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HOW AGRICULTURAL BIOTECHNOLOGY BOOSTS FOOD SUPPLY AND ACCOMODATES BIOFUELS

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ABSTRACT

Increased global demand for biofuels is placing increased pressure on agricultural systems at a time when traditional sources of yield improvements have been mostly exhausted, generating concerns about the future of food prices. This paper estimates the impact of global adoption of genetically engineered (GE) seeds on food supply by exploiting the spatial and temporal variation in the adoption of GE crops to identify the average yield effect due to GE technologies among adopters. The yield gains range from 65% for GE cotton to 12.4% for soybeans and appear to be higher in the developing world than in developed countries. The authors simulate food prices during the 2008 food crisis without GE-seed-induced yield gains. Genetically engineered crops appear to play an important role in arbitrating tensions between energy production, environmental protection, and global food supplies.

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Abstract

First-generation agricultural biotechnology is promoted as a tool to improve control of agricultural pests that damage crops and reduce yields. A number of studies have empirically tested the extent to which genetically engineered crops boost farm output by reducing crop damage. They have been limited in size and scope and have generated a wide-range of estimates that vary by country and crop. This paper exploits spatial and temporal variation in the adoption agricultural biotechnology across countries in order to estimate the impact of adoption on food supply. Genetically engineered crops are shown to significantly increase yields on adopting farms at a time when demand for farm output is growing dramatically and traditional sources of yield growth are largely depleted. Econometric estimates are used to paramterize a simple multi-market model to simulate the food price effects of GE seed during the food crisis in 2008. Food prices would have been considerably higher absent the increased supply from agricultural bitoechnology adoption. Demand for new farm land would have also been higher, as would have been the consequent greenhouse gas emissions from land conversion.

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 9 billion by 2050. In roughly the last half of the 20th 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 area under cultivation. 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 weighed heavily against the uncertain benefits. This paper 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.

2 Background

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 25 countries annually planted 8% of global cropland to transgenic crops. In 2009, U.S. farmers planted more than 80% of the sugar beet crop to 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 conventionally bred crop output. In early 2010, China was poised to approve the first use of a GE crops for human consumption.

Genetically engineered 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. 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% of total GE crop area in 2008, followed by "stacked" traits (22%) and IR traits (15%). HT soybeans occupied the majority of total GE-crop land (53%) and constituted 70% of the world soybean crop in 2008 (James 2009). GE maize constituted 30% of all GE crop area in 2008 and 24% of the world maize crop.

Adoption of GE crops has been rapid. By 2009, half of all U.S. cropland was planted to GE seed. Approximately 80% of the 2008 cotton, maize and soybean crops in the U.S. were each produced from transgenic varieties. The U.S. has been a leader in adoption, planting more than half (62.5 million hectares) of all GE area in 2008. But other countries have been similarly aggressive in their adoption. South Africa, Australia and Argentina all planted more than 90% of their 2008 cotton crops to GE varieties, up from 1-2% a decade earlier. Canada planted virtually its entire maize crop to GE seed in 2008. Of the 25 countries that planted GE crops in 2008, 15 were developed countries and 10 were developing (James 2009). Figure 1 shows the annual area planted to GE crops from 1996-2008 by country-type.

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 Council [2010]. Much of the literature on GE crop adoption follows the threshold adoption framework of David [1969]. This framework assumes that firms 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 et al. 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 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 1996-2003) 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 Council [2010]. The magnitude of these benefits varies by location, crop, and time. Table 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

