Voluntary programs to encourage compliance with refuge regulations for pesticide resistance management: results from a quasi-experiment

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Abstract

Pesticide resistance can be viewed as an open-access resource problem. While traditional economic incentives are the standard prescription for this market failure, non-pecuniary behavioral approaches have also shown promise in managing these resources. I empirically evaluate the performance of an intervention in the latter class of instruments to promote compliance with refuge regulations in the context of genetically engineered *Bacillus thuringiensis* (Bt) corn. Refuge regulations are important policies for reducing the risk of Bt resistance. To encourage refuge compliance, the agricultural company Monsanto piloted a behavioral intervention in 17 North Carolina counties in 2013/2014. Using seed sales data, I estimate econometric models combining difference-in-differences with propensity-score-matching (PSM) to identify the effect of the program on grower behavior and overall refuge planting. A simple difference-in-differences (DID) estimator implies the program increased the share of refuge (non-Bt) seed sales sold to the average grower by 2.9%, whereas the DID-PSM estimator implies an effect of 5.6%. Non-pecuniary behavioral instruments deserve further consideration as a means of managing Bt resistance.

Keywords: resistance management, quasi-experiments, moral suasion, difference-in-differences, matching

JEL codes: Q12, Q16, Q18, Q28

Introduction

One of the most widely adopted biotechnologies in agriculture is the insertion into crops of genes expressing a pesticidal toxin naturally produced by the bacterium *Bacillus thuringiensis* (Bt). Some of these toxins are lethal to specific coleopteran and lepidopteran insect pests, which are the source of most insect pest damage to staple crops like corn and cotton. So-called Bt varieties of these crops have been estimated to significantly increase crop yields in many areas at risk of pest damages (Cattaneo et al. 2006; Hutchison et al. 2010), and to reduce the need for other pest control inputs into production (Lu et al. 2012). However, since the technology's inception, there has been recognition of the possibility that pests can evolve resistance to Bt toxins, threatening their sustainability (Carrière et al. 2010). While Bt resistance has not yet risen to economically relevant levels, recent cases have been documented of field-evolved resistance to Bt in important agricultural pests (Gassmann et al. 2008; Huang et al. 2014; Reisig and Reay-Jones 2015).

Entomological research has suggested that a scientifically valid policy approach to sustaining Bt effectiveness is to create 'refuges' of non-Bt varieties to maintain the genetic viability of insect pests still susceptible to Bt toxins, as a way to reap future benefits of this technology (Tabashnik 1994; Gould 1998; Gould 2000; Gahan et al. 2001; Tabashnik et al. 2003). Economic research has subsequently investigated the intertemporal tradeoffs involved in determining the optimal refuge size, since planting more refuge likely involves sacrificing some degree of production to pest damages today in order to reduce pest damages and achieve more production in the future (Laxminarayan and Simpson 2002; Livingston et al. 2004; Grimsrud and Huffaker 2006; Qiao et al. 2008; Mitchell and Onstad 2014).

There are important open-access resource aspects to Bt susceptibility. Within a given region, pest susceptibility can be viewed as non-excludable but rival (Miranowski and Carlson 1986). Without regulation growers are free to plant Bt crops and benefit from pests'

susceptibility to Bt toxins (non-excludability), whereas greater use of Bt crops by one grower may decrease pest susceptibility available to his neighbors (rivalry).[1]

Based on this scientific evidence and economic rationale, many governments have implemented policies mandating minimum refuge sizes, i.e. a certain percentage of a grower's crop area that must be planted with non-Bt seed. The US was the first country to implement these requirements in the late 1990s, and other countries like India have followed suit. In the US Bt genes are regulated as 'plant-incorporated protectants' (PIPs) by the Biopesticides Division in the Environmental Protection Agency (EPA), with regulatory authority granted by the Federal Insecticide, Fungicide, and Rodenticide Act (FIFRA).

In general EPA's standard refuge requirement has been for at least 20% of fields planted with crops expressing a single Bt trait to be planted with non-Bt varieties, although this requirement is relaxed to a 5% non-Bt refuge under some circumstances (depending on the growing region, crop, other pest control measures or if multiple Bt genetic traits are "stacked" into a single crop variety). For the US, corn refuge requirements are generally higher in the Cotton Belt than in the Corn Belt, due to the greater potential selective pressure created by the use of Bt cotton and corn (EPA 2014; Singla et al. 2012).

Compliance with the EPA's refuge requirements has been an ongoing challenge. Although early work recognized compliance as a key issue in the effectiveness of refuge policies (EPA 2000), its measurement has proven challenging (for reasons further clarified in the following paragraph). While grower point of sale (GPOS) data would be ideal for measuring compliance, such data contain sensitive information, the public disclosure of which can pose risks of "competitive harm" to seed sellers (USDOJ 2004). Nevertheless, existing evidence from some grower surveys appears to suggest a couple of descriptive patterns in growers' refuge

compliance behavior (Hurley and Mitchell 2014). First, compliance with corn refuge requirements appeared to initially be increasing, but has more recently trended downward. Second, compliance with Bt corn refuge requirements in the Cotton Belt is lower than compliance in the Corn Belt (likely due in part to greater stringency of this refuge requirement in the Cotton Belt).

The EPA's main instrument for influencing compliance has been its authority in approving registrations of PIPs for commercial use (Bourguet et al. 2005). Part of this registration process includes insect resistance management (IRM) plans. The EPA can therefore deny registrations on the basis of low compliance with refuge regulations (though such authority has yet to be exercised). PIP registrants being the producers of GM seed products, this regulatory arrangement places the onus of monitoring and ensuring grower compliance with refuge requirements on Monsanto and its peers.

