More of Less isn't Less of More. Assessing Environmental Impacts of Genetically Modified Seeds in Brazilian Agriculture.

PRELIMINARY VERSION. DON'T CITE.

Renato Seixas[♣]

José Maria Silveira[#]

David Zilberman[*]

We investigate the environmental effects due to pesticides usage for two different genetically modified (GM) seeds: insect resistant (IR) cotton and herbicide tolerant (HT) soybeans. Using an agricultural production model of a profit maximizing competitive farm, we derive predictions that IR trait decreases the amount of insecticides used and HT trait increases the amount of less toxic herbicides. While the environmental impact of pesticides for IR seeds is lower, for the HT seeds the testable predictions are ambiguous: scale as substitution effects can lead to higher environmental impacts. We use a dataset on commercial farms usage of pesticides and biotechnology in Brazil to document environmental effects of GM traits. We explore intra-farm variation for farmers planting conventional and GM seeds to identify the effect of adoption on the environmental impact of biotechnology measured as quantity of active ingredients of chemicals and the Environmental Impact Quotient index. The findings show that the IR trait reduces the environmental impact of insecticides and the HT trait increases environmental impact due to weak substitution among herbicides.

Keywords: Brazil, environmental impact, GM seeds, HT soybeans, IR cotton, pesticides

September, 2013

[♣] PhD candidate at ARE/UC Berkeley. Corresponding author: rnlseixas@berkeley.edu.

[#] IE/UNICAMP

[*] ARE/UC Berkeley

1 INTRODUCTION

The research agenda on food supply has received increased attention since the global food crisis of 2008. Genetically modified (GM) seeds have been considered one of the major breakthroughs in technological innovation for agricultural systems and have been promoted as an effective tool for control of agricultural pests and food supply expansion by increased productivity. Their relevance can also be measured by the wide spam of controversial issues that have been raised in the related literature since their introduction. Those involve: intellectual property rights over organisms, productivity effects, economic returns, consumer safety, welfare and income distribution, and environmental effects (Qaim, 2009). Potential sources of related economic gains that include reduced crop losses, reduced expenditure on pest control, farmworker safety and health conditions, and lower variability of output (Sexton & Zilberman, 2012).

In the environmental front, benefits from adoption of GM seeds have been argued based on findings about pesticide use and agricultural practices. Insect resistant (IR) cotton has been found to reduce the use of insecticides and therefore to produce environmental, health and safety gains (Qaim & Zilberman, 2003; Qaim & de Janvry, 2005; Huang, Hu, Rozelle, Qiao, & Pray, 2002). Herbicide tolerant (HT) soybeans have been found to change the mix of herbicides applied towards less toxic products and to allow the use of no-till cultivation techniques, leading researchers to conclude (tentatively) that they also produce environmental benefits (Fernandez-Cornejo, Klotz-Ingram, & Jans, 2002; Qaim & Traxler, 2005; Brookes & Barfoot, 2012).

This paper addresses the environmental impacts, associated with the use of pesticides, resulting from adoption of GM seeds in Brazil. First, we use a model of a profit maximizing competitive farm to show how the interaction of different GM traits (HT and IR) affects the optimal use of pesticides, more specifically herbicides and insecticides. We show that the IR trait works as substitute for insecticides and hence reduces the optimal use of these products. The resulting environmental effect is straightforward: less insecticide usage leads to lower environmental impact. The HT trait, on the other hand, works as a complement to herbicides, specifically to glyphosate[1], and induces an increase in the use of this product. The resulting environmental impact is ambiguous and we argue that it depends on the interplay of a substitution effect, between herbicides of different toxicity levels, and a scale effect, of increased use of glyphosate.

We use a unique farm-level dataset that documents adoption of GM seeds and pesticide use between 2009 and 2011 for cotton, maize and soybeans cultivation by commercial farms in Brazil to present the first reduced form models estimates of environmental effects of two different biotechnology traits: IR cotton and HT soybeans. The dataset is disaggregated by fields, within a farm, cultivated with conventional or GM seeds. In other words, for each farm, we have information separated for fields cultivated with conventional or GM seeds. This setup allows us to use *intra-farm* variation for farmers that plant both conventional and GM seeds to identify the effect of adoption on the environmental impact of pesticides.

We measure the environment impact as two outcome variables: quantity (kg/ha) of active ingredients of chemicals and the Environmental Impact Quotient (EIQ) index (Kovach, Petzoldt, Degnil, & Tette, 1992). This measure of environmental impact of pesticides was designed to capture risks associated with both toxicity levels and exposure to chemical pesticides on three components of agricultural systems: farmworker, consumer and ecological. Hence, the EIQ index gives a more complete picture than just the composition of the mix of pesticides used.

The findings show that, as expected, adoption of cotton seeds with IR trait reduces the amount of insecticides used by 24.2% and, consequently, the environmental impact index by 23.4% when compared with fields cultivated with conventional seeds. For soybean seeds with HT traits, however, although farmers use more of less toxic herbicides, we estimate that the net environmental impact is higher than for conventional seeds. We find that adoption of these seeds cause an increase of 44.2% of herbicides use and a corresponding 35.6% increase in the EIQ index when compared with fields cultivated with conventional seeds. Moreover, we

[1] Glyphosate is considered a low toxicity herbicide. In the classification of environmental impacts, glyphosate is in the 145^{o} position out of 178 active ingredients classified (Kovach, Petzoldt, Degnil, & Tette, 1992)

estimate that the increase in the use of herbicides of low toxicity levels is twelvefold the decrease in the use of herbicides of high toxicity levels. This result indicates that the main mechanism driving the findings on the EIQ index is the weak substitution among herbicides of different toxicity levels.

Those results are not inconsistent with the literature on environmental effects of GM seeds. For IR cotton, Qaim & Zilberman (2003), Qaim & de Janvry (2005) and Huan et al. (2005) find significant reductions in average use of insecticides in India, Argentina and China, respectively. For HT soybeans, Fernandez-Cornejo et al. (2002) and Qaim & Traxler (2005) find increases in the use of glyphosate and some reduction in the use of more toxic herbicides, which leads them to conclude for environmental benefits due to the adoption of this type of seed. Our results confirm the environmental gains from IR cotton but suggest that the findings on the environmental effects of HT soybeans have been misled by the qualitative nature of the change in the mix of herbicides used.

The rest of the paper is organized as follows. Section 2 introduces a quick background on biotechnology and its regulation in Brazil. Section 3 describes the theoretical model that informs our hypotheses. Section 4 describes the dataset and presents the empirical strategy. Section 5 shows the results obtained and section 6 concludes.

2. SOME BACKGROUND ON BIOTECHNOLOGY AND REGULATION

Since the mid 1990's, when first-generation GM seeds were commercially introduced, adoption by farmers has grown steadily in industrialized and developing countries as they provide an alternative and more convenient way of reducing pest damage[2] (Figure 1). By 2008, 13.3 million farmers dedicated 8% of total cropland (12.5 million ha) to the cultivation of GM seeds. The leading countries in terms of share of cultivated are in 2009 were the US (50%), Argentina (17%), Brazil (13%), India (6%), Canada (6%) and China (3%) (James, 2008).

[2] Second-generation GM seeds display quality improvements in nutritional contents and third generation are designed for pharmaceutical (vaccines and antibodies) and industrial (enzymes and biodegradable plastics) applications.

The main traits that have been introduced in first generation GM seeds correspond to the herbicide tolerant (HT) and insect resistant (IR) technologies. Crops engineered with HT traits allow farmers to use more effective chemicals, like glyphosates and gluphosinates, which target a number of weeds species but causes severe damages to conventional crops when applied after germination (post-emergent weed control). Since glyphosates have been sold at lower prices compared to chemicals that are targeted to individual weeds, adoption of HT seeds is expected to reduce expenditures on damage control chemicals. IR seeds[3] are engineered to produce a natural toxin produced by the soil bacterium *Bacillus Thuringiensis*, which is lethal to a number of bollworms pests. Some crops have also been engineered with both HT and IR traits and are commonly referred as stacked varieties.

Crops that have been engineered with the above traits are: cotton, maize, rapeseed and soybean. The most used technology is HT in soybeans, which corresponded to 53% of GM seeds planted area in 2008 and is grown mostly in US, Argentina and Brazil. The second-most used technology is HT and IR maize, which accounted for 30% of GM seeds planted area in 2008 (James, 2008).

