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Abstract

Increased demand for agricultural produce for food, fiber, feed, and energy generates a tradeoff between high prices and environmentally costly land conversion. Genetically engineered (GE) seeds can potentially increase supply without recruiting new lands to production. We develop a simple adoption model to show how first-generation GE increases yield per hectare. We identify yield increases from cross country time series variation in GE adoption share within the main GE crops- cotton, corn, and soybeans. We find that GE increased yields 34% for cotton, 32% for corn, but only 2% for soybeans. The model also predicts that GE extends the range of lands that can be farmed profitably. If the output on these lands are attributed to GE technology, then overall supply effects are larger than previously understood. Considering this extensive margin effect, the supply effect of GE increases from 10% to 16% for corn, 15% to 20% for cotton, and 2% to 39% for soybeans, generating significant downward pressure on prices. Finally, we compute "saved" lands and greenhouse gasses as the difference between observed hectarage per crop and counterfactual hectarage needed to generate the same output without the yield boost from GE. We find that all together, GE saved 21 million Ha of land from conversion to agriculture in 2010, or 0.41 Gt of CO_2 emissions (using a constant CO_2/land conversion factor). These averted emissions are equivalent to roughly 1/3 the annual emissions from driving in the US.

1 Introduction

Meeting growing agricultural demand amid severe resource constraints is among the greatest challenges of the 21st century. New evidence on the environmental cost of land-use change has raised the stakes, suggesting that externalities associated with cropland expansion are more costly than previously understood (Searchinger et al., 2008). Stagnating crop yield and increasing demand from growing populations, rising meat demand in transition economies, and increasing biofuel production generate tradeoffs between environmentally costly land conversion and higher food prices (Rajagopal et al., 2007). Like manna from heaven, any technology that boosts yield per hectare helps navigate this neo-Malthusian dilemma by increasing supply without converting lands to agriculture.

Agricultural biotechnology, or genetically engineered seeds (GE), has been promoted as a new source of yield growth at a time when traditional means of growth have been largely exhausted (Qaim, 2009). A sizable empirical literature documents the yield gains associated with GE seeds, mostly from farm-level estimates of the yield gains from switching to GE from traditional seed technology (Qaim, 2009). To the extent the GE gene increases yield per hectare, the technology increases supply, lowers prices, and reduces demand for new cropland. Without GE technology, greater agricultural land-base would be needed to meet demand. In this sense, GE can be said to have preserved lands and "saved" greenhouse gas emissions (GHG) associated with land-use change.

Recent studies explain yield per hectare gains from first-generation GE within the damage control framework of Lichtenberg and Zilberman (1986).[1] In the model, improved damage control traits from GE raises the marginal product of complementary inputs, thus increasing yield per hectare. However, the model also predicts that marginal lands on which pest pressure is too high to profitably farm without the GE technology will be brought into production once GE becomes available (Qaim and Zilberman, 2003). That is, the model predicts supply increases on both the intensive margin (from plots switching from traditional seeds to GE) and the extensive margin (from new lands entering production). The extensive margin has important implications for supply and commodity prices: if GE technology enables production on extensive margin lands, then the change in supply caused by GE includes not only the yield gain on the intensive margin, but all of the production on the extensive margin as well. Thus, taking the extensive margin into account, the supply and price effects of GE technology is larger than previously realized.

In this paper, we estimate the supply, price, and land-use savings effect of GE technology taking the extensive margin into account. We first provide new estimates of the yield effect of GE using a cross-country panel of annual hectarage and output. Our approach builds on

[1] See Qaim and Zilberman (2003), Qaim (2009), Sexton and Zilberman (2011)

the work of Sexton and Zilberman (2011), which also estimates the yield, price, and land-use-saving effects of different GE crops from a country-level panel. The novel features of our work here is that we use a longer panel and estimate a different specification from Sexton and Zilberman (2011) that controls for intertemporal variation in crop area and land devoted to GE technology. Next, we derive an algorithm for quantifying the extensive margin based on the adoption model from Khanna and Zilberman (1997) and decompose total GE hectarage into intensive margin and extensive margin lands. We then compute the supply effect as the sum of the intensive margin effect and the extensive margin effect. Following Sexton and Zilberman (2011) and others (see De Gorter and Zilberman (1990)), we translate the supply effect into a price effect conditional on assumptions of elasticities of supply and demand. Finally, we compute the land-use savings associated with GE as the difference between observed hectarage devoted to different crops in 2010, and those necessary to generate the same output absent the supply effect of GE.

We estimate that in 2010, GE technology increased the world supply of corn between 10-16%, cotton 15-20%, and soybeans 2-39%. Given a range of estimated elasticities of demand and supply in the literature, these supply impacts translate into 13-27% lower corn prices, 19-33% lower cotton prices, and 2-65% lower soybean prices. Comparing our estimates to others in the literature, we find somewhat higher impacts, which is to be expected since we take complementary-input and extensive margin effects into account.

Furthermore, we find that absent the intensive margin yield effects, farmers would have needed to convert another 13 million Ha, 6 million Ha, and 1 million Ha to corn, cotton, and soybeans, respectively, to match observed 2010 output. Employing an average GHG release figure from the land-use literature of 20 tonnes per ha per year, these hectarage conversions translate into 0.41 Gt of averted GHG emissions, which is, for comparison, equivalent to about 1/3 the annual emissions from vehicle miles traveled in the US.

Together, these results suggest that the first generation of GE technology significantly increased crop production, lowered crop prices, and preserved natural land. We argue that these effects imply the poor in particular benefit from GE technology, because they spend a relatively large share of their incomes on food and because they are expected to suffer relatively large damages from climate change.

2 Model

The first generation of agricultural biotechnology introduced insect resistant (IR) and herbicide tolerant (HT) traits into 3 principle row crops in order to mitigate crop damage from insects and weeds, respectively. There have been several applications of the IR trait thus far, having been inserted into corn, cotton and soybean.[2] The most notable trait causes plants to produce the naturally occurring chemical Baccillus thuringiensis (Bt), which is toxic to common agricultural pests, like the European corn borer, but harmless to humans and relatively environmentally benign. In producing the toxin, which has been applied to plants for nearly a century and is employed in modern organic farming, GE crop plants fend off pests without chemical applications by farmers. HT crops express tolerance to glyphosates, a class of broad-spectrum, low toxicity herbicides that includes Round-Up, a Monsanto product employed also in residential settings. Such tolerance, introduced into corn, soybeans and canola, allows farmers to more easily control weeds. Absent HT varieties, farmers must rely more heavily on pre-emergence weed control, like tilling operations, and on more toxic and narrow spectrum chemicals that can target weeds without impacting the crop plant.

IR and HT seeds can be modeled as damage control agents which reduce the fraction of crop lost to pests. The framework was first introduced by Lichtenberg and Zilberman (1986) to model pesticide adoption, and subsequently applied to GE by Qaim and Zilberman (2003). A wide range of applications followed and are reviewed by Qaim (2009). We apply the generalized framework from Sexton and Zilberman (2011) to show how adoption boosts supply on the intensive margin through both a gene effect and complementary-input effects, and along the extensive margin by expanding the range of land that can be profitably farmed.