As private entities, these seed companies have a limited set of instruments at their disposal for ensuring refuge compliance. These can include limiting which seed products are available in any given market, as well as behavioral interventions to influence growers to voluntarily comply. In terms of controlling which products go on the market, "refuge in a bag" (RIB) products have been advanced as a solution to the compliance issue. RIB seed mixes Bt and non-Bt seed at predetermined proportions prior to selling the product to growers in order to meet refuge requirements. Refuge compliance in this context can thus in principle be fully controlled by making RIB seed the only Bt product available on the market. However, the efficacy of RIB relative to traditional, structured refuge remains an open research question, and it is almost certain that RIB is less effective than traditional structured refuge, due to RIB's more diffuse selection pressure on pest populations (Mallet and Porter 1992; Onstad et al. 2011) and to its

greater potential for cross-pollination between Bt and non-Bt varieties (Yang et al. 2014). This increased risk of resistance arising from RIB products relative to traditional refuge is a central reason that RIB is approved by the EPA for use as refuge in the Corn Belt but not in the Cotton Belt. Thus, RIB reflects the reality of a tradeoff between biological and human behavioral constraints (Onstad et al. 2011), and the limitations on its use necessitate alternative instruments.

This article focuses on a behavioral intervention implemented by the agricultural biotechnology company Monsanto to improve refuge compliance among North Carolina corn growers. The Southern Land Legacy (SLL) program included moral suasion and social comparison elements. I analyze GPOS data for all of North Carolina before and immediately after program implementation, including the counties eligible for the SLL program and those that were not. Using difference-in-differences methods combined with matching estimators, I find that in its pilot year the SLL program had an economically and statistically significant effect in promoting the planting of refuges. While there is precedence for recommending this type of behavioral intervention (EPA 2000; Hurley and Mitchell 2014; NCCA 2015), I am not aware of other systematic evaluations (and certainly not an econometric analysis) of such interventions.[2]

My analysis is important to consider against the traditional theory of open-access resources. The standard economic prescription for managing these resources is to impose either transferable, well-defined and enforceable quotas or per-unit user fees on the resource, in order to institutionalize excludability. Existing refuge size requirements fall under the quota approach (Vacher et al. 2006; Ambec and Desquilbet 2012). Yet two characteristics appear to be partially lacking for these quotas to comprise a well-defined property right: transferability and, as evident from the above discussion, enforceability. Transferability remains challenging to implement in the context of Bt refuges, because the geographic scope of the resource is difficult to define. If a

grower in North Carolina increases her refuge size above required levels, and sells this ‘excess refuge’ to a noncompliant grower, the bioeconomic effects of this transaction would differ depending on the purchaser’s location relative to the seller, e.g. whether the purchaser is in a nearby county or a different region of the country.

These challenges to institutionalizing well-defined property rights for refuges argue again for alternative behavioral interventions (Croson and Treich 2014). One such intervention is to leverage existing social norms (or to institutionalize new ones) to promote pro-social behavior, an approach often referred to as ‘moral suasion’ (Romans 1966). The effectiveness of such approaches in other contexts has shown mixed results (van Kooten and Schmitz 1992; Torgler 2004; Dal Bó and Dal Bó 2014). Social comparisons, whereby individuals are given information about how their behavior with respect to a policy goal (e.g. energy or water use) compares with their peers, have been shown to have small but measureable effects on promoting target behaviors, often at low cost (Allcott 2011; Ferraro and Price 2011; Brent et al. 2015). The mechanisms by which social comparisons operate has rarely been explored in the economic literature (which is more concerned with how cost-effective these approaches are), though it has been conjectured that such comparisons communicate an implicit norm to individuals and thus amount to a form of moral suasion (Ferraro and Price 2011). Cooperative approaches to open-access resource management have received attention as potentially being a more effective means of management than traditional theory would predict (Ostrom 1990; Rustagi et al. 2010). Cooperative approaches to refuge compliance could take the form of growers’ associations generating their own refuge planting rules, implementing coordination mechanisms, and enforcing these rules, e.g. through public shaming or via other ‘soft power’ measures.

The next section describes the implementation of the SLL program. The data are then described, before presenting results from econometric analysis of the data. A discussion of policy implications concludes.

Implementation of the Southern Land Legacy program

Monsanto piloted the Southern Land Legacy program in 17 contiguous counties in the coastal plain of North Carolina, the main corn-growing region of the state, in the 2014 growing season (figure 1). The program combined a philanthropic effort guided by grower input, with an advertising campaign, to promote compliance with refuge regulations. The philanthropic effort was conducted as follows: Monsanto pre-selected three local charities that would be considered for a single grant of $2,000. To select which of the three charities would receive the award, Monsanto held a vote among corn growers who (1) farmed in one of the pilot counties in 2013 and (2) planted the "required amount of Monsanto refuge seed" to accompany planting of their Bt corn. The required amount of refuge seed is clearly defined on the product tag of Monsanto's Bt products, and reflects the EPA's Bt refuge requirements.

The advertising campaign consisted of billboards and print ads, along with a website (Monsanto 2015). These materials promoted farmers who were exceptional in their refuge planting; agreeing to such promotion was voluntary and did not bring any additional compensation to farmers. In the parlance of behavioral economics and psychology, these promotional materials were used as a form of moral suasion with a social comparison element. The ads appealed to a sense of community and preserving the effectiveness of Bt seed for future generations as a reason to plant refuge, using role model growers in the community to establish a social norm of refuge compliance. Some quoted text from three such advertisements (which can be found in full at the website) are shown in figure 2.

The key message across all three quotations articulates the strong externalities involved in refuge planting, as well as the proposed means of addressing them: moral suasion to induce voluntary compliance. The externality arises through the asymmetric individual costs of planting refuge instead of Bt varieties and the diffuse community-wide benefits of preserving effectiveness of the technology for the future. Painted in this light, the rational, self-interested grower would not plant refuge (no mention is made of the EPA regulations in these quotations, or in any of the reviewed marketing materials). Yet the advertising campaign appealed to growers' concerns for their community. One could argue that such concerns could arise either for purely altruistic reasons or perhaps because of 'enlightened self-interest' (Besser 2004).

