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Land for Food and Fuel Production
The Role of Agricultural Biotechnology

Steven Sexton and David Zilberman

8.1 Introduction

The global food crisis of 2008 ended three decades of declining food prices and highlighted a growing challenge for agriculture: to supply food and clean energy to a world population growing to nine billion by 2050. In roughly the last half of the twentieth century, agriculture accommodated a near doubling of the world population through intensification. Farm yields more than doubled with the use of high-yielding seed varieties, agricultural chemicals, irrigation, and mechanization. Per capita calorie production grew despite the rapid population growth and despite an exodus of land from production. Since the 1990s, however, yield growth in staple crops has been slowing and stalling as traditional sources of yield improvements are depleted. Absent intensification, demand growth will be met by extensification, which is unpalatable amid growing concern about climate change and biodiversity loss.

First-generation agricultural biotechnology has been promoted as a tool for improving the control of agricultural pests that diminish effective yields. To the extent adoption of the technology generates yield growth, it constitutes a mechanism for expanding farm output without expanding the

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area under cultivation.[1] A number of studies in a variety of countries have documented yield gains caused by the adoption of genetically engineered (GE) crops. The studies have been limited in size and scope, however, and have generated widely varying estimates of the yield gains from GE crop adoption. Absent agreement among empiricists on the magnitude of yield improvements, agricultural biotechnology remains controversial. Potential risks to human health and the environment are weighted heavily against the uncertain benefits. This chapter overcomes some of the limitations in earlier empirical work in order to assess the degree to which the technology has increased food supply on a global scale.

8.2 Background

8.2.1 Agricultural Biotechnology

Farmers around the world have rapidly adopted GE seeds since they were first commercialized in 1996. The GE seeds are intended to reduce pest damage and lower production costs. By 2008, 13.3 million farmers in twenty-five countries annually planted 8 percent of global cropland with transgenic crops. In 2009, U.S. farmers planted more than 80 percent of the sugar beet crop with transgenic varieties that had only been introduced one year earlier (James 2009). Despite the popularity of agricultural biotechnology on the farm, its introduction in the marketplace has met strong resistance from critics who advocate a precautionary approach to the technology because of potential risks to humans and the environment. Consequently, GE seeds and crops are banned in some countries and highly regulated in others, including those that lead in adoption. The European Union, for instance, imposed a de facto ban on GE seeds in 1998. The ban was lifted in 2008 amid pressure from the United States and the World Trade Organization. Consumer sentiment against GE foods has also constrained the market for GE seed. Products derived from GE seed have been relegated to feed and fiber uses only. Producers must segregate GE crop output throughout the supply chain in order to ensure the transgenic material is not comingled with

1. Yield improvements from exogenous technical changes can, in theory, induce cropland expansion by making farming more profitable. Yield gains increase output on existing land, which tends to reduce prices, but also lowers costs of production, potentially making expansion to more marginal lands profitable, as we note in section 8.3. Feng and Babcock (2010) provide analytical results that show yield improvements in maize induce cropland expansion under unregulated free markets. However, an extensive empirical body of research suggests the opposite is true: that yield improvements are associated with reductions in cropland expansion (e.g., Waggoner 1995; Matson et al. 1997; Balmford, Green, and Scharlemann 2005). Alston, Beddow, and Pardey (2009), for instance, document dramatic increases in agricultural productivity and only "slow growth" in the use of agricultural land. Barbier (2001) estimates a negative elasticity of crop yield with respect to land expansion in tropical forests. This point is also made in Zilberman et al. (1991), Mundlak (2001), and Mundlak (2011).

conventionally bred crop output. In early 2010, China was poised to approve the first use of a GE crop for human consumption.

The GE traits have been introduced to four principal crops: cotton, maize, rapeseed, and soybean. Rapeseed and soybean seeds have been engineered to tolerate broad-spectrum herbicides like glyphosates and gluphosinates, chemicals that target a host of weed species and are lethal to conventional crops. Adoption of such herbicide-tolerant (HT) varieties permits farmers to more effectively control weeds. Absent the HT trait, farmers are forced to apply more toxic and narrowly targeted chemicals in order to kill weeds and keep the crop safe. They also use mechanical control, like tilling operations, to control weeds. Because glyphosates have historically sold at prices below the targeted chemicals, adoption of HT varieties is likely to reduce damage control expenditures. Some cotton and maize varieties have also been engineered with the HT trait, while others are engineered to produce *Bacillus thuringiensis* (Bt), a naturally occurring toxin that is lethal if ingested by a number of common insect pests. These are referred to as Bt crops or insect-resistant (IR) crops. Some maize and cotton varieties are engineered to express both traits and are commonly referred to as "stacked" varieties. The HT traits have also been introduced into sugar beets and alfalfa, though both are planted on a relatively small scale. Crops with HT traits have always been the dominant GE crop, occupying 63 percent of total GE crop area in 2008, followed by "stacked" traits (22 percent) and IR traits (15 percent). The HT soybeans occupied the majority of total GE cropland (53 percent) and constituted 70 percent of the world soybean crop in 2008 (James 2009). The GE maize constituted 30 percent of all GE crop areas in 2008 and 24 percent of the world maize crop.

