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Adoption of Best Management Practices to Control Weed Resistance by Corn, Cotton, and Soybean Growers

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This study examined adoption of 10 best management practices (BMPs) to control weed resistance to herbicides using data from a survey of more than 1,000 US corn, cotton, and soybean growers. Count-data models were estimated to explain the total number of BMPs frequently practiced. Ordered-probit regressions were used to explain the frequency of individual BMP adoption. Growers practicing a greater number of BMPs frequently had more education, but less farming experience; grew cotton; expected higher yields relative to the county average; and farmed in counties with a lower coefficient of variation (CV) for yield of their primary crop. Yield expectations and variability were significant predictors of adoption of individual BMPs. Most growers frequently adopted the same seven BMPs. Extension efforts may be more effective if they targeted the three practices with low adoption rates. Counties with a high-yield CV would be areas to look for low BMP adoption.

Key words: weed, herbicide, resistance management, corn, cotton, soybeans, adoption.

Introduction

In 2008, agricultural producers planted more than 80% of US cotton and corn acreage and more than 90% of soybean acreage to transgenic glyphosate-tolerant, Roundup Ready® (RR) seed varieties (US Department of Agriculture Agricultural Marketing Service [USDA AMS], 2008; USDA National Agricultural Statistics Service [NASS], 2008). Many studies report significant pecuniary and non-pecuniary benefits to growers from using glyphosate-resistant varieties (Gianessi, 2008; Marra, Pardey, & Alston, 2002; Marra & Piggott, 2006; Mensah, 2007; Piggott & Marra, 2008).

The evolution of glyphosate-resistant weeds threatens the sustainability of these benefits, however. The number and range of glyphosate-resistant weeds has been increasing in the United States since commercialization of RR crops (Heap, 2009). The evolution of weed resistance to herbicides also poses problems for other herbicide-resistant crops, such as LibertyLink® or Clearfield® crops. The potential for pests or weeds to develop resistance in response to frequent applications of a narrow set of chemicals with the same mode of action is well established in the literature (Carlson & Wetzstein, 1993; Holt & Lebaron, 1990; Powles & Shaner, 2001; Shaner, 1995). Beckie (2006, pp. 793) identifies, "recurrent application of highly efficacious herbicides with the same site of action" and "annual weed species that occur in high population densities" as key risk factors for the evolution of herbicide resistance in weeds.

However, strategies for reducing the risk of pest resistance are also well-documented (Burgos et al., 2006; Culpepper, York, & Kichler, 2008; Gressel & Segel, 1990; Monsanto, 2009a, 2009b; Mueller, Mitchell, Young, & Culpepper, 2005; Nalewaja, 1999; Prather, DiTomaso, & Holt, 2000; Steckel, Hayes, & Rhodes, 2004; Stewart, 2008). Commodity groups, extension specialists, and Monsanto have recommended that growers adopt various best management practices (BMPs) to prevent or delay the spread of glyphosate-resistant weeds (Burgos et al., 2006; Culpepper et al., 2008; Monsanto, 2009a, 2009b; Steckel et al., 2004; Stewart, 2008). These strategies fall under the more general rubric of integrated weed management (IWM), components of which include weed scouting; avoidance on over-reliance on a compound or compounds with a single mode of action against weeds; preventing herbicide-resistant gene spread, non-chemical control such as tillage, and crop rotations. A key element of this strategy is diversifying herbicides used, relying on multiple compounds with different modes of action.

This study examines the frequency of grower adoption of 10 different BMPs to prevent or delay weed resistance. Primary survey data on more than a thousand US corn, cotton, and soybean growers was used to characterize the nature of BMP adoption. Count-data models were estimated to explain the total number of BMPs frequently practiced. Ordered-probit regressions were used to explain the frequency of individual BMP adoption.