Data and summary statistics

To evaluate the effect of the SLL pilot, I use grower point of sale (GPOS) data from Monsanto for corn seed sales in North Carolina for 2013 and 2014. These are sales data for corn seed products sold by Monsanto in North Carolina. Because the objective of the SLL program was to increase refuge compliance, any target impacts of the program should show up in the GPOS data through increases in the proportion of seed sales which were associated with non-Bt varieties. The data are disaggregated by 13 different seed varieties, 10 of which contain Bt genes. Of the 10 Bt varieties, four include both a standard and a RIB version. Note that, while RIB may be planted in North Carolina, due to the state's designation as a "cotton growing region," RIB may not be used to satisfy refuge requirements, and is thus considered as Bt seed from a regulatory perspective. In the data I categorize "Bt varieties" as consisting of standard Bt and RIB products. Due to the proprietary nature of these data, in table 1 I only report statistics as either the in-year subsample differences from the full sample mean or the change between 2013 and 2014.

The primary outcome variable of interest is the percentage of corn seed sales which corresponded to Bt versus non-Bt varieties. Relative to the 2013 sample mean (not reported), the percentage of corn seed sales corresponding to Bt varieties in 2013 was 3.88% greater for the average grower in SLL counties, and 1.05% smaller in non-SLL counties. Between 2013 and 2014 the average grower increased her percentage of corn seed purchases for Bt varieties by 1.45%. However, in SLL counties, this percentage *decreased* by 0.82% (=3.88% - 3.06%), whereas this percentage increased by 2.06% (= 1.1% - (-1.05%)) in the non-SLL counties. To foreshadow the econometric analysis that follows, we can view the non-SLL counties as a control group and compare the 2013-2014 change in the average grower's Bt percentage of seed sales in SLL counties (the treatment group) versus non-SLL counties (the control group): this suggests that the SLL program appears to have yielded a 2.88% (= 0.82% - (-2.06%)) decrease in the Bt percentage of seed sales for the average grower in the SLL eligible counties, compared to the expected 2.06% increase that would have occurred in the absence of the SLL program – which we observe in the non-SLL counties.

This logic may be challenged by a number of confounding factors. In particular, one may question the validity of using the non-SLL counties as a control group to proxy for the counterfactual, if the SLL counties had preexisting characteristics that were significantly different from the non-SLL counties. The most notable difference between the SLL and non-SLL counties is that counties targeted by the SLL program are concentrated in intensive corn-growing areas of North Carolina (figure 1), and account for a larger volume of Monsanto's sales. Indeed, it is likely that Monsanto selected the eligible counties to focus impact on those areas accounting for a high volume of their Bt sales, and the data bare out this hypothesis. We see that the SLL-eligible counties appear to have much larger seed purchases in SLL-eligible counties reported in

table 1. On average growers in SLL-eligible counties purchased five times the volume of seed relative to the non-SLL counties (3.61/ 0.71=5.05) in 2013, before implementation of the SLL program. Moreover, this relative difference is statistically significant. Examining these data graphically in figure 3, we first note that seed sales volumes are highly right-skewed. Furthermore, a quantile-quantile plot of the sales volume data in figure 4 shows that the distribution of baseline farm sales in SLL counties in fact first-order stochastically dominates that of the non-SLL counties. One also might be concerned that the SLL program increased sales in the eligible counties, but I find no evidence for this. Mean growth in sales was of a similar magnitude in SLL and non-SLL counties, and showed no statistically significant differences.

Econometric analysis

To assess the impact of the SLL program on the target outcome, we focus on estimating the average treatment effect (ATE) of the program in terms of changes in refuge planting between 2013 and 2014 in SLL-eligible and ineligible counties. The ATE can be examined in terms of both the average grower and the average hectare of planted corn; the former focuses on measuring the effect on grower behavior whereas the latter focuses on measuring the effect on overall refuge size. Both indicators are important for assessing impact: overall refuge size is the key indicator considered in the biological modeling used to justify refuge mandates (EPA 2000), but changing grower behavior is a necessary precursor for achieving target refuge sizes and relates most closely to previous research examining refuge compliance rates (Hurley and Mitchell 2014).

Denote $r_{i,c,t}^{\tau}$ as the refuge (non-Bt) percentage of seed purchases for grower i in county c and year t, conditional on program treatment: $\tau = \text{SLL}$ or $\tau = \text{Non-SLL}$. To evaluate the impact of SLL on grower behavior, we define the relevant ATE as:

$$\alpha \equiv \mathbb{E}\left(r_{i,c,t}^{\text{SLL}} - r_{i,c,t}^{\text{Non-SLL}}\right) \tag{1}$$

Similarly, denote $\tilde{r}_{h,c,t}^{\tau}$ as the refuge (non-Bt) percentage of seed sales for hectare h of planted corn in county c and year t, conditional on program treatment τ. The ATE of the program on the area of refuge within an average hectare is $\tilde{\alpha} \equiv \mathbb{E}\left(\tilde{r}_{h,c,t}^{\text{SLL}} - \tilde{r}_{h,c,t}^{\text{Non-SLL}}\right)$. The hectare-level outcome is obtained by weighting each grower-level refuge size observation by the area planted to corn for each grower.