From the point of view of producers, GM seeds have been shown to be both technically and economically advantageous, which explains the rapid rate of adoption by farmers. From the technical perspective HT crops allow more flexibility in the weed control strategy as the farmer can use a longer window for spraying chemicals. In conventional crops, weed control has to be done in the pre-emergence phase of plant growth, since it can suffer harmful side-effects from the application of herbicides after germination. The HT trait goes around this problem by making the plant tolerant to some herbicides (eg. glyphosates and gluphosinates) that can then be applied post-emergency (Brookes & Barfoot, 2012).

IR crops have also been deemed technically and economically efficient for producers. The most straightforward one is related to savings in insecticides applications (which spams from labor time to savings in machinery use, aerial spraying etc.) targeted to bollworm killing. Besides, it has also been considered a more efficient tool for managing the risk of pest attack

[3] Also referred in the literature as Bt seeds.

than reactive application of insecticides which has been translated in reduced crop insurance premium. Other benefits pointed relate to improve safety conditions for farm workers and shorter growing season (Brookes & Barfoot, 2012).

Despite the production benefits, consumers have shown suspicious attitudes regarding the health and environmental safety of products originated from GM seeds and government regulation has ranged from cautionary permission to complete ban. The European Union, for instance, imposed a ban on GM seeds that was lifted in 2008. Also, GM seeds uses have been restricted to animal feed and fiber uses and producers are required to segregate GM crops output throughout the supply chain (Sexton & Zilberman, 2012). Other concerns relate to the undermining of traditional knowledge systems in developing countries and the possibility of monopolization of seed markets by large multinational companies and exploitation of small farmers (Sharma, 2004).

The regulation of GM seeds in Brazil originates in the first Biosafety Law from 1995, which ruled that commercialization of GM seeds is subject to approval by the National Technical Biosafety Commission (CTNBio). After a decision from CTNBio in favor of Monsanto's *Roundup Ready* seed (a type of HT soybean seed) that waved the company from releasing environmental impact studies was judicially contested in 1998, a period of ban of commercialization of GM seeds was imposed by the judiciary system, on the grounds that CTNBio's decision violated the principle of precaution espoused by the Brazilian constitution. The judiciary decision, nevertheless, wasn't fully implemented as competitive pressure by farmers from neighbor countries Argentina and Paraguay stimulated the smuggling and illegal adoption of soybean HT seeds by farmers in the southern states that bordered those countries. Also, the executive branch took a mostly favorable stance towards farmers and loosened repression of GM seeds adoption on the grounds that it would impose huge losses on southern producers, responsible for a significant share of soybean production in Brazil. After a series of temporary provisional measures designed to work around the legal ban, a new biosafety law was passed in 2005 that settled the issue in favor of the discretion of CTNBio's power to require environmental impact studies for commercial release of GM seeds (Pelaez, 2009).

In spite of the delay caused by the regulatory issues that took seven years to be resolved, adoption of GM seeds in Brazil spread rapidly and reached a level similar to neighbor country Argentina, which has a longer history of liberal policy towards adoption of GM seeds. Figure 2 illustrates the steady growth in the rates of adoption of GM seeds in cotton, maize and soybean crops. Adoption of HT soybeans increased from 45.2% in 2008 to 91.8 % of planted area. Cotton crops also observed growth in GE seeds adoption rates, ranging from 6.6% of the planted area in 2008 to 29.6% in 2011. It's worth noting the rapid adoption of GM Maize seeds, which were introduced in 2008 and reached an adoption rate of almost 80% of planted area by 2011 (Céleres, 2012). In terms of area, this equivalent to approximately 31.16 million ha of the total planted area with those crops in 2010.[4]

3. Model

We present a heuristic model that illustrates the effects of different GM traits on choices of pesticides inputs by a competitive profit maximizing farm. The model allows us to derive testable predictions that are going to guide us on in the empirical analysis. Building on previous work (Ameden, Qaim, & Zilberman, 2005) we show that the IR trait works as substitute for insecticides and hence reduce the optimal amount used whereas the HT trait works as complement for herbicides and induce more intense use of those products. The net environmental impact, which is the outcome we are ultimately interested in, will be different for each trait. For the IR trait, the result is unequivocal: less insecticide usage reduces environmental impact. For the HT trait, on the other hand, the environmental impact can't be determined a priori. HT trait makes the plant more resistant to glyphosate, which leads to a more intensive usage of this chemical. The net environmental effect will depend on how strong is the substitution between different types of herbicides.

The set-up of the model uses a damage control framework (Lichtenberg & Zilberman, 1986) that distinguishes between inputs that directly affect production, like labor, land and fertilizers and inputs that indirectly affect output by reducing the damage caused by pests like

[4] Approximately equivalent to 73% of California.

pesticides, biological control or GM seeds. Total output is given by the interaction between potential output, represented as a conventional production function of direct inputs, and a damage abatement function of indirect inputs that represents the share of output not lost by action of pests. We represent the total output function as:

$$Q = Q_i[1 - D(N_i)], i = 0, 1 \qquad \text{(eq. 1)}$$

where Q_i represents potential output, determined by direct inputs, $D(N_i)$ is a damage function that depends on the size of the pest infestation and the subscript *i* represents conventional or GM seeds respectively. We make the following regularity assumptions on the damage function:

(i) $0 < D(N_i) < 1$ and

(ii) $D' > 0$ and $D'' \geq 0$.

Pest infestation depends on the size of initial population and the fraction that survive the application of chemicals and biotechnology. It is represented by:

$$N_i = Nh(x)B_i , \qquad \text{(eq. 2)}$$

Where *N* is the initial population, $h(x)$ is the fraction of survival after application of pesticide quantity *x* and B_i is a parameter for the biotechnology effect. We also make the following regularity assumptions:

(i) $h' < 0$ and $h'' > 0$,

(ii) $B_0 = 1 \geq B_1$.

Letting *p* denote the market price for the crop and *w* the unit cost of application of pesticide, the choice of chemical input (*x*) for a competitive farm, for each trait *i* = 0, 1, is the result of the following program:

$$\max_x pQ_i[1 - D(Nh(x)B_i)] - wx. \qquad \text{(eq. 3)}$$

The first order condition for an interior solution is given by:

$$-pQ_iD'Nh'(x_i^*)B_i = w. \qquad \text{(eq. 4)}$$

Equation four represents the solution to the usual profit maximization problem where the left-hand side represents the value of marginal product of the pesticide and the right-hand side its unit cost. The interaction of the effects of different traits will determine the comparative statics of the optimal choice x_i^*.

The IR trait exerts a compound effect with the application of insecticide represented by: $B_0 = 1 > B_1$ and $Q_0 = Q_1$. The effect of adoption is them to reduce (shift down) the value of the marginal product of insecticide and, consequently, the amount of insecticide used. In this sense, the IR trait works as a *substitute* for insecticides. The left panel of figure 3 illustrates this effect.

The HT trait, on the other hand, allows tolerance to the non-selective herbicide glyphosate[5] which avoids damage to the plant. We interpret this property as an increase in potential output that can be obtained from regular inputs and is represented by: $B_0 = B_1$ and $Q_1 > Q_0$[6]. This effect increases the value of marginal product of the specific herbicide that the plant becomes tolerant to and the amount of herbicide applied. The right panel of figure 3 depicts this effect graphically.

The environmental impact that follows biotechnology adoption can be differentiated by the type of trait. For the IR trait, the effect is unequivocal: since the amount of insecticides is reduced, environmental impact is reduced with adoption.

For the HT trait the net environmental impact depends on two factors. First, it depends on the degree of substitution between different types of herbicides. Glyphosate is considered a low toxicity chemical. Hence, substitution of more toxic herbicides that are designed for specific weeds for less toxic general purpose herbicides can reduce the environmental impact of chemicals. On the other hand, there is also a scale effect: if the increase in the amount of low toxicity herbicides is much larger than the decrease in high toxicity herbicides, the net effect can be a higher environmental impact due to the use of chemicals. In a nutshell, weak substitution and large scale effect renders the net effect on environmental impact ambiguous.

[5] More recently, traits that allow resistance to other herbicides like ammonium-glufosinate have been introduced or are on the pipeline (Bidraban, et al., 2009).

[6] We should point here that this is a comparative statics result, i.e., all other factors are held constant. More importantly we're holding constant the variety of the seed in which the GM trait is being inserted.