Figure 1: GE Crop Adoption Overtime

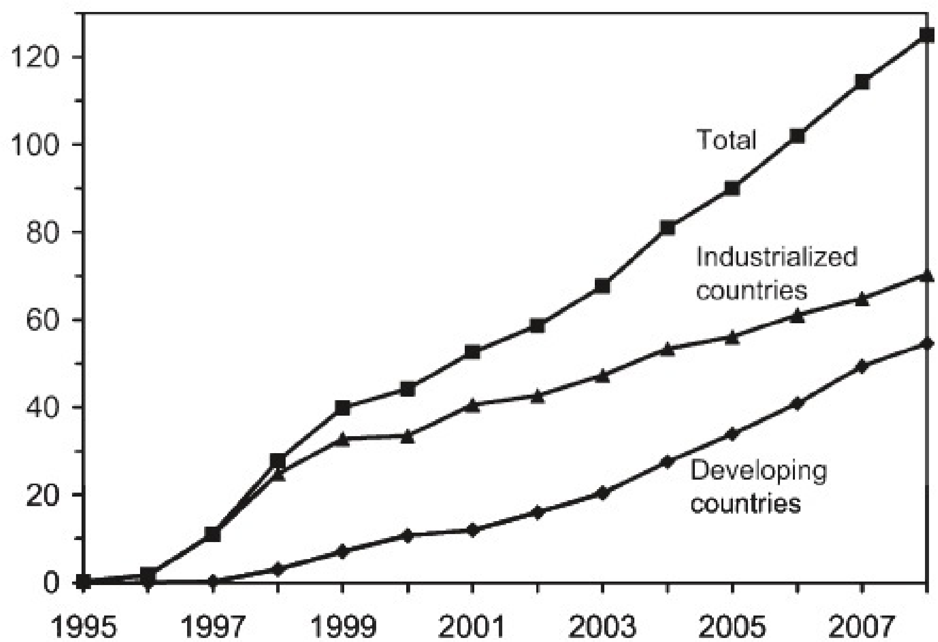

Table 1: Farm-level effects of GE crops

Country	Insecticide reduction (%)	Increase in effective yield (%)	Increase in gross margin (US$/ha)	Reference(s)
		Bt cotton		
Argentina	47	33	23	Qaim & 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 & 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
		Bt maize		
Argentina	0	9	20	Brookes & Barfoot 2005
Philippines	5	34	53	Brookes & Barfoot 2005, Yorobe & Quicoy 2006
South Africa	10	11	42	Brookes & Barfoot 2005, Gouse et al. 2006
Spain	63	6	70	Gómez-Barbero et al. 2008
United States	8	5	12	Naseem & Pray 2004, Fernandez-Cornejo & Li 2005

based on stylized assumptions about shifts in supply. These studies, too, mostly cover the earlier period of adoption of GE crops. The 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 paper, 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 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 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 GM 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.

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 et al. [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, $f_1(z,a) \geqq f_0(z,a)$. 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, i.e. $n=\delta_i N$, where $\delta_0=1$ denotes conventional seed technology and $\delta_1<1$ denotes GE seed technology. Consequently, for all x and all positive N, $g_1(x,N) \geqq g_0(z,N)$. 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:

$$\begin{aligned} x_{ij}^* &= x_{ij}^*(w, v, p, N) \\ z_{ij}^* &= z_{ij}^*(w, v, p, N). \end{aligned}$$

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 non-negative.

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 (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:

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

Then it can be shown that $\frac{d\triangle g}{dN} > 0$ and $\frac{d\triangle g}{dw} > 0$.

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 them 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:

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

where the first term on the RHS 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 $\frac{d\triangle y}{da} > 0$ and $\frac{d\triangle y}{dN} > 0$. 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 off-setting downward bias in our results.

4 Data and Methods

The empirical strategy of this paper is motivated by the global pattern of GE seed adoption. By 2008, farmers in 25 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 U.S., for instance, 12% of cotton was planted to GE seeds in 1996, but by 2007 the GE share had reached 87%. 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, i.e. 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, i.e. 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_{ji}. 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

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

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), andϵ_{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 of the United Nations (FAO). 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 1990-2008. We include data on every country that adopted any GM crop from 1996-2008, as well as the top 100 gross producers of eight principal row crops during the period 1990-2008. For these 100 countries, we include observations on each of the four major GM 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 GM 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 2 and 3.

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 4 reports results from estimation of (7).[1] In all

[1]Only coefficients of interest are reported. Full results are available from the authors by request.