To estimate the treatment effect of the SLL program, we begin with a simple difference-in-differences (DID) estimator, and then examine the robustness of this estimator by incorporating matching methods with the DID estimator. The DID estimate α_{DID} of the average treatment effect (ATE) of the SLL program is:

$$\hat{\alpha}_{DID} = \left(\bar{r}_{2014}^{\text{SLL}} - \bar{r}_{2013}^{\text{SLL}}\right) - \left(\bar{r}_{2014}^{\text{No-SLL}} - \bar{r}_{2013}^{\text{No-SLL}}\right) \tag{2}$$

where $\bar{r}_t^g$ is the mean refuge size, as proxied by the non-Bt fraction of seed sales in group g, according to SLL program eligibility, and in year t. This estimator for the grower-level ATE in equation (2) above controls for time-invariant preexisting differences in levels of refuge planting between SLL-eligible and ineligible counties. The basic DID estimator can be obtained from an OLS regression of refuge size on dummy variables for year, treatment group and their interaction:

$$r_{i,c,t} = \hat{\beta}_0 + \hat{\beta}_{2014} d_t^{2014} + \hat{\beta}_{SLL} d_c^{\text{SLL}} + \hat{\alpha}_{DID}(d_t^{2014} \times d_c^{\text{SLL}}) + \hat{\epsilon}_{i,c,t} \tag{3}$$

where $r_{i,c,t}$ is refuge size for grower i, in county c and year t, and d_t^{2014} and d_c^{SLL} are dummy variables, respectively, for year 2014 and SLL-eligibility. The corresponding regression coefficients $\hat{\beta}_{2014}$ and $\hat{\beta}_{SLL}$ reflect the independent time trend in refuge planting and the preexisting difference in refuge planting between the SLL and non-SLL counties. The DID

estimator $\hat{\alpha}_{DID}$ can be shown to equal the OLS-estimated coefficient on the interaction term ($d_t^{2014} \times d_c^{\mathrm{SLL}}$). The consistency of this estimate requires in particular that $\mathbb{E}\left(\epsilon_{i,c,t} d_c^{\mathrm{SLL}}\right) = 0$, which means in general that SLL-eligibility should not be correlated with time-varying omitted variables (with time-invariant factors already differenced out of the equation by the DID structure). The standard errors of the estimated coefficients in equation (3) above are clustered at the county-level. We test for robustness by estimating equation (3) with grower-level fixed effects.[3] We also estimate another version of (3) by weighting each observation by 2013 sales, to proxy for farm size. This provides an estimate of the hectare-level ATE $\tilde{\alpha}$.

Table 2 shows the results from these regressions. The unweighted DID estimator produces the same ATE estimate as the simple comparison of means in Table 1: the SLL program appears to have increased the non-Bt percentage of seed sales by 2.88% for the average grower. This estimate is stable, whether or not we include grower fixed effects in the regression, and is statistically significant at the 5% level in the baseline specification and at the 10% level when county fixed effects are included.

However, when we weight each grower-level observation by its volume of 2013 seed purchases, the estimated ATE decreases to 1.03% and becomes statistically insignificant, with p-values equaling 0.21 and 0.24 for the baseline and grower fixed effects specifications (columns 3 and 4). This means that while we are able to measure an effect of the SLL program on changing grower behavior, we are unable to precisely measure whether the program has a significant effect on actual refuge sizes, in terms of total planted area (proxied by sales volume). This finding could be the result of there being too few large-scale growers to detect a statistically significant effect of the program on the refuge planting behavior of these individuals. It could also suggest that large-scale growers may in fact be less responsive to the SLL program, possibly due to fact

that they may give up more in terms of absolute profit compared to smaller-scale growers when they voluntarily comply with refuge mandates.

The issue of heterogeneous farm size also potentially poses challenges for estimating the effect of the program for the average grower. Although the DID estimator controls for preexisting differences in levels of refuge planting between treatment and control, the two groups may have different refuge planting trends over time, independent of the program. This could occur, for example, if smaller growers (which are relatively more frequent in SLL ineligible counties) were shifting more quickly to non-Bt products (or at least not shifting as fast to Bt products) over time. Since SLL-eligibility is clearly correlated with size, this independent shift over time would bias the DID estimate downward, in particular due to biased construction of the counterfactual.

One strategy for correcting for this source of bias is to construct a control group which more closely resembles the treatment group in terms of preexisting characteristics. This is the motivation for matching estimators. A matching estimator is, in general, defined as follows:

$$\hat{\alpha}_{\mathrm{M}} \equiv \frac{1}{N}\sum_{i,c} \Delta\hat{r}_{i,c}^{\mathrm{SLL}} - \Delta\hat{r}_{i,c}^{\text{No-SLL}} \tag{4}$$

where $\Delta\hat{r}_{i,c}^{\tau}$ is the predicted difference in the refuge percentage of seed sales between 2013 and 2014 for grower i in county c, and for treatment level τ (SLL or non-SLL). Observed data is used for $\Delta\hat{r}_{i,c}^{d_c^{\mathrm{SLL}}}$ for the actual treatment level d_c^{SLL} for growers in county c, and a counterfactual is constructed from 'similar' observations to impute the outcome for the unobserved treatment level (Abadie et al. 2004; Abadie and Imbens 2006; Abadie and Imbens 2009):

$$\Delta\hat{r}_{i,c}^{\tau} \equiv \begin{cases} \Delta r_{i,c} & \text{if } d_c^{\mathrm{SLL}} = \tau \\ \dfrac{1}{P}\displaystyle\sum_{j\in\Omega_P(i)} \Delta r_{j,c} & \text{if } d_c^{\mathrm{SLL}} \neq \tau \end{cases} \tag{5}$$

where P is the minimum number of nearest neighbors and $\Omega_P(i)$ is the set of P nearest neighbors of observation i but with a different treatment level, as determined by an appropriate distance metric. I use propensity score matching (PSM) as the distance metric, matching observations to those with a similar likelihood of receiving the treatment (SLL eligibility) based on observable factors. Because SLL-eligibility was determined at the county level, we match observations on the county-level mean logarithm of 2013 sales.[4]

Results of the PSM estimator are reported in the last column of Table II, and some diagnostic quantile-quantile plots and statistics are shown in figures 4 and 5 and table 3. In terms of diagnostics, we can see that county-level 2013 log-sales are a strong predictor of SLL-eligibility (table 3). The logit regression using this variable to predict treatment is highly significant, and the pseudo-R2 for the regression is 0.31. We also can see that the matching procedure is successful in making distributions of county-level 2013 log-sales much more similar between the SLL-elibility conditions, as compared to the raw sample (figure 4).