Farmers are assumed to use homogeneous constant returns to scale production technologies on land that differs with respect to pest pressure n. Input and output markets are competitive. Farmers have access to two seed technologies indexed by i, with $i = 0$ denoting traditional seed varieties, and $i = 1$ denoting GE varieties. GE varieties are considered damage control inputs that affect yields only indirectly by reducing the fraction of crops not lost to pests, $g(i, x_i, n)$, which depends on the seed technology i, variable chemical pesticide application x_i, and initial pest conditions n. Seed technologies and pesticides are distinct from other inputs, like fertilizer and water, denoted z_i, that increase yields directly by expanding potential output $f(z_i)$. In this framework, realized or effective yield is the product of potential output and the fraction of crop not damaged by pests, $y = g(i, x_i, n) f(z_i)$ The undamaged crop share, $g(i, x_i, n)$, lies between 0 and 1 and is increasing in pesticide use and decreasing in pest pressure. For $g = 1$, there is no pest damage and effective output is equal to potential output. For $g = 0$, the crop is entirely destroyed by pests. Let P, w, and v denote exogenous prices of outputs, pesticides, and productive inputs, respectively, and K_i denote the fixed cost of production with technology i. Then per-hectare profits are given by:

$$\Pi_i = \max_{x_i, z_i} Pg(i, x_i, n) f(z_i) - wx_i - vz_i - K_i \quad (1)$$

[2]Another substantial feed crop that has adopted GM is rapeseed, but the hectarage and impact is much less substantial and therefore it is not addressed in this paper

Because seed companies assess technology fees for access to proprietary GE varieties, it is assumed that the fixed costs of production are greater for GE-adopting farmers, i.e., $K_1 > K_0$. We also assume the GE seeds do not worsen crop damage, i.e., $g(1, x, n) \geq g(0, x, n)$.

Producers adopt the technology that yields highest expected profits. Their problem is solved recursively. First, conditional on seed technology choice and pest pressure, they choose variable inputs (pesticides and fertilizer). Then they choose the seed that yields highest expected profits, conditional on optimal input use and provided expected profits are non-negative. Given heterogeneity in pest conditions, adoption follows the threshold model (David, 1969) (Feder et al., 1985), in which more vulnerable farmers who gain most from a new technology adopt first and aggregate adoption increases over time as the technology improves or costs of adoption fall.

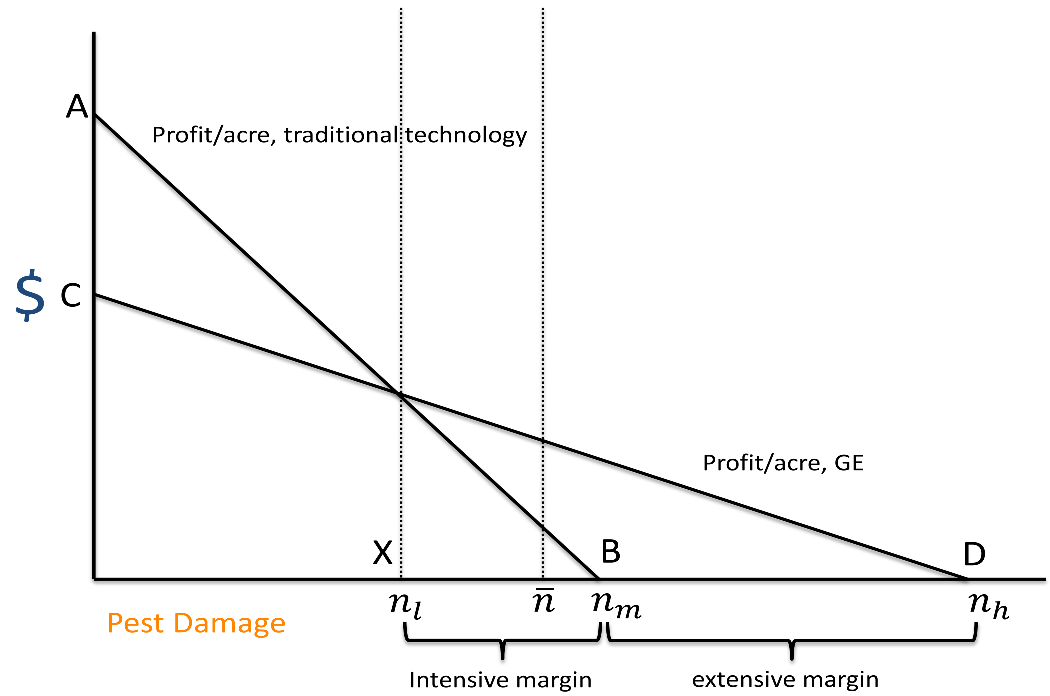
The model suggest that on locations with low pest pressure, it is profitable to farm under either seed technology, but the conventional technology yields higher profits because crop losses are too small to compensate for the technology fee. Thus, below a threshold n_l, farmers produce using the traditional technology. For pest pressure greater than n_l and less than a threshold n_m, it is profitable to use either technology, but higher crop losses from greater pest pressure make damage abatement more valuable so that the new technology yields higher profits. Above n_m and below a higher threshold of pest pressure, n_h, it is not profitable to produce under the conventional technology, but it is profitable to produce under the new technology. Above n_h, it is not profitable to produce under any technology; such land is unfarmed. Between n_m and n_h, however, farmers adopt the new technology and recruit into production land that was too marginal to be profitably farmed under the old technology. These results are depicted in Figure 1, where line segment AB depicts profit per hectare as a function of initial pest pressure under the traditional technology and line segment CD depicts the same for the new technology.

The pest pressure levels n_l, n_m, n_h determine the adoption decision, but the overall magnitude of adoption depends on the amount of land associated with each level of pest damage. If, for example, there is a small amount of hectarage between n_l and n_m and large amount of land between n_m and n_h, then the intensive margin is small in magnitude while the extensive margin is large. On the other hand, if there is no land with pest damage below $\bar{n}$ in Figure 1 where $n_m > \bar{n} > n_l$, then there is no extensive margin and all the impact is intensive.

While much of the empirical estimation of the yield impact from GE adoption was conducted via experiments that focused on the direct gene effect, GE technology likely stimulates yield gains that exceed the pure effect of the seed trait on the intensive margin.[3] The direct effect tends to reduce pest damage and tends to reduce use of alternative control of the target

[3]The gene effect need not be positive. Adoption of GE tends to reduce damage of pests targeted by the GE trait. On the other hand if the trait is not introduced in the best local variety there is a yield loss. We expect that if adoption occurs the damage reduction effect is greater than the variety effect (Qaim and Zilberman, 2003).

Figure 1: Adoption of GE Technology



pest (NRC, 2010). By reducing damage, expected value of potential output, $Pg(i, xi, n)$, is increasing. Therefore, the value of the marginal product of complementary inputs z_i - fertilizer and water- will increase, which will tend to increase their use, resulting in higher potential and effective yield. Thus, the introduction of GE results in a yield effect that is the sum of the direct seed effect and the indirect effect of the increased complementary inputs.

In summary, a simple adoption model predicts that supply increases along the intensive margin both from higher damage abatement through the gene effect and from the induced increase in application of complementary inputs. Moreover, production expands to marginal lands, further increasing supply along an extensive margin, depending on the distribution of initial pest pressures.

3 Estimation

Our empirical strategy for estimating yield effects of GE adoption follows Sexton and Zilberman (2011) in exploiting variation in adoption over time in different countries. First commercialized in 1996, GE seeds were adopted quickly, though unevenly across crops and countries. For example, the US quickly licensed Bt corn for animal feed production, and thus GE corn hectarage in the US grew to 50% within 5 years; while Bt cotton was not approved in India until

2001, after which GE cotton hectarage share grew from 0 to 85% in less than 10 years. Overall, 17 years after the commercialization of GE technology, GE corn accounts for 42 million ha worldwide across 16 countries, representing 25% of world corn hectarage, GE cotton accounts for 19 million ha worldwide across 10 countries, representing 60% of total cotton hectarage, and GE soybeans accounted for 72 million ha worldwide across 10 countries, representing 70% of total soybean hectarage. GE hectarage of the three crops in 2010 are reported by country in Figure 2 below.