Table 2: Summary Statistics: GM and Trait Shares

	All	Developing	Developed	Adopters	Non-adopters
			Cotton		
Yield	15521.02	14155.02	27981.82	19070.02	14492.22
	(9278.3)	(7954.58)	(11074.55)	(10174.24)	(8741.64)
GMO Seed Share	0.03	0.02	0.11	0.13	-
	(0.14)	(0.11)	(0.26)	(0.27)	
HT Seed Share	0.01	0.01	0.08	0.06	-
	(0.06)	(0.21)	(0.09)	(0.18)	
IR Seed Share	0.02	0.02	0.08	0.11	-
	(0.11)	(0.09)	(0.20)	(0.21)	
Observations	1326	1195	131	298	1028
			Maize		
Yield	34603.04	25987.91	68774.78	43716	31515.07
	(26844.58)	(17823.54)	(29293.47)	(25478.89)	(26601.66)
GMO Seed Share	0.01	0.01	0.03	0.05	-
	(0.09)	(0.07)	(0.13)	(0.17)	
HT Seed Share	0.00	0.00	0.01	0.01	-
	(0.03)	(0.01)	(0.07)	(0.07)	
IR Seed Share	0.01	0.00	0.02	0.05	-
	(0.07)	(0.06)	(0.09)	(0.14)	
Observations	1778	1420	358	450	1328
			Rapeseed		
Yield	16164.46	13623.73	20363.35	17313.31	15421.09
	(8082.97)	(6935.72)	(8104.34)	(7674.74)	(8259.82)
GMO Seed Share	0.02	0.01	0.05	0.05	-
	(0.11)	(0.07)	(0.18)	(0.18)	
Observations	756	471	285	297	459
			Soybean		
Yield	15760.13	14334.7	21177.71	18841.01	14559.26
	(8049.531)	(7789.70)	(6594.89)	(5634.42)	(8518.927)
GMO Seed Share	0.03	0.01	0.04	0.12	-
	(0.15)	(0.07)	(0.17)	(0.27)	
HT Seed Share	0.03	0.03	0.04	0.12	-
	(0.16)	(0.15)	(0.17)	(0.27)	
Observations	1469	1163	306	412	1119

Reported: means w/ standard deviatons in parentheses

Table 3: Summary Statistics: Harvest, GM and Trait Areas

	All	Developing	Developed	Adopters	Non-adopters
			Cotton		
Harvest Area	474349.9	428056	896649.6	1379338	212009.1
	(36980.19)	(37104.66)	(155609.4)	(145291.9)	(14420.28)
GM Area	68553.91	40843.28	321334.1	305041.9	-
	(13715.36)	(11320.57)	(90135.19)	(59087.57)	
HT Area	14809.95	794.3732	142662	65899.31	-
	(4238.486)	(326.7462)	(41290.66)	(18581.88)	
IR Area	45593.07	39889.99	97617.34	202873.9	-
	(10514.57)	(11313.96)	(25651.71)	(45686.3)	
Observations	1326	1195	131	298	1028
			Maize		
Harvest Area	1479825	1360254	1954099	4148485	575534.7
	(98446.21)	(88076.3)	(341315.7)	(355597.3)	(21051.8)
GM Area	109796.7	15909.59	482198.3	433819.1	-
	(30228.59)	(4282.138)	(147695.1)	(118219)	
HT Area	48679.08	2454.091	232029.6	192336.5	-
	(18522.17)	(861.1469)	(91386.47)	(72822.68)	
IR Area	97552.94	14295.37	427792.5	385442.5	-
	(29210.24)	(3861.429)	(143092.3)	(114434.1)	
Observations	1778	1420	358	450	1328
			Rapeseed		
Harvest Area	579795	586433.9	568823.4	1378898	62728.59
	(56032.14)	(78956.79)	(71337.53)	(129412.5)	(5906.965)
HT Area	56013.8	-	148584	142580.6	-
	(16089.23)	-	(42155.01)	(40484.63)	
Observations	756	471	285	297	459
			Soybean		
Harvest Area	955104.9	729134.4	1813940	3208778	76662.81
	(100410.5)	(78176.62)	(376048)	(333191.7)	(5633.527)
HT Area	324252.1	185842	850301	1156132	-
	(62136.7)	(42322.81)	(249257.4)	(216403.6)	
Observations	1469	1163	306	412	1119

cases, the coefficients of interest, the β_j, are statistically significant at the 99% level. Thus, the partial effect of GM seed adoption among adopters is positive and significant. Row 1 of Table 7 reports the gain in yield from adoption of GE seed as a percent of total yield per acre.[2] The GE-seed effect on yields is greatest for crops with IR traits, i.e. maize and cotton. Yield gains for GE cotton and maize–available in IR, HT and stacked varieties–are estimated to be 65% and 45.6%, respectively. Yield gains for HT rapeseed and soybean are 25.4% and 12.4%, 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.

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 (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 economic 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 paper. Nevertheless, estimated yield effects from the separate regressions of the developed and developing country samples does support the theory from Section 3. The separate estimation of GE-seed effects for developed and developing countries are reported in Tables 5 and 6, respectively. The magnitudes of these effects relative to conventional seed effects are summarized in Rows 2 and 3 of Table 7. The estimated yield gains associated with GE seed are greater in developing countries than in developed countries for each GE crop. These differences are statistically significant at the 95% level.