Adoption of GE crops has been rapid. By 2009, half of all U.S. cropland was planted with GE seed. Approximately 80 percent of the 2008 cotton, maize, and soybean crops in the United States were each produced from transgenic varieties. The United States has been a leader in adoption, planting more than half (62.5 million hectares) of all GE areas in 2008. But other countries have been similarly aggressive in their adoption. South Africa, Australia, and Argentina all planted more than 90 percent of their 2008 cotton crops with GE varieties, up from 1 to 2 percent a decade earlier. Canada planted virtually its entire maize crop with GE seed in 2008. Of the twenty-five countries that planted GE crops in 2008, fifteen were developed countries and ten were developing (James 2009). Figure 8.1 shows the annual area planted with GE crops from 1996 to 2008 by country type.

8.2.2 The Economics of Agricultural Biotechnology

There is a large and growing literature on the adoption and impact of GE crops. It is summarized in Qaim (2009) and National Research Council (2010). Much of the literature on GE crop adoption follows the threshold adoption framework of David (1969). This framework assumes that firms

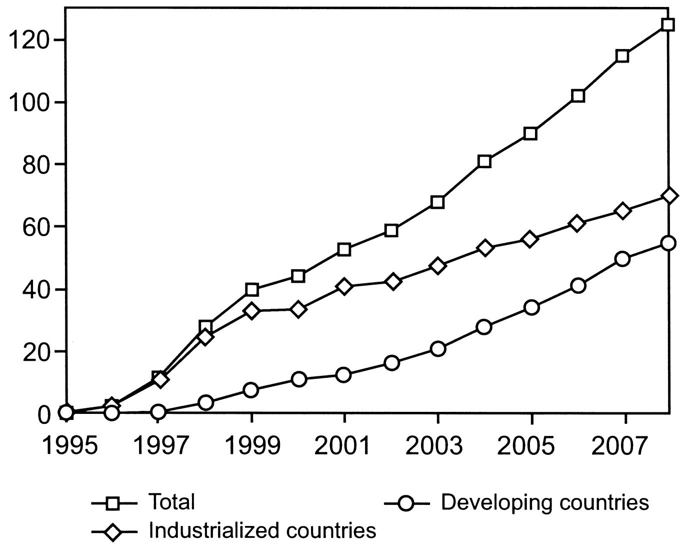

Fig. 8.1 Genetically engineered crop adoption over time

are heterogeneous, that they make choices that are consistent with an explicit economic decision-making criterion (e.g., profit maximization), and that the costs and benefits of technology adoption vary over time in response to changes in economic conditions and learning (Feder, Just, and Zilberman 1985). The threshold model is readily employed in applications with data on the behavior of individual agents by using discrete and discrete-continuous choice models.

Much of the literature on adoption of GE-crop technology estimated the factors that affect whether producers adopt the technology and the extent of adoption. These studies found that biophysical conditions (e.g., vulnerability to pest damage), economic conditions (e.g., output and input prices), and regulatory conditions affect adoption. The scale of operation and human capital are not major factors affecting adoption because GE-crop technology is simpler than alternative damage-control mechanisms and does not exhibit increasing returns to scale. Crost et al. (2007), however, did find evidence that farmers in India with higher human capital were more likely to adopt.

Another significant body of literature has investigated the impact of GE-crop technology. Most of this literature is surveyed in Qaim (2009) and National Research Council (2010). For the most part, these studies compared the performance of GE with non-GE crops under various conditions. Some conducted surveys of farmers to assess the reasons for adoption and the cause of yield changes post–GE crop adoption. Most existing studies were conducted in the early days of GE-crop adoption (from 1996 to 2003) or considered early data.

The potential gains associated with adoption of first-generation GE crops are several. They include reduced crop losses from insect pests; reduced expenditures on damage control inputs like herbicides, pesticides, and fuel; improved worker safety; greater flexibility in farm management; and lower risk of yield variability (National Research Council 2010). The magnitude of these benefits varies by location, crop, and time. Table 8.1, which is borrowed from Qaim (2009), summarizes existing empirical estimates of some of these benefits, including yield gains, gross margin impacts, and pesticide use. It demonstrates the heterogeneity of estimates in the extant literature.

There has been no rigorous assessment of the impact of adoption of GE technologies in aggregate even though there is a rich literature on the welfare implications of adoption based on stylized assumptions about shifts in supply. These studies, too, mostly cover the earlier period of adoption of GE crops. The National Research Council (2010) identified the lack of recent market impact assessments as one of the major gaps in the economic research on agricultural biotechnology. In this chapter, we employ data on acreage of major crops and the share of land for each crop that is allocated to biotechnology. We use analysis of variance to decompose yield per acre to different components. Our analysis applies an approach introduced by Just et al. (1990) to decompose variable input among crops. The approach is used to allocate output among crop types. We assume that at each time and

Table 8.1 **Farm-level effects of genetically engineered crops**

Country	Insecticide reduction (%)	Increase in effective yield (%)	Increase in gross margin (US$/ha)	Reference(s)
		Bacillus thuringiensis cotton		
Argentina	47	33	23	Qaim and de Janvry (2003, 2005)
Australia	48	0	66	Fitt (2003)
China	65	24	470	Pray et al. (2002)
India	41	37	135	Qaim et al. (2006), Sadashivappa and Qaim (2009)
Mexico	77	9	295	Traxler et al. (2003)
South Africa	33	22	91	Thirtle et al. (2003), Gouse et al. (2004)
United States	36	10	58	Falck-Zepeda et al. (2000b), Carpenter et al. (2002)
		Bacillus thuringiensis maize		
Argentina	0	9	20	Brookes and Barfoot (2005)
The Philippines	5	34	53	Brookes and Barfoot (2005), Yorobe and Quicoy (2006)
South Africa	10	11	42	Brookes and Barfoot (2005), Gouse et al. (2006)
Spain	63	6	70	Gómez-Barbero et al. (2008)
United States	8	5	12	Naseem and Pray (2004), Fernandez-Cornejo and Li (2005)