Following Sexton and Zilberman (2011), the variation in GE hectarage share across countries and time can be used to identify structural yield per hectare parameters as follows. Let Q_{it} denote country-level production of a crop in country i in year t. We write total output expressed as the sum of output of a crop produced with technology k

$$\begin{aligned} Q_{it} &= \sum_{k=1}^{K} Q_{itk} \\ &= \sum_{k=1}^{K} q_{itk} L_{itk} \end{aligned} \tag{2}$$

where q_{itk} is the composite yield per hectare for technology k (GE or traditional) and L_{itk} is land planted to technology k in country i in time t. We model the deterministic component of yield as the sum of a country effect α_i, time effect γ_t, and technology effect β_k:

$$q_{itk} = \beta_k + \alpha_i + \gamma_t \tag{3}$$

Substituting for q_{itk}, we have:

$$Q_{it} = \sum_{k=1}^{K} [\beta_k + \alpha_i + \gamma_t] L_{itk} \tag{4}$$

Dividing through by total hectarage and simplifying, we estimate

$$q_{it} = \beta_0 s_{it}^{NGE} + \beta_1 s_{it}^{GE} + \gamma_t + \phi_i + \epsilon_{it} \tag{5}$$

where q_{it} is yield per hectare and s_{it}^{NGE} ("NGE" for "Non-GE") and s_{it}^{GE} represent shares of hectarage devoted to traditional and GE technology, respectively, and β_0 and β_1 correspond directly with the structural parameters in (4). This empirical model is similar to Sexton and Zilberman (2011), but is robust to correlation between intertemporal variation in crop area and land devoted to GE technology.[4]

[4]Sexton and Zilberman (2011) estimate the technology parameters with a fixed effect model:

$$Q_{it} = \delta_0 L_{it} + \delta_1 L_{it1} + \gamma_t D_t + \alpha_i D_i + \nu_{it} \tag{6}$$

While the fixed-effect model (6) controls for country and time specific unobservables that correlate with adoption, it

Figure 2: Adopters of GE Technology

Notes: horizontal bars represent total GE hectarage in millions of Ha

For each GE crop $\in \{corn, cotton, soybeans\}$, we estimate equation (5) with the same data sources as in Sexton and Zilberman (2011), though we extend the panel to include more years. Output and hectarage by crop-country-year for 1990-2010 come from FAO Stat. hectarage planted to GE varieties was provided by Graham Brookes, who compiled the data from the International Service for the Acquisition of Agri-Biotech Applications (ISAAA). The panel for each crop includes all GE adopters (see Figure 2) and all other 100 top-producing countries. Summary statistics by crop are reported in Table 1.

As with any production function estimation, input levels (s_{it}^{GE}) are endogenous choices, and hence might be correlated with unobservable determinants of output in the error term. However, while much of the literature on yield effects are based on micro (farm level) observation, and hence should be concerned with endogenous selection at the farmer level,[5] we use aggregate data and estimate share for different nations, so heterogeneity among farmers within countries that seem to matter for micro studies will not affect our results. As long as the timing of GE licensing by individual countries is uncorrelated with yield trends, OLS estimation of (5) identifies the structural yield parameters β_0 and β_1. Since the decision to license GE is largely governed by political interests, this identification assumption is likely to hold(Sexton and Zilberman, 2011). Given endogenous selection at the farm-level, our aggregate estimates

subsumes country-time specific hectarage deviations in the error term, and thus delivers based estimates of δ_k. To see this, note that time and country dummies can be rescaled with time and country averages

$$Q_{it} = \delta_0 L_{it} + \delta_1 L_{it}^{GE} + \gamma_t D_t \bar{L}_t + \alpha_i D_i \bar{L}_i + \nu_{it} \tag{7}$$

but that a direct derivation from (4) delivers

$$Q_{it} = \delta_0 L_{it}^{NGE} + \delta_1 L_{it}^{GE} + \gamma_t D_t L_{it} + \alpha_i D_i L_{it} + \epsilon_{it} \tag{8}$$

The use of L_{it} instead of L_{it}^{NGE} does not matter, since it just alters the definition fo the excluded category. But multiplying the time and country effects $\gamma_t D_t$ and $\alpha_i D_i$ by $\bar{L}_t$ instead of L_{it} means that country-time specific deviations appear in the error term multiplied by the time and country effects γ_t and α_t:

$$\begin{aligned}
Q_{it} &= \delta_0 L_{it}^{NGE} + \delta_1 L_{it}^{GE} + \gamma_t D_t L_{it} + \phi_i D_i L_{it} + \epsilon_{it} \\
&= \delta_0 L_{it}^{NGE} + \delta_1 L_{it}^{GE} + \gamma_t D_t \left(\bar{L}_t + L_{it} - \bar{L}_t\right) + \phi_i D_i \left(\bar{L}_i + L_{it} - \bar{L}_i\right) + \epsilon_{it} \\
&= \delta L_{it}^{NGE} + \delta_1 L_{it}^{GE} + \gamma_t D_t \bar{L}_t + +\phi_i D_i \bar{L}_i + \underbrace{\gamma_t D_t \left(L_{it} - \bar{L}_t\right) + \phi_i D_i \left(L_{it} - \bar{L}_i\right) + \epsilon_{it}}_{=\nu_{it}}
\end{aligned}$$

The country-time deviations from averages $L_{it} - \bar{L}_t$ and $L_{it} - \bar{L}_i$ in ν_{it} are obviously correlated with L_{it}^{NGE} and L_{it}^{GE}. This correlation generates bias in the δ_k's, as they are picking up some of the country and time specific effects, which multiply the deviations in ν_{it}. The direction of the bias is ambiguous, but since bigger countries adopted GE more heavily, it is likely that Sexton and Zilberman (2011) overestimate the technology effect.

[5]see Crost et al. (2007), Liu (2008)

Table 1: Summary Statistics of Adopters and Nonadopters

	Cotton		Corn		Soybeans	
	Non-Adopters	Adopters	Non-Adopters	Adopters	Non-Adopters	Adopters
Yield (Lbs/Ha)	1.37	2.11	3.23	5.13	1.45	2.10
	(0.91)	(1.06)	(2.69)	(2.62)	(0.77)	(0.53)
Acreage (Million Ha)	0.14	2.12	1.01	3.16	0.22	5.69
	(0.37)	(2.93)	(3.00)	(6.81)	(1.15)	(9.18)
GE Acreage (Million Ha)	0.00	0.59	0.00	0.69	0.00	2.89
	(0.00)	(1.50)	(0.00)	(3.31)	(0.00)	(6.73)
# Countries	88	10	79	21	89	10

should be interpreted as average treatment on the treated (ATT) measures, but the ATT is properly identified by our aggregate analysis, conditional on the assumption of exogenous GE licensing.[6]

In Table 2 we report estimates of equation (5) by crop using the data described above. In Table 2, the regression coefficients for traditional and GE technology correspond directly with the structural yield parameters β_0 and β_1. The yield effect can be computed as $\frac{\beta_1}{\beta_0}$. For all crops, the coefficients for both traditional and GE yield are statistically significant at the 1% level. We find that the yield effect for cotton is 34%, maize is 32%, and soybeans is 2%. By contrast, the yield effects from Sexton and Zilberman (2011) are 65% for cotton, 45% for maize, and 13% for soybeans, again all significant at the 1% level. Our estimates here are smaller than those from the Sexton and Zilberman (2011) specification, but still substantial for cotton and maize. The yield effect from soybeans is no longer economically significant, but as we show in latter sections, there can still be a role for GE in soybean yield effect through the extensive margin.

4 Extensive Margin

The previous section estimates the increase in yields associated with switching from traditional technology to GE (intensive margin switching). The adoption model also predicts that GE brings more land into production by extending the range of land that can be profitably farmed.

