-5.6**	-10.5	**-10.5**	**-3.0**	-18.9	-2.6
		3b-ii	**-11.3**	**-19.3**	**-25.2**	**-21.8**	**6.9**	**-4.1**	-1.3	**-11.6**	**-1.6**	-19.8	0.0

Table A.3. Percentage changes in production, export, and import volumes for selected set RICE scenarios in GM-adopting countries

Set RICE	Scenario	China	Bangladesh	India	Indonesia	Philippines
Production	1	19.7	7.5	19.8	20.4	19.1
	2a	19.5	7.5	19.7	20.2	18.9
	2b	17.9	7.5	16.4	19.3	17.8
	3b-ii	19.5	7.5	19.6	20.2	18.9
Exports	1	18.3	9.8	15.3	150.7	84.5
	2a	5.6	-5.1	7.9	100.5	46.4
	2b	-18.0	-31.4	-6.0	8.0	-24.1
	3b-ii	15.6	3.0	13.5	130.4	67.6
Imports	1	-45.9	-27.0	-49.4	-65.2	-56.2
	2a	-46.1	-27.1	-49.7	-65.4	-56.4
	2b	-46.7	-27.4	-50.4	-65.8	-57.0
	3b-ii	-46.1	-27.1	-49.6	-65.3	-56.3

Source: Authors' derivations.

Table A.4. Percentage changes in production, export, and import volumes for selected set WHEAT scenarios in GM-adopting countries

Set WHEAT	**Scenario**	**China**	**Bangladesh**	**India**	**Argentina**
Production	1	9.1	-4.3	16.8	30.8
	2a	9.1	-4.3	16.8	30.8
	2b	8.3	-4.4	14.5	30.3
	3b-ii	9.0	-4.3	16.2	30.7
Exports	1	44.7	-36.8	50.5	-5.8
	2a	44.1	-36.8	50.3	-5.8
	2b	-63.8	-37.2	35.2	-6.1
	3b-ii	10.7	-36.9	45.6	-5.9
Imports	1	-43.6	-0.6	-42.7	-36.9
	2a	-43.6	-0.6	-42.7	-36.9
	2b	-44.1	-0.6	-43.3	-37.1
	3b-ii	-43.7	-0.6	-42.9	-37.0

Source: Authors' derivations.

Table A.5. Sensitivity analysis on selected set B scenarios with minimum, most likely, and maximum yield effects

SET B	1. Productivity shock Minimum		1. Productivity shock Most likely		1. Productivity shock Maximum		3b-ii. Import filter, 5% cost segregation Minimum		3b-ii. Import filter, 5% cost segregation Most likely		3b-ii. Import filter, 5% cost segregation ***Maximum***	
Region	$ million	%	$ million	%	$ million	%	$ million	%	$ million	%	$ million	%
Australia and New Zealand	-52.555	-0.016	-53.062	-0.016	-53.140	-0.016	-48.641	-0.015	-49.154	-0.015	-49.234	-0.015
China	243.542	0.031	242.399	0.031	243.025	0.031	248.426	0.032	247.285	0.032	247.918	0.032
Japan	431.796	0.014	435.365	0.014	437.256	0.014	258.273	0.008	261.864	0.009	263.763	0.009
South Korea	359.921	0.124	360.583	0.125	360.992	0.125	56.743	0.020	57.709	0.020	58.197	0.020
Rest of Asia	142.500	0.025	143.124	0.025	144.049	0.025	145.834	0.026	146.457	0.026	147.382	0.026
Indonesia	52.700	0.053	113.213	0.115	150.886	0.153	53.122	0.054	113.639	0.115	151.315	0.153
Philippines	122.944	0.196	120.197	0.191	120.345	0.192	122.664	0.195	119.918	0.191	120.065	0.191
Bangladesh	0.241	0.001	1.008	0.003	1.336	0.004	0.237	0.001	1.004	0.003	1.332	0.004
India	625.615	0.168	825.588	0.221	862.765	0.231	624.066	0.167	824.106	0.221	861.303	0.231
Canada	38.916	0.007	39.428	0.007	39.491	0.007	41.228	0.008	41.738	0.008	41.800	0.008
United States	1842.366	0.022	1848.543	0.022	1848.750	0.022	1854.163	0.022	1860.343	0.022	1860.551	0.022
Mexico	333.425	0.070	333.683	0.070	333.839	0.070	334.381	0.070	334.641	0.070	334.799	0.070
Rest of Latin America	103.728	0.020	103.975	0.021	103.965	0.021	108.362	0.021	108.608	0.021	108.599	0.021
Argentina	-281.731	-0.124	-282.945	-0.125	-283.500	-0.125	-283.338	-0.125	-284.556	-0.125	-285.137	-0.126
Brazil	28.042	0.007	27.534	0.007	27.431	0.007	15.304	0.004	14.790	0.004	14.687	0.004
European Union	495.925	0.008	506.163	0.008	508.240	0.008	275.696	0.004	286.030	0.004	288.130	0.004
Rest of Europe	42.469	0.006	43.566	0.006	43.941	0.006	25.626	0.004	26.728	0.004	27.083	0.004
North Africa and Middle East	253.074	0.031	256.574	0.032	257.765	0.032	252.918	0.031	256.414	0.032	257.606	0.032
Rest of Sub-Saharan Africa	-2.893	-0.002	-2.877	-0.002	-2.815	-0.002	-0.429	0.000	-0.420	0.000	-0.359	0.000
South Africa	20.122	0.023	20.568	0.024	20.618	0.024	19.808	0.023	20.254	0.023	20.304	0.023
Tanzania and Uganda	44.557	0.321	44.558	0.322	44.565	0.322	44.522	0.321	44.523	0.321	44.529	0.321
World	**4844.700**	**0.020**	**5127.184**	**0.021**	**5209.803**	**0.021**	**4148.963**	**0.017**	**4431.919**	**0.018**	**4514.632**	**0.018**

Source: Authors' derivations.

Table A.6. Opportunity cost ($ million/yr) of segregation of non-GM crops for exports toward final consumption under set A and set B for adopting and sensitive countries

Country	Set A	Set B
GM producers only		
China	-1.34	-1.37
Indonesia	-1.93	-0.93
Philippines	0.18	0.17
Bangladesh	-0.03	-0.06
India	4.8	4.69
Canada	3.06	3.04
USA	5.17	5.21
Mexico	-2.82	-2.84
Argentina	6.80	6.80
Brazil	19.23	19.15
South Africa	0.58	0.58
Tanzania/Uganda	-0.26	0.30
Total GM producers	**33.44**	**34.74**
Sensitive countries		
Australia/NZ	3.44	3.46
Japan	150.82	149.3
South Korea	722.12	724.21
EU	536.77	541.28
Rest of Europe	46.22	46.44
Total sensitive countries	**1459.37**	**1464.69**
WORLD		
Global	**1434.36**	**1439.62**

Source: Authors' derivations.

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