Source: Qaim (2009, 672).

location, the yield per acre of each crop with a given technology is fixed, but these yields per acre vary across crops, technologies, and time. This approach has been generalized by Lence and Miller (1998) and applied by Khanna and Zilberman (1999) to decompose aggregate data of energy generation and greenhouse gas (GHG) emissions in different locations. This rather simple approach allows us to rely upon a minimal amount of data to decompose yields. We use our estimate of the partial effect of GE adoption on yields of adopting farmers (a population averaged treatment effect on the treated) to estimate the change in food supply attributable to agricultural biotechnology and parameterize a model of the food market in 2008 in order to assess the effect of GE seeds on food prices during the food crisis.

8.3 Conceptual Model

In this section, we present a conceptual model that provides the theoretical foundation for the empirical analysis that follows in the next section. We adopt a modeling approach that follows Qaim and Zilberman (2003) and Ameden, Qaim, and Zilberman (2005) that employs the damage control framework of Lichtenberg and Zilberman (1986). This framework distinguishes between inputs that directly affect production, like capital and fertilizer, and inputs that indirectly affect production by reducing crop damage, such as pesticides and mechanical and biological control. Specifically, assume a constant-returns-to-scale agricultural production function. Let yield per acre, y, be the product of potential output, $f_j(z,a)$, and damage abatement, $g_i(x,N)$. Potential output is the output that would obtain if there were no pest damage. It is increasing in production inputs, z, like fertilizer, and a heterogeneity parameter, a, which characterizes farm quality and is a function of climate, human capital, and land quality. Potential output is also a function of seed variety, j, where $j = 0$ denotes a generic seed variety and $j = 1$ denotes a local seed variety. It is assumed that for all z and a, $f_1(z,a) \geq f_0(z,a)$. Damage abatement is the share of crop not lost due to pest damage. It is increasing at a decreasing rate in use of damage control inputs, x, like pesticides, and decreasing in effective pest pressure, n. Effective pest pressure is the product of a seed-technology parameter, δ_i, and initial pest pressure N, that is, $n = \delta_i N$, where $\delta_0 = 1$ denotes conventional seed technology, and $\delta_1 < 1$ denotes GE seed technology. Consequently, for all x and all positive N, $g_1(x,N) \geq g_0(z, N)$. Effective yield per acre under technology ij, then is given by:

$$y_{ij} = g_i(x_{ij}, N)f_j(z_{ij},a). \tag{1}$$

With this specification, farmers face at most four distinct seed technology packages: generic-conventional ($i = 0, j = 0$), local-conventional ($i = 0$, $j = 1$), generic-GE ($i = 1, j = 0$), and local-GE ($i = 1, j = 1$).

The farmer's problem is:

$$\max_{z,x,i,j} \pi_{ij} = pg_i(x_{ij}, N)f_j(z_{ij}, a) - wz_{ij} - vx_{ij} - I_{ij}, \tag{2}$$

where p, w, and v are exogenously determined prices for output, production inputs, and damage control inputs, respectively, and where I_{ij} is a technology fee associated with technology ij. It is assumed $I_{00} < I_{01} < I_{10} < I_{11}$.

Farmers adopt the technology that yields the highest expected profits. We solve the farmer's problem recursively. First, conditional on seed technology choice and farm quality endowments, producers choose inputs to maximize profits. The profit maximizing quantity of inputs given technology ij are functions of prices and land quality, such that:

$$x^*_{ij} = x^*_{ij}(w, v, p, N)$$
$$z^*_{ij} = z^*_{ij}(w, v, p, N).$$

Maximum profits under each technology are obtained by substituting the optimal input demands into the profit function. Farmers select the technology that yields highest expected profits conditional on profits being nonnegative.

Analysis of these optimality conditions yields several results important for the subsequent empirical analysis. First, the adoption of GE crops increases damage abatement, which boosts effective yield under typical conditions. This is true so long as farmers face some pest pressure, and the adoption of GE crops does not require farmers to switch to a low-yield generic seed variety that would lower potential output. In theory, effective output may decline with adoption of GE crops either because a given farmer must switch from a local seed variety to a generic variety in order to adopt the GE technology or because the insertion of the GE trait into the seed germplasm causes an interaction that reduces potential output. In order for effective yield to decline with adoption, the percentage change in potential output must exceed the percentage change in damage abatement in absolute value. In practice, such reductions in effective output with GE adoption, termed "yield drag," have not been a significant problem (National Research Council 2010). Furthermore, the optimizing farmer would only choose to adopt GE seed that exhibited these yield drag effects and thereby reduced total output if the cost savings from reduced damage control expenditures exceeded the revenue loss from foregone yields.

Second, the damage-abatement gain is increasing in pest damage and the price of conventional damage control inputs like fertilizer. We can define the change in damage abatement due to GE crop adoption, assuming no change in the j-dimension, as:

$$\Delta g = g_{1j}(x, N) - g_{0j}(x, N). \tag{3}$$

Then it can be shown that $d\Delta g/dN > 0$ and $d\Delta g/dw > 0$.