Economists that studied the issue have focused on the substitution between herbicides to conclude (somewhat tentatively) that there are environmental gains allowed by the use of HT traits (Fernandez-Cornejo, Klotz-Ingram, & Jans, 2002; Qaim & Traxler, 2005). Nevertheless, we argue that weak substitution effect and strong scale effect might undermine this conclusion as we show in the analysis that follows on the next sections.

4. DATASET AND EMPIRICAL STRATEGY

The dataset originates from a survey conducted by a private firm in Brazil among 1,143 farmers distributed in 10 states for harvest seasons 2008-2011. Information on pesticide use was collected for harvest seasons 2009-2011 and covers 839 farms. The data are disaggregated at the trait level. Hence, each observation correspond to a farm *i*, on year *t*, producing crop *j*, with trait *k*. This separation is possible since the Brazilian agricultural regulation requires segregation of fields cultivated with conventional and GM seeds. The crops covered are cotton maize (summer and winter) and soybean. The traits used are conventional (for all crops), HT (soybean) and IR (cotton and maize). For reasons of space, we show results for soybean and cotton crops since these corresponds to the different biotechnology traits analyzed in the theoretical model. Since results for IR maize are qualitatively very similar to the ones obtained for IR cotton, we decided to not report them.

Tables one, two and three show the regional distribution of the surveyed farms and descriptive statistics for the surveyed farms that cultivated cotton and soybeans between 2009-2011[7]. We can see, for example, that those are on average large operations in terms of total planted area, which also includes other crops, and net revenue. For cotton growers, the average total planted area is 2.521 ha, ranging from 60ha to 28,374 ha. For Soybean growers, the average total planted area is 1,240 ha ranging from 8ha to 13,500 ha. In terms of experience, we notice that famers report an average of 22.4 and 29.4 years for cotton and soybeans respectively. This can be interpreted as a quite high level of accumulated human capital accumulated in the

[7] The different number of observations correspond to variable that weren't surveyed every year.

activity. The variable owner indicates whether the farm is managed[8] by the owner of by some other agent (e.g. a manager). This variable documents farms that belong to a business group (eg. some investor that decides to diversify her portfolio) or to an independent farmer. We see that for cotton farms, only two percent are managed by owners, while for cotton we have 25%. In terms of geographical concentration, the region with most observation is the Central-West in both crops. This is not surprising since it's one of the largest geographical regions in terms of agricultural land in Brazil. Finally, in terms of education, we can see that the sample corresponds to farmers with quite high schooling level for cotton growers, 68% have at least a college degree, while for soybean growers 48% of them have at least a college degree.

The dataset contains information on physical production and input expenditures separated by type of crop and traits for each farmer. The variables available are:

1. Production (kg) and planted area (ha) for each field cultivated with different seed trait (conventional and GM);
2. Monetary measures by trait of seed: total and net revenue, gross operating income, expenditures on fuel, pesticides, other chemicals, fertilizers and correctives, direct labor, seeds and planting materials, royalties and fees, outsourced services (planting, defensives application, harvesting and transport), storage and processing, other direct costs,
3. Demographic aspects of farmers[9] (sex, age, schooling, years of experience with the crop);
4. Property structure of the farm: whether it's managed by owner or manager,
5. Dose (kg/ha), number of applications and formulation (percentage of active ingredients) of pesticides used (acaricides, formicides, fungicides, insecticides and herbicides).

The environmental impact of pesticides is measured by an index designed by scientists from the Integrated Pest Management program from Cornell University (NY): the

[8] By managed we mean, the person that has decision power on biotechnology use.
[9] Collected only in 2010.

Environmental Impact Quotient (EIQ). The EIQ index (Kovach, Petzoldt, Degnil, & Tette, 1992) assesses the environmental impact of pest control chemicals by considering three different components of agricultural systems: farmworker (picker and applicator), consumer and ecological (terrestrial and aquatic animals). Its general principle is that the environmental impact for each component is given by the product of the toxicity level of the chemical substance (active ingredient) and the risk of exposure (e.g. half-life of substance on ground and plant surface, leaching potential). Figure 4 gives a schematic description of the different components of the index.

The researchers propose an index that weights all those components in a single measure of environmental impact for each active ingredient contained in pesticides. Starting with this measure, a field EIQ for pesticide is obtained by multiplying the active ingredient's EIQ by the product formulation (the percentage of active ingredient in the pesticide), the dose of pesticide application (weight per area) and the number of applications. The impact of a pest management strategy is given by the sum of the field EIQ's for each pesticide used. Hence, a pest management strategy that uses less toxic pesticides but in very large amounts can have a higher EIQ than a pest management strategy that uses small amounts of a high toxic pesticide.

Since the survey collects information on dose, number of applications and formulation of pesticides used in each field (seed trait) used, we can calculate EIQ indexes for fields with conventional and GM seeds. Hence we have a more complete measure of the environmental impact of pesticides that goes beyond the simple distinction of types of pesticides used.

As participation in the survey is voluntary, attrition rates are very high; hence, use of panel data techniques cannot be applied to the data. Nevertheless we can use other sources of variation to identify the effect of adoption on the use of pesticides. The level of data disaggregation – fields with conventional and GM traits – allows us to explore within farm variation between fields cultivated with conventional and GM seeds to identify the effect of biotechnology traits on the use of pesticides and corresponding environmental impact. This empirical strategy holds constant all farm-level characteristics that might affect simultaneously the choices of pesticide use and biotechnology adoption such as: management skills, input/output prices, location, weather shocks, etc. Hence, for instance, if soybean farmers that adopt biotechnology have some intrinsic preference for pest management strategies that are more intensive in herbicides than mechanical control (like tillage) the effect of GM traits could be overestimated. Likewise, if cotton farmers that adopt IR traits are more efficient and also use less insecticide in their pest management strategies, the effect of IR trait will be underestimated. The use of within farm variation, i.e., comparing the pesticide use and corresponding environmental impact for farmers that cultivate fields with conventional and fields with GM seeds gets around these sources of bias on the coefficient that measures the effect of the GM trait.

Two main caveats still need to be addressed. First, there may be systematic differences across fields within the farm that might affect adoption and use of pesticides. This can be particularly important in the case of soybean HT seeds if the presence of weeds is related to soil quality, for example, and if farmers tend to use GM seeds in more fertile fields, which would introduce an upward bias in the coefficient of the GM trait. Also, if farmers use no-till farming in fields that are cultivated with HT seeds, the coefficient on HT trait will be upward biased as well since the effect of no-till will be confounded with the effect of HT trait.

To address the issues related to differences in fields we rely on two findings. First, we compare levels of expenditure per hectare on inputs across fields with conventional and GM seeds to look for evidence of soil quality that might drive more intense use of inputs. Specifically we look at expenditures on fertilizers as evidence of systematic differences in soil quality. Tables 4 and 5 show that, for cotton and soybeans crops respectively, we don't observe statistically significant differences in the average expenditure on inputs for fields cultivated with conventional and GM seeds. The results for expenditures on fertilizers give us confidence that systematic differences in soil quality are not introducing significant bias in our results[10]. With

[10] Even if those expenditures don't correspond to pre-treatment observations, we believe that this is the best evidence we can provide on the degree the relative homogeneity of fields cultivated with conventional and GM seeds. Also, anecdotal evidence from personal conversation with the company staff that implemented the survey shows that farmers in Brazil are not sophisticated enough to measure soil quality in parts of the farm and condition the use of GM seeds on that. Hence, even if there are such

respect to the use of no-tillage farming, since the survey collects information on the planting system used for each field, we control for the use of conventional versus no-till in the equations for soybean, the crop associated with the use of herbicides. We also estimate the model considering only farmers that don't use different farming systems across fields.

The second caveat relates to the sample of farmers chosen to perform the estimation, i.e., farmers that cultivate both conventional and GM seeds. This choice can potentially introduce a selection bias since it only considers adopters. In fact, tables 6 and 7 show that there are significant differences between farmers included and excluded from the sample. For cotton farms, the sample is more concentrated in the northeastern region and less in the Central-West. With respect to schooling, we see that farmers in the sample tend to have more of college (not statistically significant) and graduate degrees and less of basic and high school. For soybean farms, we see statistically significant differences for more variables. Specifically, they have larger operations (planted area), spend more on fertilizers, are younger and less experienced, although with in a still high level, more concentrated in the northeastern and southeastern regions and less in the southern region and are also more educated (less concentrated in basic school).