The ATE constructed using the PSM estimator implies that the SLL program yields a 5.6% increase in the average grower's refuge area, relative to what would have occurred in the absence of the program. This estimate is notably larger than the raw DID estimate of 2.88%, which is consistent with the hypothesis that smaller growers may have been independently shifting to non-Bt products (or at least shifting more slowly towards Bt products), regardless of the SLL program. Examining the quantile plots in figure 5, we can see that the PSM estimator obtains this ATE estimate by shifting probability mass around the center of the distribution of the outcome measure, conditional on SLL eligibility.

The PSM estimator also permits an examination of the predicted individual treatment effects. Figure 6 plots a nonparametric density estimate for predicted individual treatment

effects. The mean of this density equals the PSM estimate of the ATE (of 5.6%). Yet we also see significant heterogeneity of the distribution of these treatment effects, with 50% of the probability mass between a treatment effect of -2.5% and 14%.

Discussion

This article examines whether a non-pecuniary behavioral intervention had a measureable effect on increasing efficiency in the use of an open-access resource. In this case the resource is characterized as the proportion of the pest population which remains susceptible to Bt toxins which are expressed by some genetically engineered varieties of corn. Previous economic analysis of instruments for improving refuge compliance have mostly been theoretical, or based on simulation models. Moreover, most of this work has focused on the sort of standard, pecuniary instruments that are typically prescribed for open-access resource management. The intervention I focus on here – in which farmers were motivated through appeals to sustainability, protecting future generations and by offering indirect monetary rewards to local charities – is more in keeping with the literature on alternative governance of commons using social norms and cooperation (Ostrom 1990).

My analysis provides robust evidence that a behavioral program to improve refuge Bt compliance had a significantly positive effect on increasing refuge planting (as proxied through seed purchases) for the average grower. The sign and significance of this effect is consistent across a number of econometric specifications. However, when I weight these regressions by grower size (proxied by seed sales volume), the estimated effect of the SLL program on the area of land planted to refuge versus Bt corn is smaller and statistically imprecise. When I implement a matching estimator that controls for significant differences in farm sizes between treatment and control groups, I find that the estimated effect of the SLL program on average grower behavior

increases. This is consistent with (though does not confirm) the hypothesis that smaller-scale growers would have increased their share of Bt products less than larger-scale growers between 2013 and 2014 in the absence of the SLL program.

The main implication of these results is that non-pecuniary interventions deserve additional attention as a potential means of improving Bt refuge compliance. The effect of the program examined here is significant both economically and statistically significant. As a back-of-the-envelope calculation, previous research suggests that the effect of planting Bt corn on a given hectare in the US could be expected to increase yield by around 20% relative to planting non-Bt corn (Hutchison et al. 2010; Fernandez-Cornejo and Wechsler 2012). And according to Fernandez-Cornejo and Wechsler (2012), previous research has also shown that Bt adoption significantly increases variable profits, and that the majority of these profit increases are attributable – and approximately proportional – to yield increases. Combining these back-of-the-envelope calculations with our findings would suggest that the SLL program is causing the average grower to forego between 0.6% (using the DID estimate) and 1.1% (using the PSM estimate) of their profits due to increased refuge planting.

In the absence of explicit enforcement of refuge regulations, non-pecuniary behavioral interventions like this represent important tools for sustaining Bt refugia. Continued evaluation of the SLL program going forward is important for assessing whether program impact can be sustained and expanded, as well as whether a one-off program can have a persistent impact on grower behavior even after the program has ended. Further investigation into these tools should examine how they can complement technical approaches to refuge management, such as RIB, which are not suitable in all contexts (for example, they are currently prohibited from use as refuge in Cotton Belt states in the US).

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Tables

Table 1. Summary Statistics for Bt and Non-Bt Corn Seed Sales in SLL and Non-SLL Counties

	Full sample	**SLL counties**	**Non-SLL counties**
Total growers	429	91	338
Number of counties	96	17	79
Relative Bt share of corn seed sales[a]			
2013	0	+3.88%***	-1.05%
	--	(0.835%)	(0.927%)
2014	+1.45%	+3.06%	+1.01%
	(0.826%)	(1.20%)	(1.00%)
Relative 2013 seed sales[b]	1	3.61	0.714***
	--	(0.732)	(0.104)
Seed sales growth, 2013-2014	2.67%	3.93%	2.14%
	(2.56%)	(5.08%)	(2.98%)

Note: Standard errors of mean estimates in parentheses, clustered by grower county. [a] Mean percentage of seed sales which were for Bt products. Mean statistics calculated relative to 2013 full sample (by subtracting 2013 full sample mean, not reported). [b] Geometric mean of seed sales, divided by geometric mean for full sample. *, ** and *** indicate a statistically different estimate for SLL-eligible and -ineligible county subsamples for that year, at the 1%, 5% and 10% levels respectively.

Table 2. Econometric Estimates of SLL Program Impact Between 2013 and 2014

	Dependent variable: Non-Bt fraction of seed sales				
	DID (OLS)				PSM
	(1)	(2)	(3)	(4)	
2014 year dummy	-0.0206*	-0.0206*	-0.00660	-0.00660	
	(0.0114)	(0.0113)	(0.00492)	(0.00491)	
SLL county	-0.0493***	--	-0.00683	--	
	(0.0124)		(0.0113)		
2014 year dummy	0.0288**	0.0288**	0.0103	0.0103	0.0560**
× SLL county	(0.0138)	(0.0138)	(0.00827)	(0.00827)	(0.0266)
Grower fixed effects	No	Yes	No	Yes	No
Weight by 2013 sales	No	No	Yes	Yes	No
Growers	429	429	429	429	429
Counties	96	96	96	96	96
R-squared	0.013	0.009	0.002	0.006	

Note: Standard errors in parentheses. *,** and *** denotes statistical significance at the 10%, 5% and 1% levels respectively. OLS standard errors clustered at the county level. Standard errors for the matching estimator computed using robust method proposed by Abadie et al. (2004, 2006). The PSM estimator was implemented using the *teffects* package in Stata®, with a minimum of one match per observation (with multiple matches used in the case of ties).