Third, GE crop adoption causes an increase in the use of production inputs like fertilizer. It boosts potential output as long as it does not require a switch from a local seed variety to a generic seed variety. As damage abatement increases, so, too, does the value of marginal product of production inputs increase, holding prices constant. Therefore, farmers employ more production inputs. The increase in production inputs raises potential output, which boosts effective output by more than the reduction in crop damage. Though we are unable to test impacts of GE crop adoption on input-use in the subsequent empirical analysis due to a lack of global data on input-use, this result suggests that the yield gain associated with GE crop adoption exceeds the "gene effect" estimated in much of the previous literature. Our empirical estimates of the yield gain associated with GE crop adoption incorporates this additional yield effect that operates through the potential yield function as opposed to the damage abatement function. This makes our yield estimates unique among the estimates of previous analyses.

Fourth, the change in yield due to GE crop adoption is increasing in farm quality, a, and pest pressure, N. We can decompose the total change in effective yield due to GE crop adoption as:

$$\Delta y = y_{1j} - y_{0j} = f_{1j_0}\Delta g + \Delta f_z g_{1j_1} + \Delta f_j g_{1j_1}, \tag{4}$$

where the first term on the right-hand side of the second equality is the damage abatement effect, the second term is the production input effect, and the third term is the yield drag effect, which can be negative but is typically zero (i.e., if $j_0 = j_1$ or if $j_0 = 0$ and $j_1 = 1$). It is easy to show, then, that $d\Delta y/da > 0$ and $d\Delta y/dN > 0$. We do not observe α and N in our data, so to the extent these theoretical predictions hold in practice, our empirical estimates of the yield gain associated with GE crop adoption may be biased. Failure to control for farm quality may induce an upward bias in the results. However, because the yield gains are expected to be greater with high pest pressure and because high pest pressure may be associated with low-quality farms, failure to control for pest pressure may induce an offsetting downward bias in our results.

8.4 Data and Methods

The empirical strategy of this chapter is motivated by the global pattern of GE seed adoption. By 2008, farmers in twenty-five countries had planted at least one of the four major GE crops. In most cases, the share of these crops planted to GE seed increased year over year in adopting countries from 1996 to 2008. In the United States, for instance, 12 percent of cotton was planted to GE seeds in 1996, but by 2007, the GE share had reached 87 percent. Some countries adopted multiple GE crops. Many others did not adopt any GE crops. Even some countries that are expected to experience significant benefits from adoption have not adopted because of political economy considerations. This was the case in European and African countries until 2010. Germany and Romania had deregulated GE technologies but then banned them for political reasons unrelated to their performance on the farm. Countries that did adopt GE crops continued to plant other crops exclusively to conventional seed either because GE alternatives did not exist or because regulation banned some GE crops.

The variation in GE adoption across countries and across time enables the econometrician to control for confounding factors at the country level by employing a panel fixed effects approach that relies on assumptions similar to, but weaker than, those required for estimation in triple differencing procedures. This procedure controls for endogeneity of adoption at the country level, that is, endogeneity of GE crop deregulation. However, estimation of a population average effect of GE crop adoption is subject to the biases described at the end of the preceding section, which stem from the endogeneity of adoption at the farm level, that is, selection on farm quality, which is unobservable in this data. These biases do not impede estimation of a population average effect of GE adoption among adopters, which is the critical coefficient for estimating the increase in food supply attributable to GE technologies.

Motivated by Just et al. (1990), we observe that total output of crop j in country i at time t, Q_{jit}, is the sum of output produced by each seed technology, k. Thus:

$$Q_{jit} = \sum_{k=1}^{K} Q_{jitk}, \tag{5}$$

where Q_{jitk} is the unobserved quantity of crop j produced by country i at time t using seed technology k. Define L_{jitk} as the amount of land planted to crop j with seed technology k in country i at time t. Then $q_{jitk} = Q_{jitk}/L_{jitk}$ is the output of crop j per unit of land using seed technology k in country i at time t. The deterministic component of the q_{jitk}, which is denoted q^*_{jitk}, can be decomposed into a crop-specific average seed-technology effect, β_{jk}, a crop specific time effect, γ_{jt}, and a country-specific crop effect, δ_{jt}. Then q^*_{jitk} is given by:

$$q^*_{jitk} = \beta_{jk} + \gamma_{jt} + \delta_{ji}. \tag{6}$$

The β_{jk} are of interest and can be estimated by:

$$Q_{jit} = \delta_j L_{jit} + \beta_{j1} L^{\mathrm{GE}}_{jit} + \gamma_{jt}\mathbf{D_{jt}} + \varepsilon_{jit}, \tag{7}$$

where L_{jit} is total land planted to crop j in country i at time t, L^{GE}_{jit} is the land planted to GE seed for crop j in country i at time t, $\mathbf{D_{jt}}$ is a crop-specific time dummy (the time dummy for the year 2008 is omitted), and ε_{jit} is a random deviation that is assumed normal and identically distributed. Equation (7) is estimated using fixed effects to control for country effects and secular trends. The fixed effects regression also controls for correlated random trends (Wooldridge 2005). Results are reported with White robust standard errors. The δ_j is the average yield on land that does not adopt GE seeds. The β_{j1} is the marginal effect on yield attributable to adoption of GE seeds ($k = 1$ denotes GE seed technology).