To alleviate this issue we rely on the observation that the farmers in the sample are more educated than the excluded ones. Hence, we can conjecture that the selection bias is in the downward direction. If more educated farmers are also more efficient, them the effect of adoption will be smaller for them than the effect for the whole population. In other words, the results are underestimating the true value of the effect of adopting GM seeds on the outcome variables of interest: pesticides quantities and environmental impact.[11]

The models are estimated for cotton and soybean crops separately. The dependent variables are quantity (kg/ha) of pesticides used (insecticides for cotton and herbicides for

---

differences, it seems reasonable to assume that they're not observed by the farmers which in turn act as if they were randomly selecting the fields in which to cultivate conventional and GM seeds.

[11] A second conjecture might be that, by using only farmers that adopt GM seeds, we are approximating the treatment effect on the treated, that is on farmers that have intrinsic characteristics that make them more likely to adopt GM seeds.

soybean) and EIQ index for each field. The traits considered are the most common ones for each crop: IR for cotton and HT for soybean. The estimated equations have the following form:

$$y_{itf} = \alpha + \beta trait_f + \gamma_i + \theta_t + \varepsilon_{itf} \ . \qquad \text{(eq. 4)}$$

Subscripts i, t and f indicate farmer, year and field (each field cultivated with conventional or GM seed). We include farmers (γ_i) and time dummies (θ_t) that capture farm-specific and year specific effects. Although these variables are orthogonal to the field level effects that we are interested, they provide efficiency gains in the estimation that prove worth keeping them.

5. RESULTS

To recap and as derived by the model outlined in section three, for cotton crops (IR trait) we expect a negative coefficient for trait in the equation for quantity of insecticides and for the EIQ index. For the soybean model (HT trait) we expect to find a positive coefficient for trait in the equation for quantity of herbicides but in the EIQ equation, the trait coefficient can go either way. To give a better picture of the intensity of substitution between different types of herbicides, for soybean crop, we estimate separate equations for each type of toxicity class of herbicides. We expect to find positive coefficients for quantities of low toxicity (classes III and IV) and negative (or non-significant) coefficient for quantities of high toxicity (classes I and II) herbicides. The magnitudes of those coefficients might shed light to the process of substitution of herbicides that is induced by the HT trait is soybean crops.

The regression results that we obtained are consistent with the predictions of the model. For IR cotton, we observe a reduction in the quantity of insecticides and environmental impact. For HT soybean, on the other hand, we observe increased quantities (kg/ha) of low toxicity herbicides and no corresponding reduction for high toxicity ones. The net result is an increase in EIQ index of herbicides applied.

Tables 8 and 9 show estimates of the effect of adoption of IR trait in cotton crops for quantities (kg/ha) applied of different types of pesticides – acaricides, fungicides, herbicides insecticides and total – considering all farms in the survey and the restricted sample respectively. The only statistically significant coefficient is the one for insecticides, an indication that the IR trait doesn't affect the use of other pesticides. The point estimates in the restricted sample are significant lower (in absolute terms) than the ones in the full sample, which indicates that bias due to uncontrolled unobserved variables is an issue. The coefficient of the IR trait indicates that it allows a reduction of 0.956Kg/ha of active ingredients of insecticides. Table 10 shows the results estimated with farm and year fixed effects, which shows efficiency gains reflected in lower standard errors obtained, and a log-linear specification that estimates the proportional effect of adoption on the dependent variable. The result shows a decrease of 24% in the amount of insecticides[12] used and 9.2% in total amount of active ingredients.

Table 11 is the counterpart of table 10 for the EIQ index. Consistent with the reduction in quantity of insecticides, the coefficient indicates a reduction of 34.225 EIQ points. To gain some perspective on this magnitude, in comparison with the general classification of active ingredients for insecticides, this is higher than the median EIQ index of 32.07. The log-linear specification shows a proportional reduction of 23.4% in the EIQ index. Hence, it can be considered a significant reduction in terms of environmental index.

The results so far are all consistent with the current state of the literature on environmental effects of IR seeds. Studying IR cotton seeds in India, Qaim & Zilberman (2003) found reduction of 1 kg/ha on average use of insecticides (70% compared with the baseline conventional field) while Qaim & de Janvry(2005) found reductions between 1.2kg/ha and 2.6Kg/ha of active ingredients used in Argentina, which represents about 50% reduction in comparison with conventional plots. For China, Huan et al. (2005) found even bigger reductions of about 49kg/ha of average insecticide use (80.5% compared to the average of 60.7 Kg/ha in conventional fields).

---

[12] We also estimate similar models per toxicity class (I-IV in decreasing level of toxicity) which indicate reductions in all classes, the most prominent effect being for class III (medium-low level of toxicity) with a proportional decrease of 40%. Results available upon request.

For soybeans, the regression estimates on tables 12 and 13 (all farms and restricted sample respectively) show that adoption of HT trait only affects herbicides quantities: no significant coefficients are found for fungicides or insecticides. The point estimate for the coefficient of the HT trait effect on the use of herbicides in the restricted sample is considerably bigger than the one in the full sample and indicates that it causes an increase of 0.996Kg/ha of active ingredients of herbicides Table 14 shows the results including year and farmer fixed effects, which provide efficiency gains in the estimation and a log-linear specification that shows a proportionate increase of 44.2% in the quantity of active ingredients of herbicides and 26.2% in total.

Table 15 breaks the effects on herbicides by categories of toxicity level (1 to 4 in decreasing order). Categories 3 and 4 show significant increases of 0.64 and 0.44 kg/ha of active ingredients respectively while categories 1 and 2 show reductions of 0.084 and 0.005 (not statistically significant) respectively. Hence, the increase in less toxic herbicides is twelve fold the reduction in more toxic herbicides. This result reflects two points on the pattern of herbicide use. First, the substitution effect among different toxicity classes is very low, which indicates that this channel of environmental benefits is very limited. Second, the scale effect is not so big as compared to the effect found in other countries. Nevertheless, these results show that farmers are increasing the use less toxic herbicides on top of the more toxic ones, which suggests more environmental impact as a result of adoption of HT seeds.

The environmental effect is shown in Table 16 that reports the results for HT trait coefficient on the EIQ index equation. The weakness of the substitution among herbicides of different toxicity categories is reflected in higher environmental impact as shown by the coefficient that indicates an increase of 13.847 EIQ points. In comparison with the general EIQ classification for herbicides, this is lower than the median value for EIQ index of 19.5. The EIQ for glyphosate is also larger than this result: 15.33. The proportional effect on the EIQ index is shows an increase of 35.6% in the EIQ index for herbicides and 16.2% in total. Hence, we can conclude for a relatively modest increase in environmental impact caused by HT soybeans. Tables 17 and 18 show the results for active ingredients and EIQ, respectively, controlling for the use of no-tillage cultivation in the field. The estimates are qualitatively and quantitatively very similar to the ones obtained before.

The results suggest that previous findings on the environmental effects of HT soybeans might have been biased by the qualitative nature of the mix of herbicides. Fernandez-Cornejo et al. (2002) found evidence of reduction in the use of acetamide herbicides and increase in the use of glyphosate in USA. Qaim and Traxler (2005) studying HT seeds in Argentina found a total increase of 107% in the use of herbicides, which are divided in a decreases of 87% and 100% in toxicity classes two and three, respectively, and an increase of 248% in toxicity class four. The authors suggest that this change is basically due to the use of no-till farming by adopters of HT soybeans.

Our results are not totally incompatible with those previous findings. In fact, we also observe a change in the composition of the mix of herbicides used towards less toxic products. This movement is predicted by the theoretical analysis that shows how the HT trait increases the value of marginal product of herbicide (glyphosate) and, therefore, the optimal amount used. On the other hand, we also find very weak substitution among herbicides of different toxicity classes, which suggests that the environmental impact of herbicides in being magnified. The analysis with the EIQ index confirms that this is not only a possibility: even inducing more use of a less toxic herbicide, HT seeds cause higher environmental impact, even when controlling for the use of no-till farming.

6. Conclusion

In this paper we analyze the environmental effects related to the use of pesticides arising from adoption of GM seeds in cotton and soybean crops. Cotton crops are genetically engineered to display IR traits that make the plant produce a natural toxin that helps fight certain types of harmful bollworms. Soybeans are modified to display HT trait that make the plant resistant to glyphosate, a general purpose low toxicity herbicide. We use a model of profit maximizing competitive farm to show how the introduction of these traits affects the optimal choices of pesticides. We show that the IR trait works as a substitute for insecticides and reduces the quantity used whereas the HT trait works as a complement for the herbicide glyphosate and so induces more usage of this product.