[6]This approach of using macro data to identify productivity parameters has a long history in agricultural research (Huffman and Evenson, 1992)

Table 2: Yield Effects of GE Technology

	(1) Cotton	(2) Maize	(3) Soybean
Traditional	2.13***	4.08***	2.09***
	(0.00)	(0.06)	(0.02)
GE	2.85***	5.38***	2.13***
	(0.25)	(0.19)	(0.15)
Country Fixed Effects	Yes	Yes	Yes
Year Fixed Effetcs	Yes	Yes	Yes
Number of Observations	1868	1978	1831
R squared	0.96	0.98	0.96

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

If this relationship is causal, as the model predicts, then output on the extensive margin should be credited to the GE technology, thereby increasing the supply effect of GE seeds. It is beyond the scope of this paper to assess empirically whether GE seeds expand the productive land base, but with aggregate data, we can estimate the quantity of new land converted to a given crop since GE was introduced. That is, we can *quantify* the extensive margin, though we cannot *attribute* the extensification to GE. Assessing the magnitude of the extensive margin gives a sense of how important it could be for aggregate supply and price effects.

With plot-level data, the task of decomposing the supply effect into an intensive and extensive margin effect is a simple matter of separating the plots that switched from traditional to GE from those newly planted to GE and summing over the yield increases in each group. Since our data is country-level, additional structure is needed to guide the calculation. We appeal to the adoption model from Section 2 again to generate the necessary structure.

To illustrate the strategy, consider again Figure 1. In some base year- prior to GE entry- the profit curve with traditional technology is given by line segment AB. In a future period, GE becomes available and generates profit curve CD. Total hectareage expands between the two periods by $\Delta L = D - B$, and GE hectareage expands by $\Delta L_G = D - X$, where X indicates the break-even point on GE technology. As described in Section 2, the extensive margin, denoted ext_G, is given by $n_h - n_m$, or

$$ext_G = \Delta L = D - B \tag{9}$$

Furthermore, the intensive margin, denoted int_{NG} ("NG" for "switching from N to G"), is given by $n_m - n_l$, or

$$int_{NG} = \Delta L_N = B - X \tag{10}$$

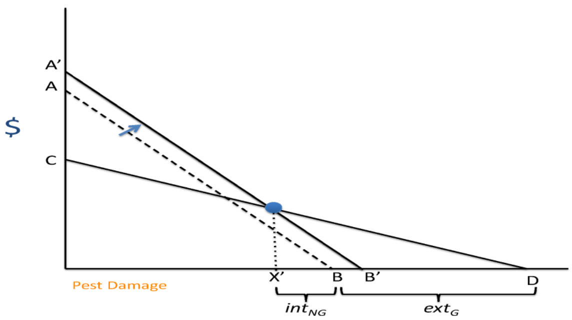
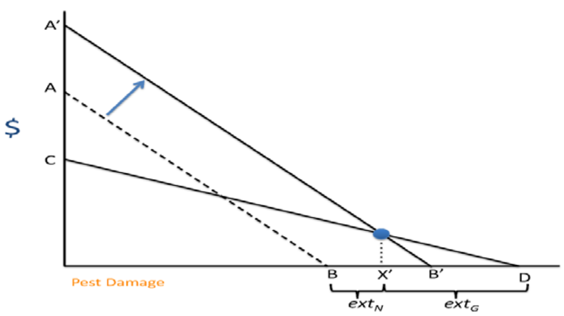
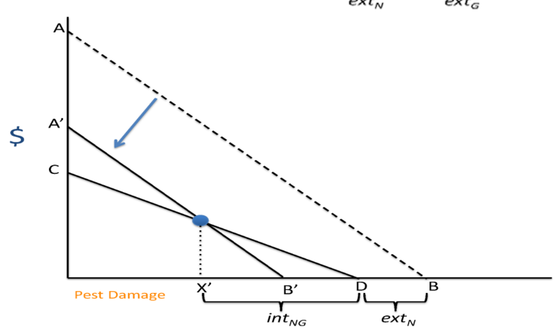
where ΔL_N is the change in traditional technology hectareage ("N" for "Non GE"), given by $\Delta L - \Delta L_G$. Thus, in this case, all we need to compute the intensive and extensive margins are the change in total hectareage ΔL and the change in traditional technology hectareage ΔL_N, which are both data.

While this simple example illustrates how the adoption model generates enough structure to calculate intensive and extensive hectareage from the aggregate data, the example is not sufficiently general to handle all cases. In particular, we have assumed that the traditional technology profit curve does not change over time. In this case, we have $\Delta L_G > \Delta L > 0$, and thus equations (6) and (7) yield the intensive and extensive margins. However, in reality, prices, growing conditions, and policy all change from year to year, which shifts the traditional technology profit curve. If this profit curve shifts concurrently with the entry of GE technology, we could observe $\Delta L > \Delta L_G > 0$, for example. In this case, the switchover point X would exceed the x-intercept of the original traditional technology profit curve, implying that all traditional technology hectares from the base year remain traditional technology hectares in the future year. Ie, in such a case there is no intensive margin switching. All GE hectares should be counted as extensive margin. Furthermore, it's possible that the traditional technology curve shifts in such that $\Delta L < 0$. In this case, no new lands enter production in the future year, so there can be no extensive margin. In this case, all GE lands should be considered intensive margin.

The general structure for these three cases are presented in Table 3. The three cases are distinguished by the ordering of ΔL_G, ΔL, and 0. In the first case (which includes the first example above), $\Delta L_G > \Delta L > 0$, and there is adoption on both the extensive and intensive margin.[7] For this ordering to occur, it is possible that the traditional profit technology curve shifts in or out, but it must be that X', the observed break-even point in the future period, lies to the left of the initial x-intercept, B. That is, in order for the change in GE hectarage to exceed the change in total hectarage, there must be some intensive margin switching, which implies the break-even point exceeds the initial marginal hectare. In Table 3, we illustrate this case in the first row with a small outward shift of the line segment AB to $A'B'$. The column labeled "Ordering" describes the case, and the columns "int_{NG}" and "ext_G" give the calculation of the intensive and extensive margins. We find that the intensive margin is readily computed as the negative of the change in traditional technology hectarage $(B - X')$, while

[7]This will only occur if there is land available on the extensive margin and the land with the highest pest damage has more pest damage than n_h in Figure 1. See Section 2.

Table 3: Computation of the Intensive Extensive margins

		Ordering	int_{NG}	ext_G
Case 1		$\Delta L_G > \Delta L > 0$ Ie $X' < B$	$-\Delta L_N = B - X'$	$\Delta L = D - B$
Case 2		$\Delta L > \Delta L_G > 0$ Ie $X' > B$	0	$\Delta L_G = D - X'$
Case 3		$\Delta L_G > 0 > \Delta L$	$\Delta L_G = D - X'$	0

the extensive margin is computed as the change in total hectarage ($D - B$). In case 2, we have a large outward shift in AB such that $X' > B$. In this case, the total extensive margin is given by the change in total hectarage $D - B$, but these hectares are divided between extensive margin traditional hectares, $ext_N = X' - B$, and extensive margin GE hectares $ext_G = D - X'$. There are no intensive margin hectares.[8] In case 3, AB shifts in such that the total hectarage decreases. With no new hectares entering production, $ext_G = 0$, and any GE hectare come from the intensive margin $int_{NG} = \Delta L_G = D - X'$.[9]

The three cases in Table 3 exhaust the possible outcomes when comparing any post-adoption year to the pre-adoption base year.[10] With the data described in Section 3, we compute ΔL and ΔL_G for every country-crop-year in the sample where $\Delta L = L_{it} - L_{ib}$ and $\Delta L_G = L_{it1}$ for some pre-adoption base year b. In every case, the base year is defined as the year immediately prior to the first positive value for GE hectarage for the given country-crop observation. Given ΔL and ΔL_G, we classify every country-crop-year as case1, case2, or case3 and compute the corresponding intensive and extensive margins according to the formulas in Table 3.[11] We then sum over the given year to generate world hectarage by crop divided between traditional seed technology, GE intensive margin hectarage, and GE extensive margin hectarage. We present results for corn, cotton and soybeans in Figure 3.