Data on total crop output are reported in tonnes and come from the Food and Agriculture Organization (FAO) of the United Nations. Total crop area is reported in hectares by FAO. The area of land planted to GM crops and specific traits was developed by Graham Brookes using data from the International Service for the Acquisition of Agri-Biotech Applications (ISAAA). The data cover the period 1990 to 2008. We include data on every country that adopted any GE crop from 1996 to 2008, as well as the top 100 gross producers of eight principal row crops during the period 1990 to 2008. For these 100 countries, we include observations on each of the four major GE crops (corn, cotton, soybean, and rapeseed) and each of four other principal row crops: wheat, rice, sorghum, and oats. These data comprise 10,717 annual country-level observations on crop output and GE seed area covering 627 country-crop groups. Because not all countries planted all eight crops in every year, the data constitute an unbalanced panel. Summary statistics are provided in tables 8.2 and 8.3.

8.5 Empirical Results

In the first econometric analysis of the global yield effects of GE seed adoption, we find that agricultural biotechnology generally produces significant yield improvements relative to non-GE seed on adopting farms. Table 8.4 reports results from estimation of equation (7).[2] In all cases, the coefficients of interest, the β_j, are statistically significant at the 99 percent level. Thus, the partial effect of GE seed adoption among adopters is positive and significant. Row (1) of table 8.5 reports the gain in yield from adoption of GE seed as a percent of total yield per acre.[3] The GE-seed effect on yields is greatest for crops with IR traits, that is, maize and cotton. Yield gains for GE cotton and maize—available in IR, HT, and stacked varieties—are estimated to be 65 percent and 45.6 percent, respectively. Yield gains for HT rapeseed and soybean are 25.4 percent and 12.4 percent, respectively. These estimates reflect the theoretical prediction that yield gains are larger for seeds expressing IR traits than for seeds expressing only HT traits because the HT trait largely permits substitution to cheaper and less-toxic chemicals. The primary effect of HT seed, then, is to reduce the cost of damage control and lessen the toxicity of chemicals applied to fields. As damage control becomes more cost-effective, however, increased damage control effort will be undertaken, which boosts effective yields and may boost potential yield as well.

2. Only coefficients of interest are reported. Full results are available from the authors by request.

3. Determined as $100 \cdot \delta_{ji}/\beta_{jk}$.

Table 8.2 Summary statistics: Genetically engineered and trait shares

	All	Developing	Developed	Adopters	Nonadopters
Cotton					
Yield	15,521.02	14,155.02	27,981.82	19,070.02	14,492.22
	(9,278.30)	(7,954.58)	(11,074.55)	(10,174.24)	(8,741.64)
Seed share					
Genetically engineered	0.03	0.02	0.11	0.13	
	(0.14)	(0.11)	(0.26)	(0.27)	
Herbicide tolerant	0.01	0.01	0.08	0.06	NA
	(0.06)	(0.21)	(0.09)	(0.18)	
Insect resistant	0.02	0.02	0.08	0.11	NA
	(0.11)	(0.09)	(0.20)	(0.21)	
No. of observations	1,326	1,195	131	298	1,028
Maize					
Yield	34,603.04	25,987.91	68,774.78	43,716.00	31,515.07
	(26,844.58)	(17,823.54)	(29,293.47)	(25,478.89)	(26,601.66)
Seed share					
Genetically engineered	0.01	0.01	0.03	0.05	NA
	(0.09)	(0.07)	(0.13)	(0.17)	
Herbicide tolerant	0.00	0.00	0.01	0.01	NA
	(0.03)	(0.01)	(0.07)	(0.07)	
Insect resistant	0.01	0.00	0.02	0.05	NA
	(0.07)	(0.06)	(0.09)	(0.14)	
No. of observations	1,778	1,420	358	450	1,328
Rapeseed					
Yield	16,164.46	13,623.73	20,363.35	17,313.31	15,421.09
	(8,082.97)	(6,935.72)	(8,104.34)	(7,674.74)	(8,259.82)
Genetically engineered seed share	0.02	0.01	0.05	0.05	NA
	(0.11)	(0.07)	(0.18)	(0.18)	
No. of observations	756	471	285	297	459
Soybean					
Yield	15,760.13	14,334.70	21,177.71	18,841.01	14,559.26
	(8,049.53)	(7,789.70)	(6,594.89)	(5,634.42)	(8,518.93)
Seed share					
Genetically engineered	0.03	0.01	0.04	0.12	NA
	(0.15)	(0.07)	(0.17)	(0.27)	
Herbicide tolerant	0.03	0.03	0.04	0.12	NA
	(0.16)	(0.15)	(0.17)	(0.27)	
No. of observations	1,469	1,163	306	412	1,119

Notes: Means with standard deviations in parentheses. NA = not applicable.