Table 3. First Stage Propensity Score Estimation

Model: logit	SLL-eligibility
County-level mean log(2013 sales)	1.559***
	(0.477)
Constant	-8.682***
	(2.343)
Observations	429
Counties	96
Degrees of freedom	1
Wald χ^2-test statistic	10.69***
Pseudo-R2	0.307

Note: Robust standard errors in parentheses, clustered at the county level. *,** and *** denotes statistical significance at the 10%, 5% and 1% levels respectively.

Figures

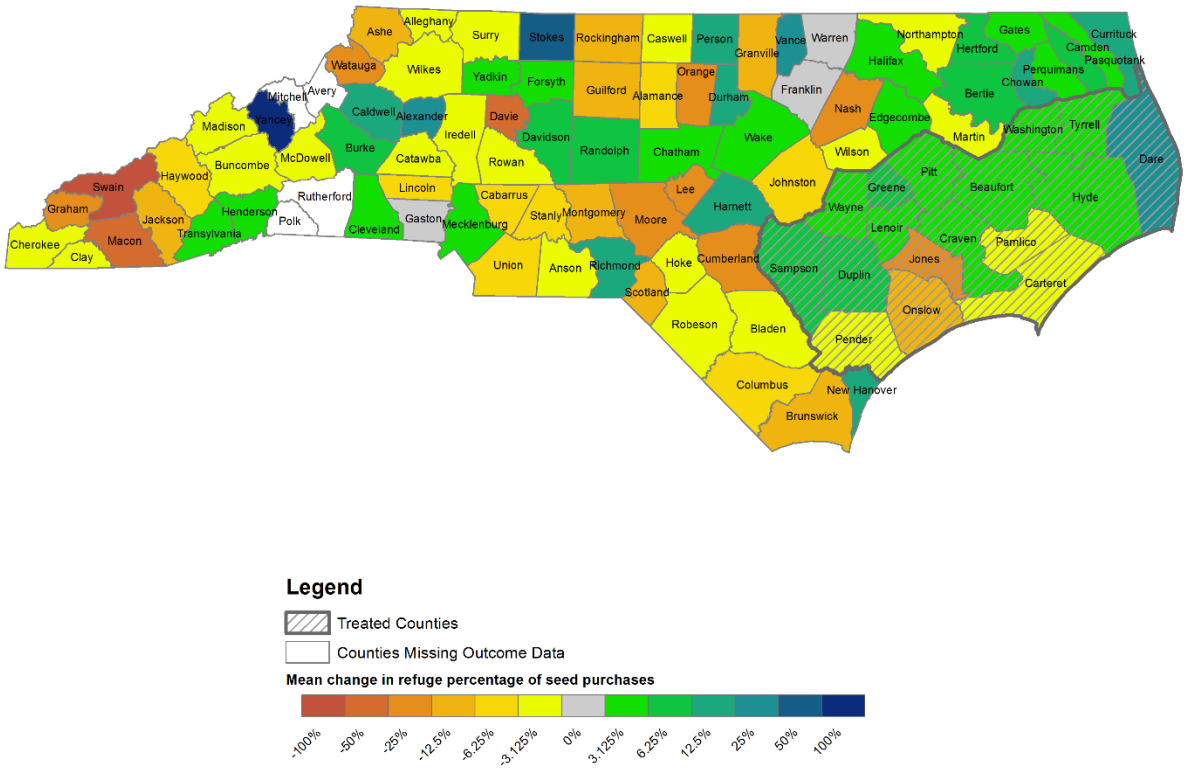

Figure 2. North Carolina refuge seed purchasing and Southern Land Legacy program in 2014 pilot

Advertisement 1

"I've always been told that the right thing and the hard thing are the same thing. And when times are tough, those decisions get tougher to make. But with refuge planting, we can't afford to take chances. As farmers, we have a duty to protect the land and the technology, not just for ourselves, but for our community."

Advertisement 2

"As a second-generation farmer, most of what I know I learned from my father. He taught me the basics like seed planting and soil health, but he also taught me that our farm is an important resource to the community. Our neighbors are counting on us for food and jobs, so to ensure my farm will always be there, I can't just focus on the here and now. I have to be thinking ahead, I have to plant a refuge."

Advertisement 3

"It's easy to think that buying refuge seed is just another of the many choices we make each fall as farmers. But it's a decision that's bigger than farming. When I buy seed, I have to think about the wellbeing of my community, the people counting on me every day for jobs, food, and support. If I base seed decisions on my priorities alone, what does that say about my commitment to those who matter most?"