In Figure 3, we find that for corn, most adoption of GE occurred on the intensive margin, with the extensive margin only accounting for 16% of total GE hectarage in 2010. The share of GE corn hectarage in total corn hectarage is not very large (26%), but because total corn hectarage is so large (the largest world hectarage of all crops) absolute extensification is still substantial. In cotton, overall GE cotton adoption rates are much higher (57%), though mostly still on the intensive margin (only 12% extensive margin). By contrast, adoption of

[8]Of course, extensification only occurs if there exists lands with pest damage that is greater than point B

[9]Note that the magnitude of both the extensive and intensive margins depends on the distribution of land at various levels of pest infestation. The analysis above suggests that if all of the lands in a country have sufficiently low levels of pests that allowed them to be utilized before GE was introduced, then the introduction of GE would not result in an extensive margin effect.

[10]A fourth case corresponds to the possibility that AB shifts out so much that traditional technology profits dominate GE profits for any initial pest pressure. In this case, GE hectarage equals 0, so trivially $ext_G = int_{NG} = 0$. We leave this case out of Figure 3 to reduce clutter, but we allow it in the empirical exercise.

[11]The model predicts extensification onto marginal lands that presumably were not used for anything before the introduction of GE. In this sense, the extensive margin is extensive to agriculture overall. However, we want to quantify the extensive margin *to a given crop* so that we can compute supply effects by crop. Defining the extensive margin as crop-specific means that extensive margin lands might be coming from any previous employment other than the production of the given crop, including the production of other crops. This definition of the extensive margin is broader than the one proposed by the model, however, absent plot-level time-series data, it is impossible to know from where the extensive margin is recruited. Thus, defining the extensive margin as all hectarage not previously devoted to a specific crop is as precise as we can be given data constraints.

GE soybeans has been high (70%) and more concentrated on the extensive margin than the other crops (49%). Soybean hectarage grew more than 50% since the introduction of the GE seed. Breaking down hectarage by country, we find that most of the extensive margin gains in soybeans came from Brazil and Argentina.

The data shows that much of the potential of GE has been realized in cotton and soybean. In the case of cotton, there is a relatively small extensive margin effect, and the adoption of most of the GE has occurred on land previously in production. However, GE cotton is the only GE crop that has been adopted globally, as it did not suffer from bans that apply to corn and soybean. In the case of soybean, the high rate of adoption of GE is because it was associated with an expansion of the hectarage of the crop (thus the large extensive margin effect), and virtually all of the adoption of GE soybean occurs in the U.S., Brazil, and Argentina. In the case of corn, a majority of corn in the world is located in countries in China, Europe, and Africa that have banned the adoption of GE corn, and therefore overall adoption is below 30% of global hectarage. Since according to Figure 3 yield per hectare of adopters is higher than of non-adopters, the share of GE corn of total corn is about 43%. Nevertheless, there is a large potential for increased adoption of GE corn if practical bans on the technology are removed.

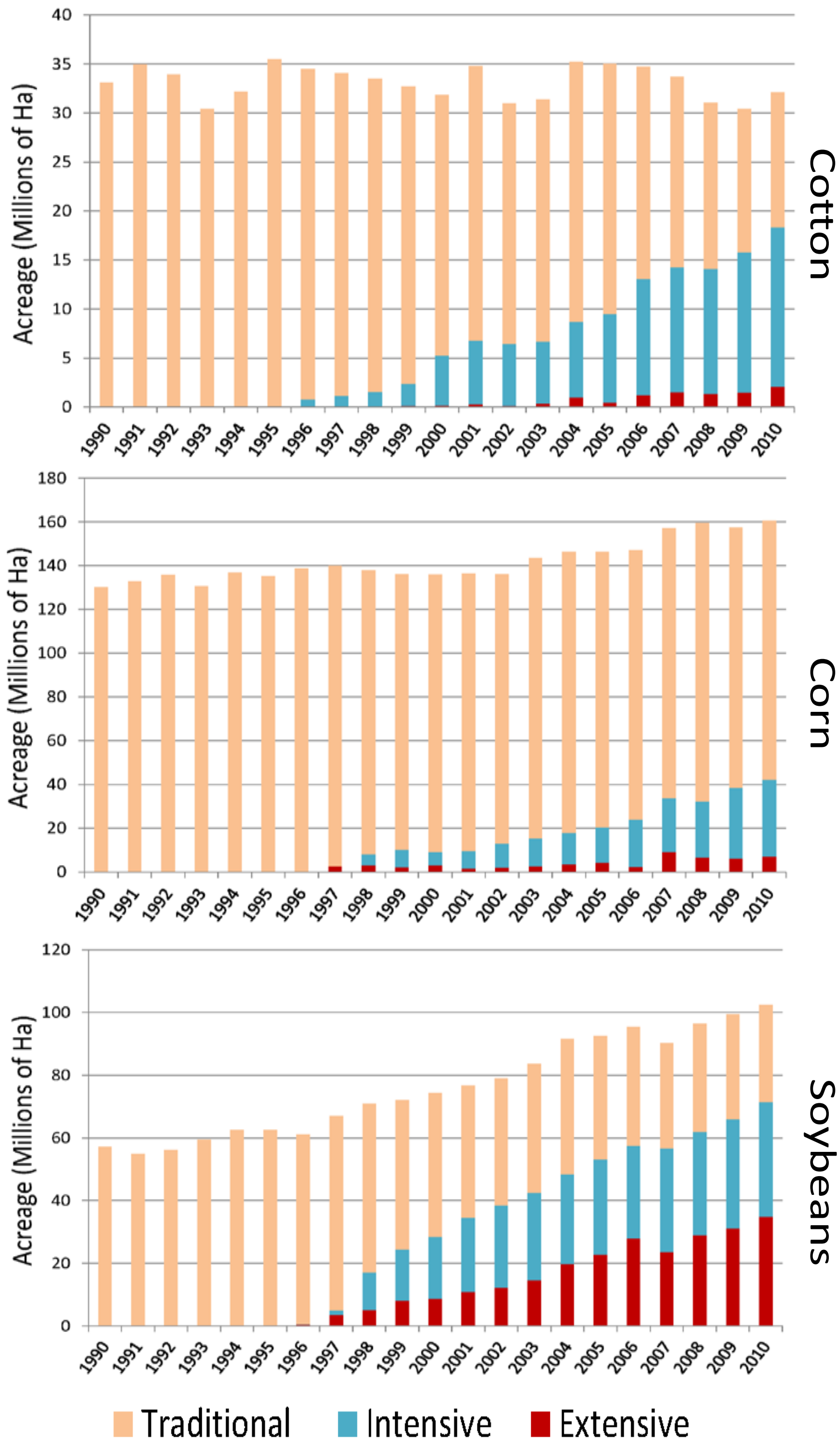
As discussed above, absent plot-level data, it is difficult to determine from which uses extensive margin lands are recruited. Extensive margin switching could come from other crops or other nonagricultural purposes (such as forest or marginal lands). Because of the nature of world agricultural land-use data, what is here included as extensive margin changes might actually be second-season cropping on the same physical land, as opposed to new plots. In fact, "double-cropping" is believed to account for a substantial share of increased soybean hectarage (Trigo and Cap, 2006). When double-cropping, farmers produce in the shoulder seasons when pest damage is typically too high for profitable production. It is consistent with our model that GE technology permits double-cropping by extending the range of initial pest pressures accommodated by profitable farm operations. For example, HT varieties permit control of weeds after the crop plant has emerged from the ground, lessening demand for preemergence weed control, which often induces sufficient delay to preclude maturation of a follow-on crop.[12]

5 Estimated Impacts

Equipped with estimated yield gains on the intensive margin and the hectarage of the extensive margin, supply, price, and hectarage for the three primary GE crops are computed for the counterfactual of no GE technology. The supply effect is computed as a range depending

[12]For example, Trigo and Cap (2006) estimate that GE technology induced a 9.9 million-hectare expansion of soybean area in Argentina.