In order to test the theory that yield gains from GE crop adoption will be greatest in regions that suffer high pest pressure and have diminished access to chemical pest control agents, we estimate equation (7) separately for developed and developing countries. Because many developing countries effectively employ chemical pest control agents and because pest pressure is expected to be greatest in tropical regions, categorizing countries by eco-

Table 8.3 **Summary statistics: Harvest, genetically engineered, and trait areas**

	All	Developing	Developed	Adopters	Nonadopters
		Cotton			
Harvest area	474,349.90	428,056.00	896,649.60	1,379,338.00	212,009.10
	(36,980.19)	(37,104.66)	(155,609.40)	(145,291.90)	(14,420.28)
Area					
Genetically engineered	68,553.91	40,843.28	321,334.10	305,041.90	NA
	(13,715.36)	(11,320.57)	(90,135.19)	(59,087.57)	
Heat tolerant	14,809.95	794.37	142,662.00	65,899.31	NA
	(4,238.49)	(326.75)	(41,290.66)	(18,581.88)	
Insect resistant	45,593.07	39,889.99	97,617.34	202,873.90	NA
	(10,514.57)	(11,313.96)	(25,651.71)	(45,686.30)	
No. of observations	1,326	1,195	131	298	1,028
		Maize			
Harvest area	1,479,825.00	1,360,254.00	1,954,099.00	4,148,485.00	575,534.70
	(98,446.21)	(88,076.30)	(341,315.70)	(355,597.30)	(21,051.80)
Genetically engineered area	109,796.70	15,909.59	482,198.30	433,819.10	NA
	(30,228.59)	(4,282.14)	(147,695.10)	(118,219.00)	
Heat-tolerant area	48,679.08	2,454.09	232,029.60	192,336.50	NA
	(18,522.17)	(861.15)	(91,386.47)	(72,822.68)	
Insect resistant area	97,552.94	14,295.37	427,792.50	385,442.50	NA
	(29,210.24)	(3,861.43)	(143,092.30)	(114,434.10)	
No. of observations	1,778	1,420	358	450	1,328
		Rapeseed			
Harvest area	579,795.00	586,433.90	568,823.40	1,378,898.00	62,728.59
	(56,032.14)	(78,956.79)	(71,337.53)	(129,412.50)	(5,906.97)
Heat-tolerant area	56,013.80		148,584.00	142,580.60	NA
	(16,089.23)		(42,155.01)	(40,484.63)	
No. of observations	756	471	285	297	459
		Soybean			
Harvest area	955,104.90	729,134.40	1,813,940.00	3,208,778.00	76,662.81
	(100,410.50)	(78,176.62)	(376,048.00)	(333,191.70)	(5,633.53)
Heat-tolerant area	324,252.10	185,842.00	850,301.00	1,156,132.00	NA
	(62,136.70)	(42,322.81)	(249,257.40)	(216,403.60)	
No. of observations	1,469	1,163	306	412	1,119

Note: See table 8.2 notes.

nomic status is admittedly crude. The development literature has struggled, however, to develop appropriate country classifications according to agro-ecological factors and doing so is beyond the scope of this chapter. Nevertheless, estimated yield effects from the separate regressions of the developed and developing country samples does support the theory from section 8.3. The separate estimation of GE-seed effects for developed and developing countries are reported in tables 8.6 and 8.7, respectively. The magnitudes of these effects relative to conventional seed effects are summarized in rows (2) and (3) of table 8.5. The estimated yield gains associated with GE seed

Table 8.4 Genetically engineered seed adoption effects

Crop	Total area (1)	Genetically engineered area (2)
Cotton	1.313***	0.854***
	(0.220)	(0.130)
Maize	6.363***	2.902***
	(0.548)	(0.419)
Rapeseed	1.499***	0.382***
	(0.128)	(0.107)
Soybean	2.461***	0.307***
	(0.203)	(0.112)
Oats	1.202***	
	(0.0917)	
Rice	5.094***	
	(0.545)	
Sorghum	1.236***	
	(0.194)	
Wheat	2.257***	
	(0.254)	
Constant	–366,994	
	(239,633)	
No. of observations	10,717	
No. of groups	627	
R^2	0.728	

Note: Robust standard errors in parentheses.
***Significant at the 1 percent level.

Table 8.5 Yield gain from genetically engineered seed as percent of yield

Variable	Cotton (1)	Maize (2)	Rapeseed (3)	Soybean (4)
All countries	65.042	45.607	25.484	12.475
Developed countries	22.886	15.193	24.057	7.040
Developing countries	109.510	56.403	NA	30.189

Note: NA = not applicable.

are greater in developing countries than in developed countries for each GE crop. These differences are statistically significant at the 95 percent level.

We further estimate equation (7) with the addition of GE and non-GE time trends. These results are reported in table 8.8. We find a positive and significant trend associated with non-GE crop yields for cotton, maize, rapeseed, rice, and wheat. These correspond to 1.37 percent, 0.99 percent, 2.17 percent, 0.65 percent, and 1.16 percent annual growth from 1990 to 2008 for each of these crops, respectively. The GE cotton, rapeseed, and soybean exhibited statistically significant positive yield growth over the same time period, suggesting that learning by doing and learning

Table 8.6 **Genetically engineered seed adoption effects in developed countries**

Crop	Total area (1)	Genetically engineered area (2)
Cotton	1.407***	0.322***
	(0.267)	(0.105)
Maize	12.440***	1.890***
	(2.867)	(0.485)
Rapeseed	1.538***	0.370***
	(0.126)	(0.099)
Soybean	2.784***	0.196
	(0.624)	(0.164)
Oats	2.149***	
	(0.115)	
Rice	5.381***	
	(1.154)	
Sorghum	4.572***	
	(0.366)	
Wheat	2.189***	
	(0.222)	
Constant	–453,968*	
	(262,868)	
No. of observations	2,208	
No. of groups	150	
R^2	0.848	

Note: Robust standard errors in parentheses.
***Significant at the 1 percent level.
*Significant at the 10 percent level.

by using have fueled yield growth that dominates declines caused by the pattern of adoption (i.e., expansion of GE seed to farms that benefit less) and development of resistance to complementary chemicals. When the GE-seed trends are introduced, however, significance of the average GE-seed effect is lost except in maize.