The environmental effects are also different for each type of trait. The IR trait has unequivocal benefits since it's basically a chemical saving technology. The HT trait, on the other hand, has ambiguous effects: it induces more usage of a less toxic herbicide but we argue that the total effect depends on the substitution among herbicides of different toxicity classes and on the scale of additional usage of glyphosate. Increased environmental impact can arise from a combination of low substitution and high scale effect.

Using intra-farm variation across fields treated with conventional and GM seeds, we find that the IR trait reduces the amount of insecticides applied to cotton crops, measured by kg/ha of active ingredients applied to the fields. HT trait, on the other hand, leads to more usage of herbicides. Specifically, we see increased usage of herbicides from lower toxicity classes (3 and 4) and very small reductions in herbicides from higher toxicity classes (1 and 2). This finding evidences a very weak substitution among herbicides which raises the possibility of higher environmental impact.

To assess the environmental effect of GM traits due to the use of pesticides, we use a measure developed by integrated pest management scientists that takes into account levels of toxicity of active ingredients, risk of exposure and application in the field (dose and number of applications): the EIQ index. Intra-farm analysis shows that IR trait reduces the environmental impact by about 23% in the treated fields compared to fields cultivated with conventional seeds. This is consistent with the previous result on kg/ha of insecticides and confirms the environmental impact saving nature of the IR technology.

The resulting environmental impact for HT trait, on the other hand, is found to be positive. The estimates imply an increase of 35.6% on the impact of herbicides compared to fields cultivated with conventional seeds. This finding confirms that the weak substitution among herbicides makes adoption of HT seeds to increase the environmental impact from pesticide use.

We believe this to be an important result for two reasons. First, it contributes to uncover environmental effects that have been hidden by the qualitative nature of the mix of herbicides induced by HT trait. Second, environmental policy makers designing policies for biotechnology adoption might consider this new evidence to differentiate among GM traits that produce positive or negative externalities.

REFERENCES

Ameden, H., Qaim, M., & Zilberman, D. (2005). Adoption of Biotechnology in Developing Countries. In J. Cooper, L. Lipper, & D. Zilberman, *Agricultural Biodiversity and Biotechnology in Economic Development* (pp. 329-357). New York: Springer.

Bidraban, P., Franke, A., Ferraro, D., Ghersa, C., Lotz, L., Nepomuceno, A., . . . van de Wiel, C. (2009). *GM-related sustainability: agro-ecological impacts, risks and opportunities of soy production in Argentina and Brazil.* Wageningen: Plant Research International B.V.

Brookes, G., & Barfoot, P. (2012). *GM Crops: Global Socioeconomic and Environmental Inpacts 1996 - 2010.* Dorchester: P.G. Economics.

Céleres. (2012). *The Economic Benefits from Crop Biotechnology in Brazil: 1996 - 2011.* Report prepared for the Brazilian Association of Seeds Producers (ABRASEM), Uberlândia (MG). Retrieved June 2012, from http://www.cib.org.br/estudos/Rel_BiotechBenefits_2009_Economico_Eng.pdf

Fernandez-Cornejo, J., Klotz-Ingram, C., & Jans, S. (2002). Farm-level effects of adopting herbicide-tolerant soybeans in the U.S.A. *Journal of Agricultural and Applied Economics*, 149-163.

Huang, J., Hu, R., Rozelle, S., Qiao, F., & Pray, C. (2002). Transgenic Varieties and Productivity of Small-Holder Cotton Farmers in China. *The Australian Journal of Agricultural and Resource Economics, 46*, 367 - 387.

James, C. (2008). *Global Status of commercialized Biothech/GM Crops: 2008.* Int. Serv. Acquis. Agri-Biothech Appl., ISAAA, Ithaca, NY.

Kovach, J., Petzoldt, C., Degnil, J., & Tette, J. (1992). *A method to measure the environmental impact of pesticides.* Ithaca, NY: New York State Agricultural Experiment Station, a division of the New York State College of Agriculture and Life Sciences, Cornell University.

Lichtenberg, E., & Zilberman, D. (1986). The Econometrics of Damage Control: Why Specification Matters. *American Journal of Agricultural Economics, 68*(3), 261 - 273.

Pelaez, V. (2009). State of Exception in the Regulation of Genetically Modified Organisms in Brazil. *Science and Public Policy, 36*(1), 61 - 71.

Qaim, M. (2009). The Economics of Genetically Modified Crops. *Annual Review of Resource Economics, 1*, 665 - 694. Retrieved from http://www.annualreviews.org/doi/abs/10.1146/annurev.resource.050708.144203

Qaim, M., & de Janvry, A. (2005). Bt Cotton and Pesticide use in Argentina: Economic and Environmental Effects. *Environment and Development Economics, 10*, 179 - 200.

Qaim, M., & Traxler, G. (2005). Roundup Ready soybeans in Argentina: farm level and aggregate welfare effects. *Agricultural Economics*, 73-86.

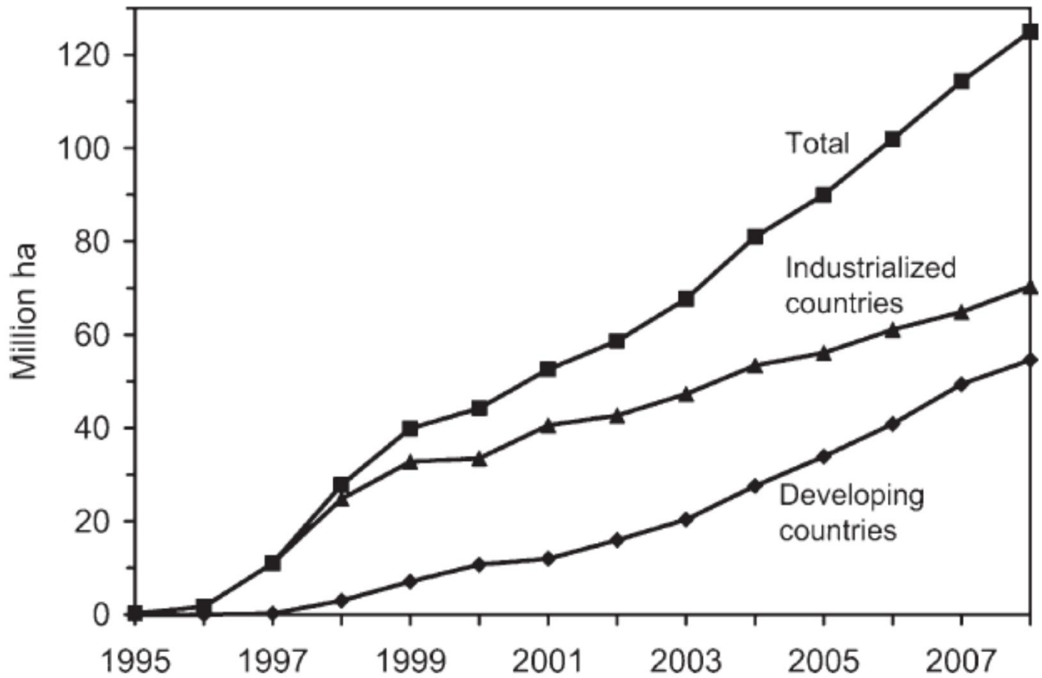
Qaim, M., & Zilberman, D. (2003). Yield Effects of Genetically Modified Crops in Developing Countries. *Science, 299*(5608), 900 - 902.

Sexton, S., & Zilberman, D. (2012). Land for Food and Fuel Production: The Role of Agricultural Biotechnology. In J. Zivin , & J. Perloff, *The Intended and Unintended Effects of U.S. Agricultural and Biotechnology Policies* (pp. 269 - 288). Chicago: University of Chicago Press.

Sharma, D. (2004). Food and Hunger: a View from the South. *Forum on Biotechnology and Food Security.* New Delhi.