Figure 3: World hectarage of GE Crops by Technology and Intensive/extensive Margins



on the attribution of extensive margin lands to GE. The price effect is also computed as a range depending both on the assumptions of the supply effect and the assumptions of elasticities of supply and demand. Land-use savings effects are computed as the difference between observed hectarage and counterfactual hectarage needed to generate the same output absent GE technology.

5.1 Supply Effect

We compute the supply effect of GE technology for the three principle GE crops as the percentage difference between observed 2010 production and two different counterfactual supplies corresponding to different assumptions about the extensive margin. Counterfactual supplies are computed country by country and then aggregated to a world figure. We first compute the implied traditional variety yield $\hat{q_{it0}}$ by solving

$$\begin{aligned} Q_{it} &= q_{it0}L_{it0} + q_{it1}L_{it1} \\ &= q_{it0}\left(L_{it0} + \left(1+\hat{\beta}\right)L_{it1}\right) \\ \implies \hat{q_{it0}} &= \frac{Q_{it}}{L_{it0} + \left(1+\hat{\beta}\right)L_{it1}} \end{aligned} \tag{11}$$

where $\hat{\beta}$ represents the estimated yield effect of the GE technology for the given crop. In the estimated impacts that follow, we use both our own estimated yield impacts from section 3, and a range of other yield impacts from the literature. Assuming that production would have occurred on extensive margin lands even without the use of GE technology, then the counterfactual supply is given by

$$Q_{it}^{c1} = \hat{q_{it0}}L_{it} \tag{12}$$

We sum over country-specific counterfactual supplies to find the world total counterfactual supply Q_t^{c1} and compute supply effect $s_1 = \frac{Q_t - Q_t^{c1}}{Q_t}$. If however, it is assumed that production on the extensive margin would not have occurred without the GE technology, i.e., that GE seeds cause the increase in hectarage, then the production on the extensive margin would have to be subtracted from Q_{it}^{c1} to yield counterfactual supply 2:

$$Q_{it}^{c2} = \hat{q_{it0}}\left[L_{it} - L_{it1}^{ext}\right] \tag{13}$$

where L_{it1}^{ext} denotes the extensive margin computed in Section 4. The corresponding supply effects defined analogously as above.

In Figures 4 and 5, we report world supply effect for GE corn and cotton for the year 2010 conditional on yield effects from several different studies. Supply effects based on our estimates from section 3 are denoted with large red triangles. Other markers correspond to

Figure 4: Supply Effect of GE Corn

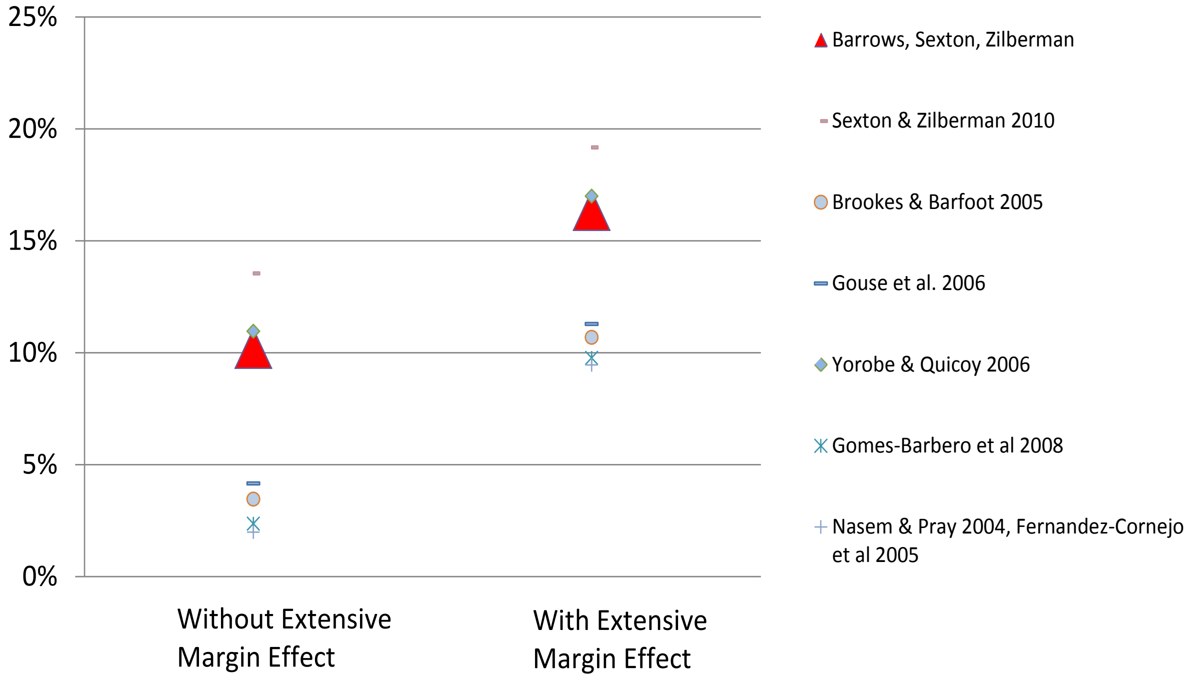
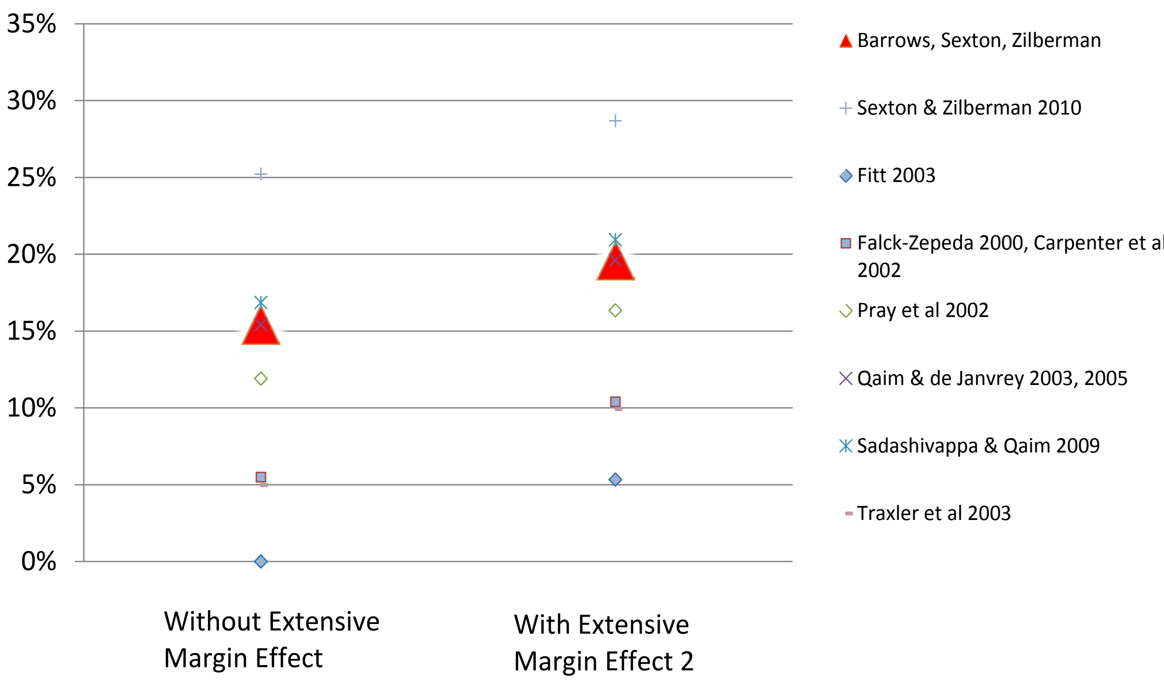


Figure 5: Supply Effect of GE Cotton



the supply effects based on yield effects from Sexton and Zilberman (2011) along with all the studies reviewed in Qaim (2009). Estimates are reported according to the extensive margin assumption. The left column, labeled "Without Extensive Margin Effect," reports the resulting supply effects when we assume that extensive margin lands could have been profitably farmed with traditional seeds. The right column, labeled "With Extensive Margin Effect," reports supply effects after subtracting all production on extensive margin lands.