Source: Monsanto, http://southernlandlegacy.com/

Figure 1. Example text from Southern Land Legacy advertising campaign

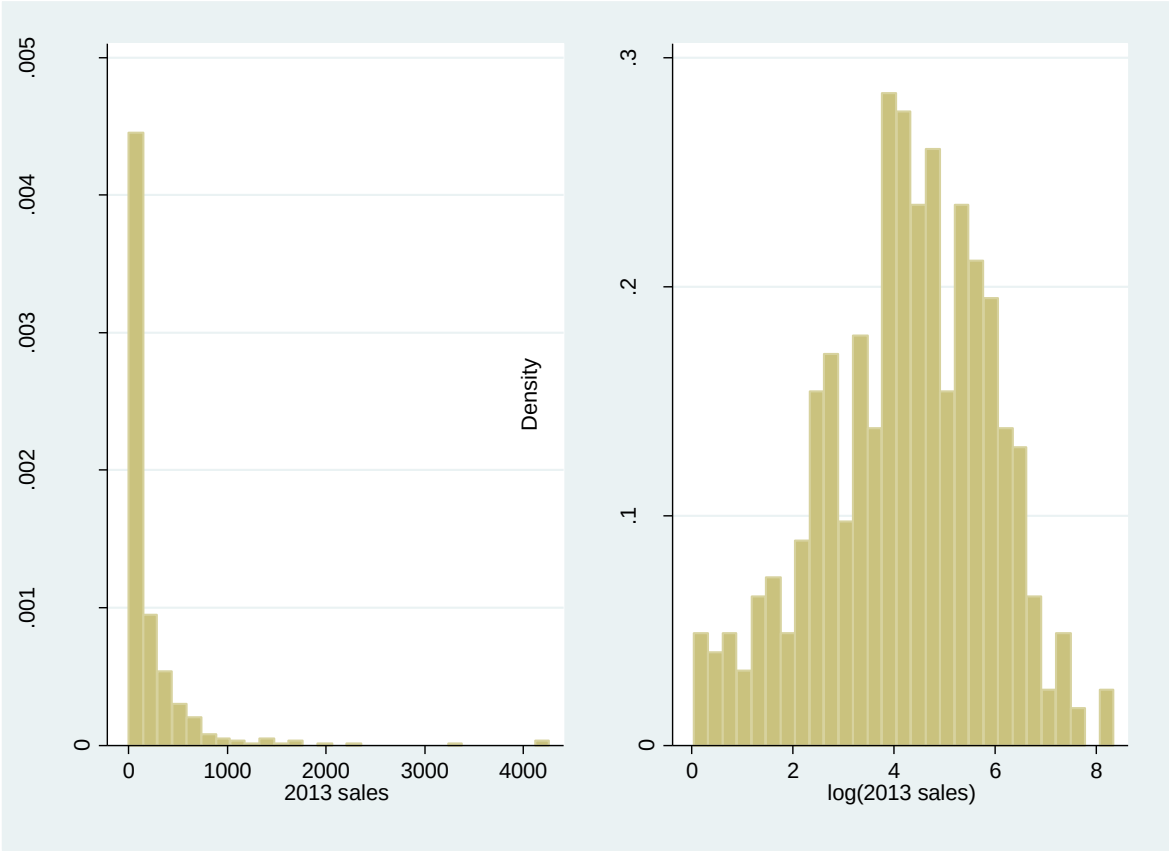

Figure 3. Histograms of raw and log-transformed 2013 seed sales volume

Note: These data are shifted by a randomly drawn constant to protect the proprietary aspects of the dataset.

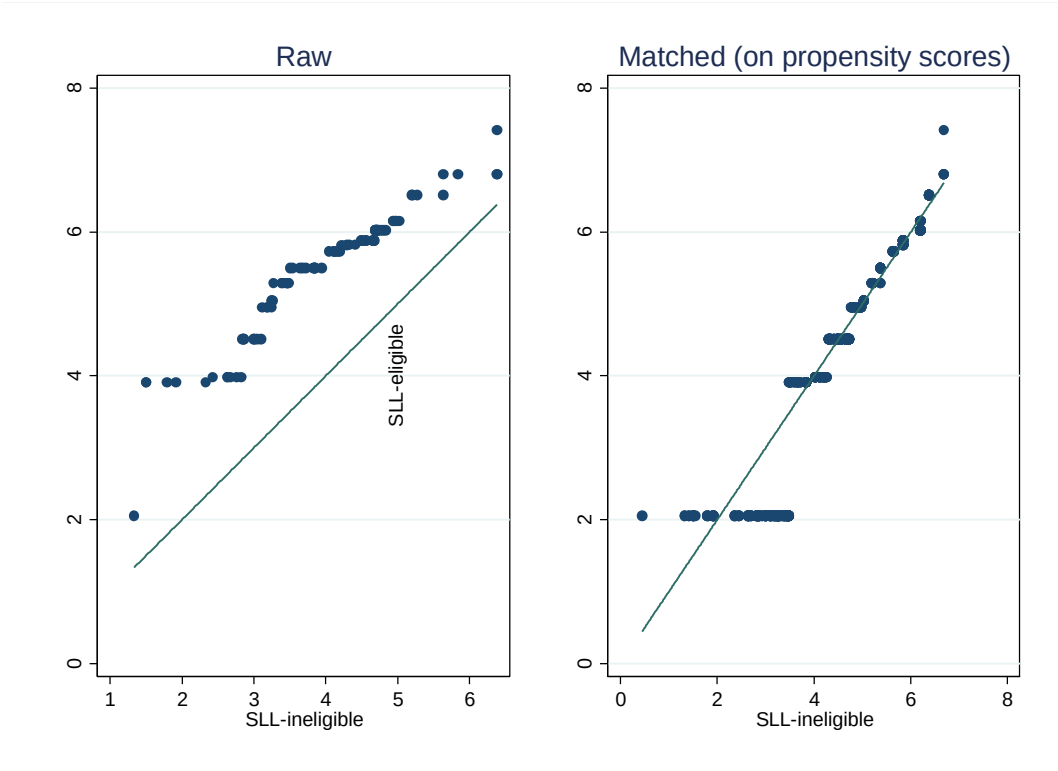

Figure 4. Quantile-quantile plot of county-level mean log(2013 sales), SLL-eligible v. ineligible growers