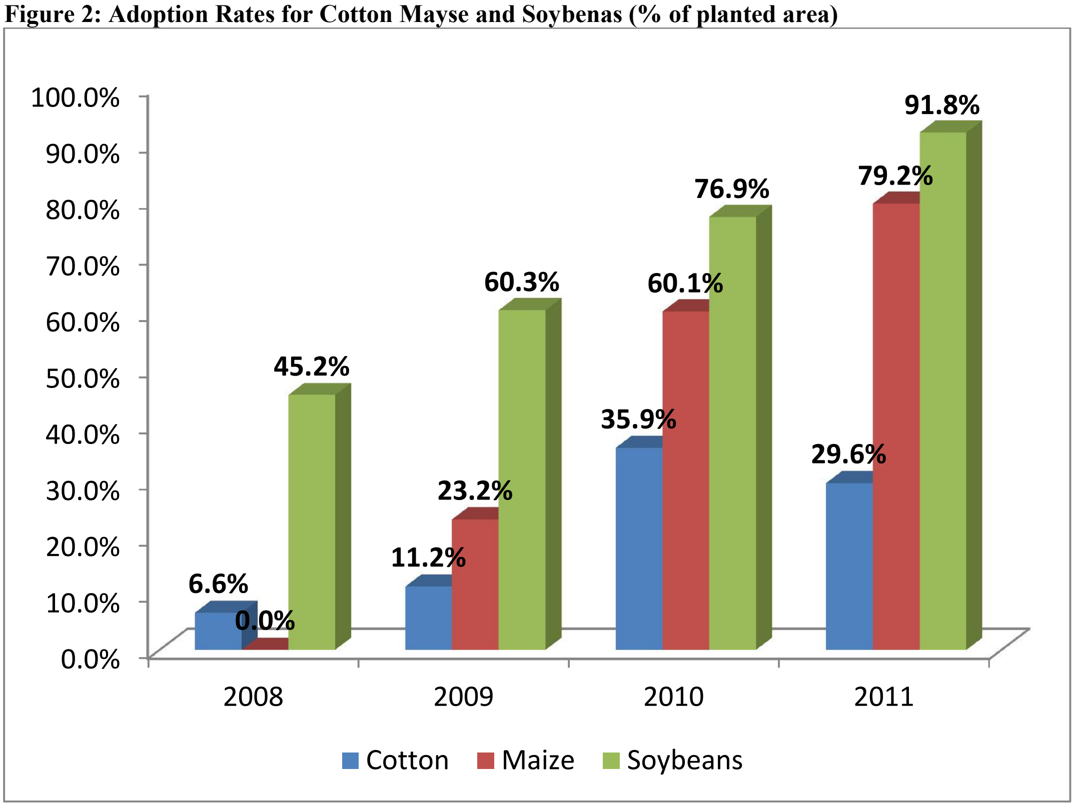
Tables and Figures

Figure 1: Global Planted Area Using GM Crops



Source: Qaim (2009).

Figure 2: Adoption Rates for Cotton Mayse and Soybenas (% of planted area)



Source: own elaboration based on Celeres (2012)

Figure 3: Effect of GM Traits on Pesticide Use

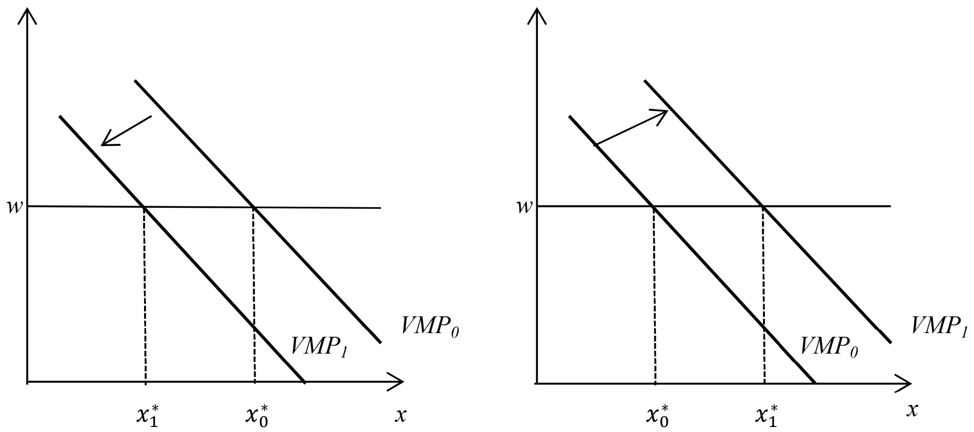


Figure 4: EIQ Components

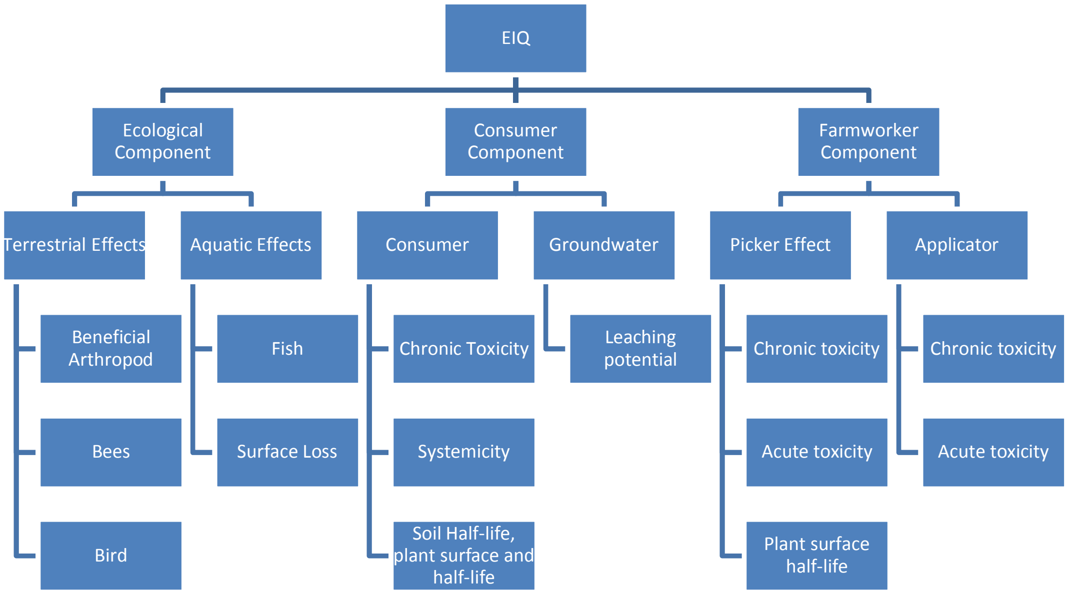


Table 1: Distribution of Farms by Region

	N	pct.	cum.
Central-West	250	56.56	56.56
South	95	21.49	78.05
Northeast	75	16.97	95.02
Southeast	22	4.98	100.00
Total	442	100.00	

Table 2: Farm-Level Descriptive Statistics for Cotton Growers

	mean	sd	min	max	count
Total Area (ha)	2.521.0	3.538.5	60.0	28,374.0	255
Net Rev. (US$/ha)	3.344.1	1.364.9	791.6	7,171.2	255
Gross Margin (US$/ha)	1.495.5	1.112.4	-6.2	4.988.8	255
Costs (US$/ha)	1.848.6	412.0	604.6	2.586.7	255
Pesticides (US$/ha)	588.2	194.9	99.9	1144.9	255
Fertilizers (US$/ha)	1,007.2	270.7	304.5	1927.5	255
Age	37.3	9.6	23.0	57.0	105
Experience	22.4	14.8	2.0	58.0	105
Owner	0.02	0.2	0.0	1.0	255
Central-West	0.65	0.5	0.0	1.0	255
Northeast	0.32	0.5	0.0	1.0	255
Southeast	0.04	0.2	0.0	1.0	255
Basic School	0.05	0.2	0.0	1.0	116
High School	0.27	0.4	0.0	1.0	116
College	0.58	0.5	0.0	1.0	116
Graduate Degree	0.10	0.3	0.0	1.0	116

Table 3 Farm-Level Descriptive Statistics for Soybean Growers

	mean	sd	min	max	count
Total Area (ha)	1,240.3	1,771.8	8.0	13,500.0	291
Net Rev. (US$/ha)	1,164.8	484.9	334.3	3,711.6	291
Gross Margin (US$/ha)	499.3	352.7	-140.4	2,115.5	291
Costs (US$/ha)	665.6	248.2	283.6	1998.2	291
Pesticides (US$/ha)	135.5	86.8	17.0	630.1	291
Fertilizers (US$/ha)	478.3	190.2	0.0	1,383.4	291
Age	44.0	12.1	23.0	73.0	145
Experience	29.4	16.4	3.0	66.0	145
Owner	0.25	0.4	0.0	1.0	291
Central-West	0.48	0.5	0.0	1.0	291
Northeast	0.09	0.3	0.0	1.0	291
South	0.38	0.5	0.0	1.0	291
Southeast	0.05	0.2	0.0	1.0	291
Basic School	0.27	0.4	0.0	1.0	147
High School	0.26	0.4	0.0	1.0	147
College	0.38	0.5	0.0	1.0	147
Graduate Degree	0.10	0.3	0.0	1.0	147