In Figures 4, we find that GE technology increased the supply of corn in 2010 between 10-16% based on the yield effects from section 3, depending on how much of the extensive margin is attributed to GE. Thus, even though extensive margin lands represent a small share of total GE corn hectarage, accounting for the extensive margin can potentially make a large difference for the supply effect. Compared to estimates from other studies, our supply effects are usually larger, since our estimated yield effects were larger, but the supply effects computed from other yield estimates still generate significant impacts. Estimates range from 2-4% without the extensive margin, and 9-11% with the extensive margin. The notable exceptions are Sexton and Zilberman (2011) and Yorobe and Quicoy (2006), which generates slightly larger supply estimates than ours.

In Figure 5, our estimates imply that GE technology increased the supply of cotton between 15-20% in 2010, depending on the extensive margin. Again, these estimate are larger than what would be implied from the yield effects in the Qaim (2009) review.

Finally, for soybeans, we find that because the estimated yield effect is small and the estimated extensive margin effect is large, almost all of the supply effect comes from the extensive margin. We estimate that the supply effect was only 2% without the extensive margin, but as large as 39% with the full extensive margin.[13]

5.2 Price Effects

The supply effect from GE technology can be translated into price effects using a methodology from De Gorter and Zilberman (1990). Suppose that without GE technology, the supply curve shifts in by a factor of η, where η corresponds to the supply effect from the previous section. In the new equilibrium:

$$(1-\eta)\, Q_s\,(p) = Q_d\,(p) \tag{14}$$

[13]There are no similar studies with which to compare this result.

where $Q_s(p)$ and $Q_d(p)$ represent quantities supplied and demanded, respectively, as a function of output price p. Totally differentiating with respect to η and p, yields

$$\begin{aligned}
(1-\eta)\frac{\partial Q_s(p)}{\partial p}dp - Q_s d\eta &= \frac{\partial Q_d(p)}{\partial p}dp \\
&\Longrightarrow dp\left[(1-\eta)\frac{\partial Q_s(p)}{\partial p} - \frac{\partial Q_d(p)}{\partial p}\right] = Q_s d\eta \\
&\Longrightarrow \frac{dp}{p} = \frac{\partial \eta}{\epsilon_s - \epsilon_d} \qquad (15)
\end{aligned}$$

where the last line follows from setting $\eta = 0$. Equation (15) states that the percentage change in equilibrium price (the price effect) is equal to the supply effect divided by the difference between price elasticity of supply and price elasticity of demand. Thus, estimation of the price effect simply requires that the supply effect from the previous section is scaled by parameters obtained from the literature. In our estimates, $\epsilon_s = 0.3$ and a low elasticity scenario is parameterized with $\epsilon_d = -0.3$ and a high elasticity scenario uses $\epsilon_d = -0.5$. For each elasticity scenario, we also vary the assumption on the extensive margin as before. For each of these 4 scenarios {low elasticity, no extensive margin ; low elasticity with extensive margin; high elasticity, no extensive margin; high elasticity, with extensive margin} price effects are computed conditional on yield estimates from each of the studies mentioned in section 5.1 and plotted in Figure 6 for corn and Figure 7 for cotton.[14]

In Figure 6, we find that corn prices would have been between 13-27% higher, depending on the assumption of elasticity and extensive margin effect. The price effects in Yorobe and Quicoy (2006) and Sexton and Zilberman (2011) are higher than our estimates, while other studies are roughly 10 percentage points lower. We find that in all cases, the estimates are more sensitive to the inclusion of the extensive margin than the assumption of demand elasticity. Cotton prices would have been 19-33% higher without GE technology, as shown in Figure 7. Again, the estimates are higher using our yield impacts instead of others in the literature, but even low yield estimates as in Traxler and Godoy-Avila (2004) and Falck-Zepeda et al. (2000) predict that cotton prices would have been 7-19% higher.[15] Finally, for soybeans, the price effect depends heavily on the extensive margin assumption. Without the extensive margin, the price effect is between 2-3%. Including the extensive margin, the price effect is between 49-65%.

[14]Roberts and Schlenker (2010) suggest that supply elasticities vary between 0.08 and 0.13 for supply of grain calories and demand elasticities vary between -0.05 and -0.08. Thus, the magnitude of the price effect should be greater than five times the magnitude of the supply effect, which are greater than the impacts estimated here.

[15]of course, the estimates from Fitt (2003) yield even lower price effects, but that is because Fitt estimate no yield impact