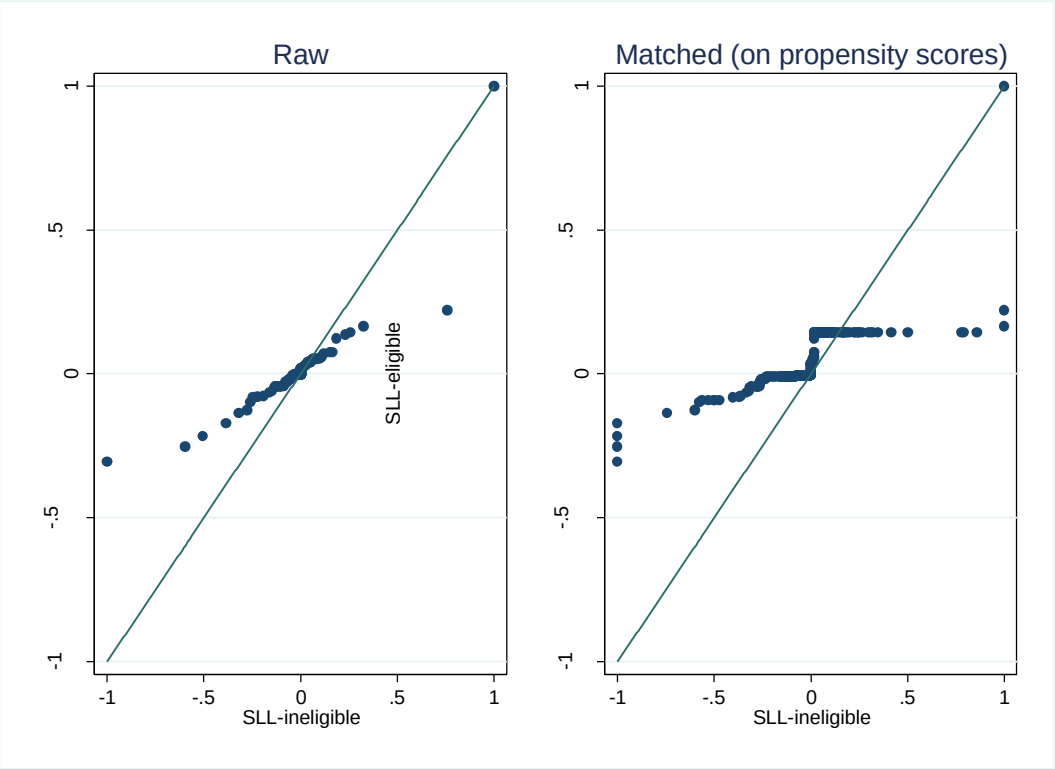

Figure 5. Quantile-quantile plot of change in refuge share of seed sales between 2013 and 2014, SLL-eligible v. ineligible growers

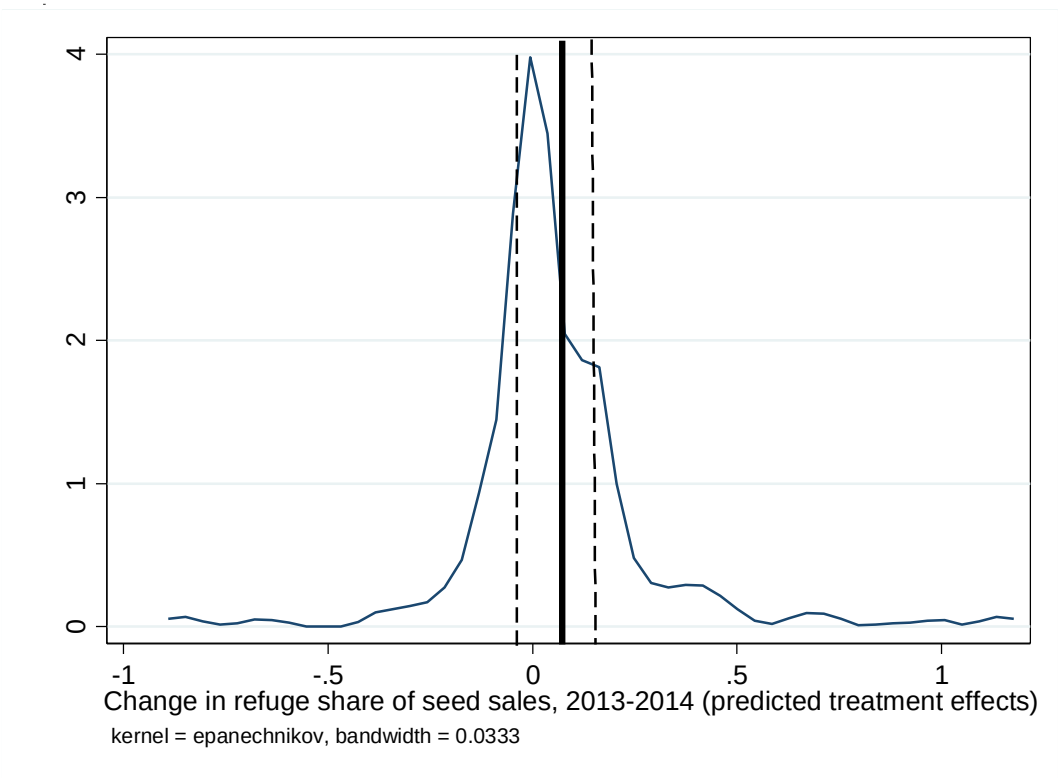

Figure 5. Nonparametric density plot of predicted individual treatment effects of the SLL program

Note: Counterfactual outcome predicted using PSM. Solid vertical line is mean of distribution (0.0560) and dotted lines are 1st and 3rd quartiles (-0.0249 and 0.143).

Footnotes

[1] A complication in this context is that there are likely countervailing public goods aspects to Bt adoption, whereby one grower's deployment of the technology has spillover, pest-reduction benefits to the grower's neighbors. This biological effect has been documented in cases of European corn borer reductions resulting from areawide adoption of Bt corn (Hutchison et al. 2010). The economic implications of this effect comprise a topic that the author of this article is exploring in related research.

[2] Generally speaking, 'behavioral' approaches to increasing refuge compliance would also include the standard approach of fining noncompliance as a way to dis-incentivize this behavior. However, the research focus here is on behavioral alternatives to conventional pecuniary approaches to enforcement.

[3] These fixed effects are collinear with the main effect $\hat{\beta}_{SLL}$ of the treatment dummy d_c^{SLL}, which is thus dropped in these regressions.

[4] As a robustness check I also use a nearest neighbor matching estimator, with the distance between nearest neighbors calculated using the Euclidean norm of the logarithm of 2013 county-level sales. Results are qualitatively the same and similar in magnitude.