Table 4: Intra-Farm Descriptive Statistics – Cotton

	CO	IR	Total	Diff.
Area (ha)	1741.9	1087.2	1414.6	654.7
	[2442.4]	[1948.8]	[2224.5]	[1.62]
Productivity (Kg/ha)	3871.8	3560.2	3716.0	311.6
	[521.9]	[1120.3]	[884.2]	[1.95]
Net Rev. (US$/ha)	5980.2	6077.3	6027.5	-97.08
	[2253.7]	[2273.0]	[2253.9]	[-0.23]
Direct Costs (US$/ha)	3563.3	3533.3	3548.7	30.03
	[433.0]	[480.6]	[455.1]	[0.36]
Gross Margin (US$/ha)	2416.9	2544.0	2478.8	-127.1
	[2156.2]	[2178.2]	[2158.5]	[-0.32]
Fertilizers (US$/ha)	992.1	981.4	986.9	10.63
	[214.9]	[219.7]	[216.4]	[0.26]
Observations	60	60	120	120

Standard errors and t statistics in parentheses
Standard errors and t statistics in brackets
[*] $p < 0.05$, [**] $p < 0.01$, [***] $p < 0.001$

Table 5: Intra-Farm Descriptive Statistics – Soybean

	CO	HT	Total	Diff.
Area (ha)	692.6	706.6	699.6	-14.01
	[992.0]	[773.2]	[886.7]	[-0.10]
Productivity (Kg/ha)	3148.1	3146.8	3147.5	1.240
	[512.9]	[603.6]	[558.4]	[0.01]
Net Rev. (US$/ha)	1865.3	1850.9	1858.0	14.42
	[390.8]	[419.2]	[404.2]	[0.23]
Direct Costs (US$/ha)	1180.3	1193.3	1186.8	-12.92
	[241.4]	[247.4]	[243.8]	[-0.34]
Gross Margin (US$/ha)	685.0	657.6	671.2	27.34
	[439.7]	[442.3]	[439.9]	[0.40]
Fertilizers (US$/ha)	489.0	488.0	488.5	0.936
	[180.3]	[179.1]	[179.2]	[0.03]
	85	85	170	170

Standard errors and t statistics in brackets
[*] $p < 0.05$, [**] $p < 0.01$, [***] $p < 0.001$

Table 6: Descriptive Statistics for Cotton Farms

	Non-Sample	Sample	Total	Diff.
Total Area (ha)	2371.5	3006.6	2521.0	-635.1
	[3273.7]	[4284.0]	[3538.5]	[-1.06]
Net Rev. (US$/ha)	3403.3	3151.7	3344.1	251.6
	[1323.3]	[1487.7]	[1364.9]	[1.17]
Gross Margin (US$/ha)	1547.6	1326.2	1495.5	221.4
	[1051.1]	[1286.9]	[1112.4]	[1.21]
Costs (US$/ha)	1855.7	1825.5	1848.6	30.25
	[429.7]	[350.7]	[412.0]	[0.55]
Pesticides (US$/ha)	592.1	575.5	588.2	16.55
	[205.5]	[156.0]	[194.9]	[0.66]
Fertilizers (US$/ha)	1001.8	1024.7	1007.2	-22.91
	[279.9]	[239.9]	[270.7]	[-0.62]
Age	38.24	34.76	37.28	3.478
	[9.165]	[10.44]	[9.611]	[1.58]
Experience	23.70	19.03	22.41	4.663
	[15.93]	[10.93]	[14.82]	[1.71]
Owner	0.0103	0.0667	0.0235	-0.0564
	[0.101]	[0.252]	[0.152]	[-1.70]
Central-West	**0.749**	**0.317**	**0.647**	**0.432*****
	[0.435]	**[0.469]**	**[0.479]**	**[6.34]**
Northeast	**0.241**	**0.567**	**0.318**	**-0.326*****
	[0.429]	[0.500]	[0.466]	[-4.56]
Southeast	**0.0103**	**0.117**	**0.0353**	**-0.106***
	[0.101]	**[0.324]**	**[0.185]**	**[-2.51]**
Basic School	0.0595	0.0313	0.0517	0.0283
	[0.238]	[0.177]	[0.222]	[0.70]
High School	**0.321**	**0.125**	**0.267**	**0.196***
	[0.470]	**[0.336]**	**[0.444]**	**[2.50]**
College	0.571	0.594	0.578	-0.0223
	[0.498]	[0.499]	[0.496]	[-0.22]
Graduate Degree	**0.0476**	**0.250**	**0.103**	**-0.202***
	[0.214]	**[0.440]**	**[0.306]**	**[-2.49]**

Standard errors in and *t* statistics in brackets
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Descriptive Statistics for Soybean Farms

	Non-Sample	Sample	Total	Diff.
Total Area (ha)	**868.2**	**2142.3**	**1240.3**	**-1274.1*****
	[1201.7]	**[2480.1]**	**[1771.8]**	**[-4.52]**
Net Rev. (US$/ha)	1160.5	1175.5	1164.8	-14.99
	[415.2]	[625.2]	[484.9]	[-0.20]
Gross Margin (US$/ha)	**530.1**	**424.5**	**499.3**	**105.6***
	[344.6]	**[362.8]**	**[352.7]**	**[2.29]**
Costs (US$/ha)	**630.4**	**750.9**	**665.6**	**-120.6****
	[192.3]	**[334.8]**	**[248.2]**	**[-3.12]**
Pesticides (US$/ha)	**122.9**	**166.2**	**135.5**	**-43.38****
	[64.33]	**[120.6]**	**[86.76]**	**[-3.14]**
Fertilizers (US$/ha)	**443.8**	**561.9**	**478.3**	**-118.1*****
	[159.7]	**[229.5]**	**[190.2]**	**[-4.33]**
Age	**46.55**	**38.94**	**43.98**	**7.613*****
	[11.06]	**[12.65]**	**[12.13]**	**[3.57]**
Experience	**34.20**	**20.08**	**29.43**	**14.12*****
	[15.53]	**[13.80]**	**[16.35]**	**[5.58]**
Owner	0.248	0.271	0.254	-0.0230
	[0.433]	[0.447]	[0.436]	[-0.40]
Central-West	0.466	0.518	0.481	-0.0516
	[0.500]	[0.503]	[0.501]	[-0.80]
Northeast	**0.0291**	**0.235**	**0.0893**	**-0.206*****
	[0.169]	**[0.427]**	**[0.286]**	**[-4.32]**
South	**0.490**	**0.118**	**0.381**	**0.373*****
	[0.501]	**[0.324]**	**[0.487]**	**[7.52]**
Southeast	**0.0146**	**0.129**	**0.0481**	**-0.115****
	[0.120]	**[0.338]**	**[0.214]**	**[-3.06]**
Basic School	**0.367**	**0.0612**	**0.265**	**0.306*****
	[0.485]	**[0.242]**	**[0.443]**	**[5.11]**
High School	0.235	0.306	0.259	-0.0714
	[0.426]	[0.466]	[0.439]	[-0.90]
College	0.337	0.469	0.381	-0.133
	[0.475]	[0.504]	[0.487]	[-1.53]
Graduate Degree	0.0612	0.163	0.0952	-0.102
	[0.241]	[0.373]	[0.295]	[-1.74]

Standard errors and *t* statistics in brackets
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: OLS Estimates (Cotton). Dependent Variable: Active Ingredients (Kg/ha)

	AC	FU	HE	IN+	TT+
IR trait	0.003	-0.063	-0.346	**-1.279*****	**-1.790*****
	[0.049]	[0.091]	[0.366]	**[0.264]**	**[0.485]**
Constant	0.428***	0.956***	4.933***	**4.914*****	**12.352*****
	[0.023]	[0.042]	[0.170]	**[0.163]**	**[0.314]**
N	312	312	312	**312**	**312**
r2	0.000	0.002	0.003	**0.046**	**0.025**
F	0.003	0.481	0.894	**23.426**	**13.620**
ll	-121.093	-313.003	-746.627	**-714.624**	**-915.832**