Figure 6: Price Effect of GE Corn

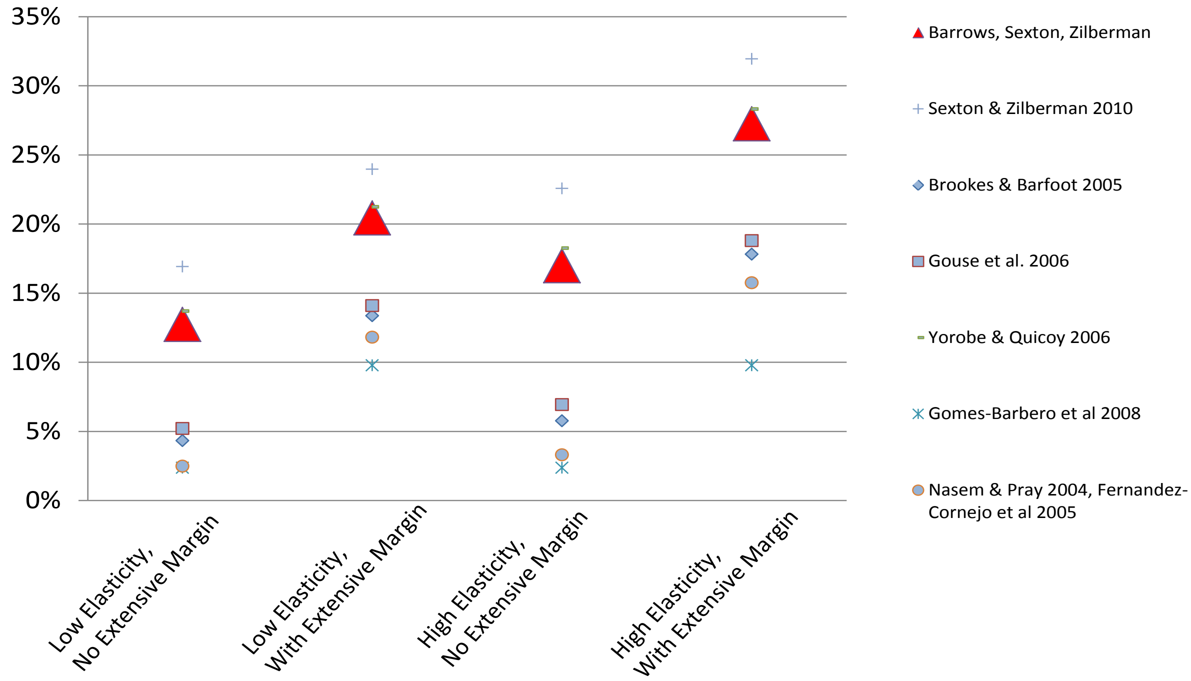


Figure 7: Price Effect of GE Cotton

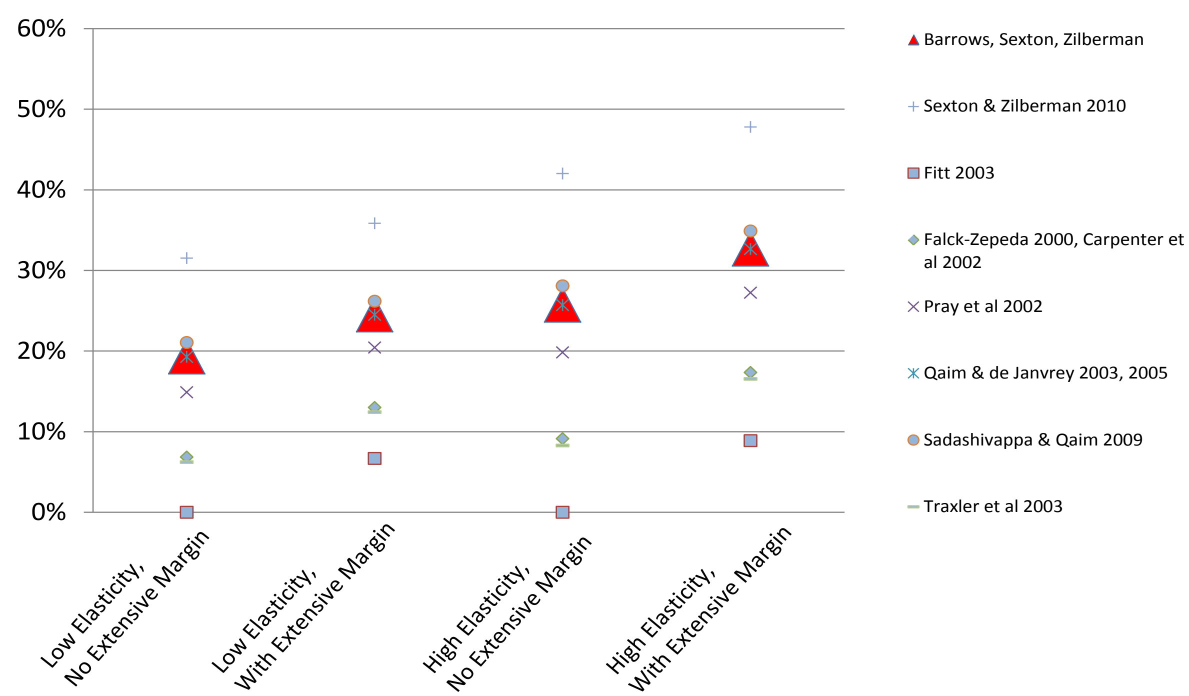


Table 4: Land-Use Saving Effects

	2010 Acreage *Millions of Ha*	Acreage Saved *Millions of Ha*	CO2 Saved *Gt*
Cotton	32	6	0.12
Maize	161	13	0.26
Soybeans	102	1	0.03
Total	295	21	0.41

5.3 Land-Use Saving Effects

Lastly, we estimate land-use saving effects and the corresponding GHG emissions savings due to GE technology. hectarage "saving" is computed as the difference between observed hectarage in 2010 and counterfactual hectarage that would be needed to produce the same output without the GE supply effects. Formally, counterfactual hectarage without considering the extensive margin effect is computed as

$$L_{it}^{c1} = \frac{Q_{it}}{\hat{q_{it0}}} \tag{16}$$

Country-specific hectarages are aggregated to the world level and observed 2010 hectarage is subtracted to compute world hectarage savings

$$L_t^{c1} = \sum_i \left(L_{it}^{c1} - L_{it} \right) \tag{17}$$

These estimates are reported by crop in the second column of Table 4. We estimate the land use savings associate with GE cotton are 6 million Ha, or roughly 20% of observed 2010 cotton hectarage. Maize land-use savings equals 13 million Ha, or 8% of observed maize hectarage. Finally, soybean land-use savings are negligible, at less than 1% of total soybean hectarage. In the last column of Table 4, we translate land-use savings into Gt of averted CO_2 emissions by multiplying the hectarage savings by a constant CO_2/Ha/year figure.[16] We find that across

[16] we use a constant CO_2/Ha/year of 20 Gt taken from the ILUC literature, See Renate Schubert, Future bioenergy and Sustainable Land Use (2010), we convert hectarage savings into annual CO_2 savings.

all three crops, GE technology saved $0.41Gt$ of CO_2 emissions in 2010. To put this figure in perspective, the total emissions from all passenger cars in the US in 2010 was roughly 1.28 Gt of CO_2[17], which means the land-use savings effects of GE technology was roughly 1/3 the size of all emissions from cars in the US.

The preceding analysis considers only landuse change effects, but a full GHG accounting would consider other auxiliary effects of GE technology. In fact, the impact of GE on GHG emissions is likely to be significantly greater than the land saving effect associated with the intensive margin for several reasons. First, some of the extensive margin effect is associated with double cropping, and providing the output of this hectarage would require expanding the land footprint of agriculture and more GHG emissions. Secondly, much of the land utilizing herbicide tolerant varieties has switched to low or no tillage, which contributes to soil carbon sequestration that may add up to 7 tons per hectare per 10 years (Paustian et al., 2004). Third, the reduction in agricultural footprint because of GM varieties also reduced other inputs that complement land (i.e. fertilizer, pesticides, water, etc.) leading to reduced GHG emissions. Finally, the environmental effect we are concerned with includes the impact on water and chemical inputs of agriculture, and since adoption of GE tends to reduce hectarage needed to produce a given volume of crop, it also tends to reduce water and use of other inputs.

6 Conclusion

Demand is growing for food, feed, fiber and energy, and unless new lands are recruited into production of the staple crops from which these goods are made, prices must rise to equilibrate the market, or new sources of intensive margin yield gains are needed. Rising prices for these products have disastrous effects on the poor, while clearing lands for agriculture is extremely expensive from a greenhouse gas perspective. Agricultural biotechnology can potentially increase per hectare yields, thus boosting supply and preserving lands. In this paper, we generate new estimates of the yield effect which takes account of complementary input use and find larger impacts than most studies in the literature. We also develop a methodology for decomposing observed hectarage into intensive and extensive margin. While we cannot say if GE technology has *caused* the increase in the range of lands that can profitably be farmed, we have found that hectarages have increased since the introduction of GE technology, and counterfactual supply scenarios suggest that the extensive margin effect could make a large difference in computing supply, price, and land-use saving effects. Future research using ex-

[17]The EPA calculates that the average passenger vehicle in the US generates 5.1 metric tons of CO_2 per year, and the National Transportation Statistics table 1-11 reports there were 250,272,812 passenger vehicles in the US in 2010, which implies that total CO_2 emissions from passenger vehicles equaled $5.1 * 250,272,812 * \frac{1}{1,000,000,000} = 1.28$Gt.

perimental variation to identify the causal link between GE adoption and the extensive margin would constitute a significant contribution.

We found that adoption of GE has significant impact on the price of cotton, corn, and soybeans. As corn and soybeans are used extensively in the production of food, these price effects likely translate into significant impacts on the price of food consumed by the poor in developing countries (Hochman et al., 2011). The analysis suggests that while there has been a relatively high rate of adoption of GE cotton and soybean that has contributed to a significant price reduction in these commodities, bans and other regulations limited the adoption of GE corn to less than 30% of total corn hectarage, reducing its total price effect. If adoption of corn is expanded globally, we expect much larger increases in supply both because of reduction in pest damage as well the complementary input effect, resulting in further corn price reductions, which will benefit the poor. The use of GE is practically banned everywhere for major food grains like wheat and rice, even though existing traits could reduce pest damage in these two crops. Our analysis suggests that developing new GE varieties in these crops has the potential to reduce their prices as well as the environmental side effects from these crops.

Additionally, we find that even this first-generation of GE has had significant environmental effects, preventing greenhouse gas emissions on the same order of magnitude as 1/3 the annual GHG emissions caused by driving in the US.

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