The foregoing results demonstrate that GE crop adoption generally has statistically and economically significant effects on yields. As the threshold adoption model introduced in section 8.3 demonstrates, farmers select to adopt GE technologies based on their expected gain. These gains are expected to increase in pest pressure and farm quality. Our estimates do not control for the selection at the farm level. To the extent that GE crops are adopted on farms of higher quality, these estimates will be upwardly biased estimates of the population average treatment effect (PATE). However, they represent unbiased estimates of the population-average treatment effect of the treated (Imbens and Wooldridge 2009). These estimates of yield gains among adopters are not inconsistent with some estimates in the existing literature based on field trials that control for the farmer selection problem.

Table 8.7 **Genetically engineered seed adoption effects in developing countries**

Crop	Total area (1)	Genetically engineered area (2)
Cotton	1.062***	1.163***
	(0.239)	(0.219)
Maize	5.404***	3.048***
	(0.508)	(0.409)
Rapeseed	1.476***	
	(0.210)	
Soybean	2.120***	0.640***
	(0.273)	(0.191)
Oats	1.123***	
	(0.091)	
Rice	5.058***	
	(0.549)	
Sorghum	0.966***	
	(0.124)	
Wheat	2.250***	
	(0.390)	
Constant	–453,968*	
	(262,868)	
No. of observations	8,509	
No. of groups	477	
R^2	0.650	

Note: Robust standard errors in parentheses.
***Significant at the 1 percent level.
*Significant at the 10 percent level.

Furthermore, unlike studies based on field trials, we have not endeavored to estimate a "gene" effect, but rather the "GE-adoption" effect, which incorporates behavioral responses to GE adoption, including the adoption of other technologies and farming practices and changes in production input-use (e.g., fertilizer-use) that theory predicts will boost potential output. The GE-adoption effect that we estimate should dominate the gene effect estimated in the extant literature.

While the potential for upward bias of a PATE estimate is real, it should also be noted that the upward bias traditionally associated with the endogeneity of technology adoption should be somewhat minimized in this case for several reasons. First, the technology under consideration serves to reduce the complexity of farming, suggesting that farmers with less human capital may benefit the most from adoption. Second, while theory predicts the gains increase in land quality, it also suggests the benefits of adoption will be greater where pest pressure is higher. It is not clear this land will be of higher quality than land with less pest pressure. It is quite possible that pest pressure is negatively correlated with land quality such that the positive

Table 8.8 Genetically modified and conventional seed yield trends

Crop	Total area (1)	Genetically engineered area (2)	Conventional trend (3)	Genetically engineered trend (4)
Cotton	1.240***	–0.164	0.017**	0.077***
	(0.294)	(0.297)	(0.009)	(0.026)
Maize	5.055***	2.586***	0.050**	–0.033
	(1.610)	(0.515)	(0.024)	(0.030)
Rapeseed	1.262***	–0.049	0.027***	0.016***
	(0.101)	(0.092)	(0.009)	(0.005)
Soybean	2.374***	0.005	0.008	0.026**
	(0.158)	(0.122)	(0.015)	(0.012)
Oats	1.336***		0.015	
	(0.092)		(0.012)	
Rice	5.267***		0.034***	
	(0.545)		(0.002)	
Sorghum	1.250***		0.002	
	(0.194)		(0.007)	
Wheat	2.584***		0.030***	
	(0.254)		(0.007)	

Note: Robust standard errors in parentheses.

***Significant at the 1 percent level.

*Significant at the 5 percent level.

selection bias will be muted. Depending on the distribution of pest pressure and quality, the selection bias could be negative. Third, GE seed is adopted on marginal land that was not profitably farmed before the introduction of the technology. This land expansion effect further diminishes the likelihood that the quality of farms that adopt GE crops far exceeds the quality of farms that do not adopt.

8.6 Simulating Impacts during the 2008 Food Crisis

In 2008, a global food crisis induced hunger and starvation in poor regions of the world as prices for grains rose dramatically and major food producing countries slashed exports to protect domestic markets. Food prices reached near-record levels in 2008, with some commodity prices nearly doubling in just a few years and food indexes climbing 56 percent in one year. The dramatic run-up in food prices in 2008 coincided with record biofuel production, so much of the blame for food insecurity was leveled at the diversion of harvest from food to fuel uses.

Without the increased food supply afforded by agricultural biotechnology adoption, prices would have climbed even higher. Using partial equilibrium analysis, it is possible to consider what would have happened to food markets in 2008 if observed levels of biofuel production had prevailed and the

Table 8.9 Simulation scenarios

	Scenario 1	Scenario 2	Scenario 3
Own-price elasticity of demand	–0.300	–0.500	–0.300
Own-price elasticity of supply	0.300	0.300	0.300
Cross-price elasticities of demand	0.050	0.050	0.050
Cross-price elasticities of supply	–0.100	–0.100	–0.075

additional output attributable to GE seed adoption had not. To this end, we employ a multimarket framework to model the impacts of 2008 biofuel production on soybean, maize, wheat, and rapeseed. We assume a global market for commodities and simulate three separate assumptions on own and cross-price elasticities of demand and supply. These scenarios are summarized in table 8.9. Scenario 1 is characterized by reasonable elasticity assumptions based on estimated elasticities in the literature. Scenario 2 is characterized by more elastic demand, and Scenario 3 incorporates greater substitutability among crop supply. The supply attributable to GE crop adoption is determined by multiplying the estimated GE yield gain by the area planted to GE crops for each crop.[4] We further parametrize the model based on observed prices and quantities in 2008. We then consider the price effect of biofuel production by subtracting biofuel demand and finding the new equilibrium price.