Pesticides: Acaricides (AC), Fungicides (FU), Herbicides (HE), Insecticides (IN) and Total (TT).
+ Robust standard errors in brackets.
* p < 0.05, ** p < 0.01, *** p < 0.001

Table 9: Intra-Farm OLS Estimates (Cotton). Dependent Variable: Active Ingredients (Kg/ha)

	AC	FU	HE	IN	TT
IR trait	-0.011	0.007	-0.056	**-0.956****	**-0.980**
	[0.065]	[0.107]	[0.352]	**[0.362]**	**[0.568]**
Constant	0.461***	0.865***	4.636***	**4.630*****	**11.551*****
	[0.046]	[0.075]	[0.249]	**[0.256]**	**[0.402]**
N	120	120	120	**120**	**120**
r2	0.000	0.000	0.000	**0.056**	**0.025**
F	0.029	0.004	0.026	**6.992**	**2.972**
ll	-45.195	-104.726	-248.201	**-251.251**	**-305.518**

Pesticides: Acaricides (AC), Fungicides (FU), Herbicides (HE), Insecticides (IN) and Total (TT).
* p < 0.05, ** p < 0.01, *** p < 0.001

Table 10: Intra-Farm OLS Estimates (Cotton). Dependent Variable: Active Ingredients (Kg/ha)

	IN+	TT	LOG_IN	LOG_TT
IR trait	-0.956***	-0.980***	-0.242***	-0.092***
	[0.155]	[0.252]	[0.037]	[0.024]
Constant	8.721***	19.018***	2.346***	3.025***
	[0.712]	[1.415]	[0.207]	[0.134]
N	120	120	120	120
r2	0.905	0.896	0.913	0.878
F	939.055	10.046	12.215	8.340
ll	-113.199	-171.096	59.783	111.488

Pesticides: insecticides (IN) and total (TT).
Linear and log-linear specifications.
Fixed effects for farmers and years.
+ Robust standard errors.
* p < 0.05, ** p < 0.01, *** p < 0.001

Table 11: Intra-Farm OLS Estimates (Cotton). Dependent Variable: EIQ

	IN+	TT	LOG_IN	LOG_TT+
IR trait	-34.225***	-36.856***	-0.234***	-0.120***
	[5.525]	[7.482]	[0.035]	[0.026]
Constant	316.085***	557.297***	6.041***	6.455***
	[23.144]	[42.071]	[0.198]	[0.082]
N	120	120	120	120
r2	0.906	0.905	0.918	0.886
F	48.981	11.134	12.972	75.140
ll	-541.746	-578.135	64.966	103.410

Pesticides: insecticides (IN) and total (TT).
Linear and log-linear specifications.
Fixed effects for farmers and year.
+ Robust standard errors.
* p < 0.05, ** p < 0.01, *** p < 0.001

Table 12: OLS Estimates (Soybean). Dependent Variable: Active Ingredients (Kg/ha)

	FU	**HE+**	IN	**TT+**
HT Trait	-0.047	**0.762*****	-0.131*	**0.546*****
	[0.046]	**[0.099]**	[0.064]	**[0.150]**
Constant	0.445***	**1.741*****	0.841***	**3.284*****
	[0.040]	**[0.075]**	[0.056]	**[0.121]**
N	376	**376**	376	**376**
r2	0.003	**0.091**	0.011	**0.025**
F	1.025	**59.114**	4.216	**13.192**
ll	-164.634	**-540.274**	-287.305	**-669.969**

Pesticides: Fungicides (FU), Herbicides (HE), Insecticides (IN) and Total (TT).
+ Robust standard errors in brackets.
* p < 0.05, ** p < 0.01, *** p < 0.001

Table 13: Intra-Farm OLS Estimates (Soybean). Dependent Variable: Active Ingredients (Kg/ha)

	FU	**HE+**	IN	**TT+**
HT Trait	0.021	**0.996*****	-0.007	**0.995*****
	[0.061]	**[0.138]**	[0.084]	**[0.202]**
Constant	0.443***	**1.769*****	0.843***	**3.315*****
	[0.043]	**[0.074]**	[0.059]	**[0.122]**
N	170	**170**	170	**170**
r2	0.001	**0.236**	0.000	**0.126**
F	0.114	**51.766**	0.006	**24.194**
ll	-84.613	**-222.749**	-138.028	**-287.319**

Pesticides: Fungicides (FU), Herbicides (HE), Insecticides (IN) and Total (TT).
+ Robust standard errors in brackets
* p < 0.05, ** p < 0.01, *** p < 0.001

Table 14: Intra-Farm OLS Estimates (Soybean). Dependent Variable: Active Ingredients (Kg/ha)

	HE+	TT+	LOG_HE	LOG_TT
HT Trait	0.996***	0.995***	0.442***	0.262***
	[0.089]	[0.096]	[0.056]	[0.027]
Constant	1.710***	2.229***	0.522*	0.841***
	[0.178]	[0.179]	[0.261]	[0.126]
N	170	170	170	170
r2	0.836	0.899	0.755	0.888
F	90.919	249.438	3.278	8.383
ll	-91.801	-104.275	-13.861	110.256

Pesticides: herbicides (HE) and total (TT).
Linear and log-linear specifications.
Fixed effects for farmers and years.
+ Robust standard errors in brackets.
* p < 0.05, ** p < 0.01, *** p < 0.001

Table 15: Herbicides Estimates per Toxicity Class. Dep. Var.: Active Ingredients (Kg/ha)

	HE1	HE2	HE3	HE4
HT Trait	-0.084***	-0.005	0.635***	0.438***
	[0.021]	[0.054]	[0.098]	[0.090]
Constant	0.090***	0.003	-0.317	1.941***
	[0.012]	[0.027]	[0.318]	[0.497]
N	168	168	168	168
r2	0.887	0.777	0.855	0.845
F	508.764	404.682	20.309	12.929
ll	153.300	-7.015	-106.387	-91.237

Toxicity levels I - IV in decreasing order.
Robust standard errors in brackets.
* p < 0.05, ** p < 0.01, *** p < 0.001

Table 16: Intra-Farm OLS Estimates (Soybean). Dependent Variable: EIQ

	HE	TT	LOG_HE	LOG_TT
HT Trait	13.847***	14.329***	0.356***	0.162***
	[1.639]	[2.054]	[0.049]	[0.023]
Constant	27.300***	45.423***	3.312***	3.864***
	[2.997]	[2.837]	[0.119]	[0.108]
N	170	170	170	170
r2	0.836	0.936	0.790	0.933
F	634.267	1378.593	142.869	556.876
ll	-587.012	-625.347	8.279	135.754

Pesticides: herbicides (HE) and total (TT).
Linear and log-linear specifications.
Fixed effects for farmers and years.
Robust standard errors in brackets.
* p < 0.05, ** p < 0.01, *** p < 0.001

Table 17: Intra-Farm OLS Estimates (Soybean). Dependent Variable: Active Ingredients (Kg/ha)

	HE	TT	HE+	TT+
HT Trait	0.983***	0.983***	0.892***	0.876***
	[0.089]	[0.096]	[0.089]	[0.095]
Tillage	0.736	3.303***		
	[0.599]	[0.639]		
Constant	1.716***	2.236***	1.762***	2.289***
	[0.184]	[0.185]	[0.228]	[0.236]
N	168	168	154	154
r2	0.833	0.899	0.829	0.887
F	248.083	363.742	864.663	4047.737
ll	-90.108	-102.656	-76.095	-86.464

Standard errors in brackets
+ Conventional planting
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18: Intra-Farm OLS Estimates (Soybean). Dependent Variable: EIQ

	HE	TT	HE+	TT+
HT Trait	13.457***	13.944***	12.151***	11.951***
	[1.613]	[2.043]	[1.667]	[2.047]
Tillage	12.416	92.123***		
	[9.255]	[12.126]		
Constant	27.495***	45.615***	28.148***	46.612***
	[3.179]	[3.013]	[3.809]	[3.950]
N	168	168	154	154
r2	0.828	0.937	0.814	0.928
F	355.885	1213.411	308.650	1698.950
ll	-576.378	-616.095	-526.957	-558.570

Standard errors in brackets
+ Conventional planting
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$