We further estimate (7) with the addition of GM and non-GM time trends. These results are reported in Table 8. We find a positive and significant trend associated with non-GM crop yields for cotton, maize, rapeseed, rice and wheat. These correspond to 1.37%, 0.99%, 2.17%, 0.65%, and 1.16% annual growth from 1990-2008 for each of these crops, respectively. GM cotton, rapeseed and soybean exibited statistically significant positive yield growth over the same time period, suggesting that learning by doing and learning 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 complimentary chemicals. When the GM-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 3 demonstrates, farmers select to adopt GE technologies based on their expected gain. These gains are epected 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

[2] Determined as $100 \cdot \frac{\delta_{ji}}{\beta_{jk}}$.

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. 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 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.

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 over just a few-year window and food indexes climbing 56% 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 additional output attributable to GE seed adoption had not. To this end, we employ a multi-market 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 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.[3]

[3]We employ the developing and developed country estimates in the simulations.

Table 4: GE Seed Adoption Effects

	(1)	(2)
CROP	Total Area	GE Area
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	-366994	
	(239633)	
Observations	10717	
Number of groups	627	
R-squared	0.728	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: GE Seed Adoption Effects in Developed Countries

	(1)	(2)
CROPS	Total Area	GE Area
Cotton	1.407***	0.322***
	(0.267)	(0.105)
Maize	12.44***	1.890***
	(2.867)	(0.485)
Rapeseed	1.538***	0.370***
	(0.126)	(0.0994)
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	-453968*	
	(262868)	
Observations	2208	
Number of groups	150	
R-squared	0.848	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: GE Seed Adoption Effects in Developing Countries

CROP	(1) Total Area	(2) GE Area
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***	
	(0.0912)	
Rice	5.058***	
	(0.549)	
Sorghum	0.966***	
	(0.124)	
Wheat	2.250***	
	(0.390)	
Constant	-453968*	
	(262868)	
Observations	8509	
Number of groups	477	
R-squared	0.650	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Yield Gain from GE Seed as Percent of Yield

VARIABLES	(1) Cotton	(2) Maize	(3) Rapeseed	(4) Soybean
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	-	30.189

Table 8: GM and Conventional Seed Yield Trends

CROP	(1) Total Area	(2) GE Area	(3) Conventional Trend	(4) GE Trend
Cotton	1.24***	-0.164	0.017**	0.077***
	(0.294)	(0.297)	(0.009)	(0.026)
Maize	5.055***	2.586***	0.05**	-0.033
	(1.61)	(0.515)	(0.024)	(0.03)
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	
	(0.0917)		(0.012)	
Rice	5.267***		0.034***	
	(0.545)		(0.002)	
Sorghum	1.25***		0.002	
	(0.194)		(0.007)	
Wheat	2.584***		0.03***	
	(0.254)		(0.007)	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Simulation Scenarios

	Scenario 1	Scenario 2	Scenario 3
Own-price elasticity of demand	-0.30	-0.5	-0.30
Own-price elasticity of supply	0.30	0.30	0.30
Cross-price elasticities of demand	0.05	0.05	0.05
Cross-price elasticities of supply	-0.10	-0.10	-0.075

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%) 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% of the global rapeseed harvest and 2% of the global soybean harvest. This increased demand for maize, soybean and rapeseed increased prices 67%, 40%, 36% and 57% for maize, soybean, wheat, and rapeseed, respectively. As reported in Table 10, world prices for these for commodities would have been between 26% and 40% 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% higher, soybean prices 43% higher, wheat prices 27% higher, and rapeseed prices 33% higher.[4] As is also shown in Table 10, even under the assumptions of more elastic demand (Scenario 2) and supply substitutability (Scenario 3), GE crop adoption in 2008 alone significantly reduced food prices. The cumulative effect of GE yield gains over the past 14 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.

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 must expand without expanding into natural lands. This paper 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. Con-

[4]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 GM-induced percentage increase in yield and the country-crop-year specific GM-crop share. These estimates determined GM-induced output gains to constitute 5%,11% and 4% of total output for maize, soybean, and rapeseed, respectively.

Table 10: Simulating Food Price Effects of Biofuel with and without Biotechnology

	2008 Price	No biofuel	No biotech	%Change No biofuel	%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	385.7	802.32	-36.24	32.63
Scenario 2: Elastic demand					
Corn	223.13	178.7	256.4	-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	385.7	685.91	-36.24	13.38
Scenario 3: Increased substitutability					
Corn	223.13	157.19	274.76	-29.55	23.14
Soybean	474.74	390.711	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

sistent with the theory developed in this paper, 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 20 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 greenhouse gas 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 21st 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.

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