Global biofuel production in 2008 recruited 86 million tons (10 percent) of global maize production and 8.6 million tons of global vegetable oil, which we assume was equally drawn from soybean and rapeseed production to constitute 7 percent of the global rapeseed harvest and 2 percent of the global soybean harvest. This increased demand for maize, soybean, and rapeseed increased prices 67 percent, 40 percent, 36 percent, and 57 percent for maize, soybean, wheat, and rapeseed, respectively. As reported in table 8.10, world prices for these four commodities would have been between 26 percent and 40 percent lower without biofuel demand given the assumptions of Scenario 1. Without the yield gains of global biotechnology production, 2008 prices would have been considerably higher. Corn prices would have been 35 percent higher, soybean prices 43 percent higher, wheat prices 27 percent higher, and rapeseed prices 33 percent higher.[5] As is also shown in table 8.10, even under the assumptions of more elastic demand (Scenario 2) and supply substitutability (Scenario 3), GE crop adoption in 2008 alone

4. We employ the developing and developed-country estimates in the simulations.

5. An estimate of the global production gains attributable to biotechnology adoption was determined for each maize, soybean, and rapeseed by multiplying observed country-level production in 2008 by the country-appropriate estimate of the GE-induced percentage increase in yield and the country-crop-year-specific GE-crop share. These estimates determined GE-induced output gains to constitute 5 percent, 11 percent, and 4 percent of total output for maize, soybean, and rapeseed, respectively.

Table 8.10 **Simulating food price effects of biofuel with and without biotechnology**

	2008 price	No biofuel	No biotech	Percent change No biofuel	Percent change No biotech
			Scenario 1: Base		
Corn	223.13	133.28	300.24	–40.27	34.56
Soybean	474.74	337.96	676.55	–28.81	42.51
Wheat	268.59	197.87	342.25	–26.33	27.42
Rapeseed	604.92	385.70	802.32	–36.24	32.63
			Scenario 2: Elastic demand		
Corn	223.13	178.70	256.40	–19.91	14.91
Soybean	474.74	337.96	575.33	–28.81	21.18
Wheat	268.59	197.87	293.51	–26.33	9.27
Rapeseed	604.92	385.70	685.91	–36.24	13.38
			Scenario 3: Increased substitutability		
Corn	223.13	157.19	274.76	–29.55	23.14
Soybean	474.74	390.71	623.64	–17.70	31.36
Wheat	268.59	227.95	310.92	–15.13	15.76
Rapeseed	604.92	451.37	732.85	–25.38	21.15

significantly reduced food prices. The cumulative effect of GE yield gains over the past fourteen years is likely greater still, as inventories carried into 2008 would have been larger, serving to dampen upward pressure on prices. Given the degree of suffering that near-record-high commodity prices in 2008 induced among poor populations, it is likely that agricultural biotechnology adoption helped to avert starvation and death. A more complete characterization of the welfare effects of biofuel and biotechnology adoption is the subject of ongoing research.

8.7 Discussion and Conclusions

In 2008, food riots and the doubling of commodity prices in some regions served as a reminder that with slowing agricultural productivity growth and growing demand for farm output, the victory over hunger could only be ephemeral. Agricultural production must grow in order to feed and fuel a global population that is at once increasing in size and wealth. Because of growing concern about climate change and biodiversity loss, production may need to grow without expanding into natural lands. This chapter provides new econometric analysis of aggregate farm yields that suggests that among adopting farms, agricultural biotechnology boosts yields of the four main crops in which it has been introduced. Consistent with the theory developed in this chapter, we find that the yield gains are greatest in developing countries, which are generally characterized by high pest pressure and limited access to insecticides. We also show that the yield effect of

GE crop adoption is growing over time, suggesting that learning effects have dominated the effects of expansion into less suitable applications and the development of resistance. This analysis, which points to the capacity for agricultural biotechnology to drive productivity growth, is constrained by data limitations that preclude controls for farm-level endogeneity of adoption. Consequently, our estimates can conservatively be interpreted as a population average treatment effect on the treated.

Simulation analysis based on the econometric estimation shows that, at the height of the 2008 global food crisis, the additional output generated by GE-crop yield gains mitigated price increases, perhaps saving lives in poor countries. Absent the intensification permitted by agricultural biotechnology, an additional twenty million hectares of land—an area equal in size to the state of Utah—would have been required to produce the 2008 harvest of staple crops. Such expansion of farmland would come at a cost in terms of GHG emissions (from land conversion) and risk to biodiversity, especially if forests were cleared to accommodate the additional crops. This analysis suggests that agricultural biotechnology constitutes a tool to overcome challenges posed by macro trends at the outset of the twenty-first century. First-generation GE crops permit the intensification of agriculture, which effectively frees land for production of biofuel, or at least diminishes the demand for new cropland induced by rising food and fuel needs. In future research, we intend to investigate the capacity for yield improvements associated with increased adoption of agricultural biotechnology and to explore empirically the degree to which agricultural biotechnology adoption is land-saving.

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