Previous Studies

There are four strands of literature pertinent to the understanding of grower adoption of BMPs. First, weed science studies describe how weed resistance to herbicides evolves, the approaches to prevent and respond to resistance, and the roles of different BMPs in prevention and response (e.g., Beckie, 2006; Green, 2007). These are not economic studies *per se*, but do consider economic incentives and trade-offs. Second are normative, economic modeling approaches (e.g., Gorddard, Pannell, & Hertzler, 1995; Llewellyn, Lindner, Pannell, & Powles, 2001; Pannell & Zilberman, 2001; Weersink, Llewellyn, & Pannell, 2005). Here, the susceptibility of weeds to herbicides is examined as an exhaustible resource. Growers face an intemporal trade-off between weed-management practices that maximize short-run returns versus practices that delay resistance. Delaying resistance may be less profitable in the short-run, but more profitable in the long run. Third, positive, empirical analyses collect and analyze data on grower perceptions and behavior regarding weed resistance (e.g., Hammond, Luschei, Boerboom, & Nowak, 2006; Johnson & Gibson, 2006; Wilson, Tucker, Hooker, LeJeune, & Doohan, 2008). While the economic models highlight how growers *should* manage resistance, these empirical studies examine what steps growers *actually take* to manage it. These studies also shed light on grower rationales for their behavior. Fourth, there is the econometric approach (Llewellyn et al., 2007). The first step in this approach is to develop a dynamic economic model of weed management, including resistance management. Results from the theoretical model guide variable selection and statistical specification for multivariate regression analysis. Finally, the multivariate regression analysis tests hypotheses generated from the theoretical model. Thus, the prescriptive, theoretical model informs specification of the descriptive, statistical model. In turn, statistical model results test the validity of and hypotheses generated by the theoretical model.

Conceptual Framework

Following Llewellyn et al. (2001, 2007), we treat the adoption of weed resistance BMPs as a dynamic optimization problem. A grower chooses application rates of a preferred herbicide, H_t, and adoption of different BMPs, $\boldsymbol{M}_t$, to maximize the net present value (NPV) of returns.

$$\text{Max } NPV = \textstyle\sum_{t=0\ldots n} \{P_t Y_t[1 - \delta_t (N_t, R_t, H_t, \boldsymbol{M}_t)] - C_H H_t - C_M (M_t) - V_t\}\, \beta \qquad (1)$$

with respect to H_t, $\boldsymbol{M}_t$, subject to

$$R_t - R_{t\text{-}1} = f(N_t, R_t, H_t, \boldsymbol{M}_t, X_t);\ \partial f / \partial H_t > 0;\quad \partial f / \boldsymbol{M}_t < 0;\ \partial f / X_t > 0, \qquad (2)$$

where

- P_t = crop price
- Y_t = crop yield
- δ_t = percent yield loss from weed damage
- N_t = pre-treatment weed population
- R_t = weed resistance to the herbicide
- H_t = level of herbicide use
- $\boldsymbol{M}_t$ = vector of resistance management practices
- X_t = behavior of neighbors or external factors that increase resistance
- C_H = cost of herbicide treatment
- C_M = cost of resistance management
- V_t = other variable costs
- β = discount factor

Equation 2 characterizes the evolution of resistance. Initially, use of the herbicide reduces damage ($\partial\delta_0/\ \partial H_t < 0$), but also increases resistance ($\partial f / \partial H_t > 0$). Evolution of resistance renders the herbicide less effective ($\partial^2\delta_0/\ \partial H_t\ \partial R_t > 0$). Resistance-management BMPs, $\boldsymbol{M}_t$, slow the evolution of resistance ($\partial f / \boldsymbol{M}_t < 0$), but entail additional costs, $C_M(\boldsymbol{M}_t)$. BMPs may reduce damage in the current period ($\partial\delta_t / \partial\boldsymbol{M}_t < 0$). However, these alternatives may be less effective or more expensive than frequent applications of the preferred herbicide. For example, repeated applications of glyphosate may be more profitable (at least in the short-run) than applying tank mixes or additional residual herbicides.[1] Many growers manage herbicide-resistant crops in combination with no-till practices. While supplemental tillage offers the option of non-chemical control, it would require growers to forego some benefits of no-till systems (such as reduced fuel costs or soil erosion).

This stylized model captures key features of weed BMP adoption. First, BMPs are costly to adopt. Yet they

1. *The model presented here treats use of multiple herbicides with different modes of action as part of the set of BMPs in* $\boldsymbol{M}_t$. *A more complete, but more complicated, model could consider resistance evolution of different classes of herbicides, not just the preferred herbicide. This would involve multiple equations such as f(), but could allow for examination of the "optimal rotation" of herbicides.*

slow resistance and can, in some cases, substitute for herbicide applications in reducing current damage. Thus, some BMPs may be profitable to adopt apart from their contribution to resistance management. If BMPs reduce current profitability, however, growers will not adopt them unless (a) they effectively slow resistance, (b) their contribution to future profitability counteracts their short-run costs, and (c) growers recognize the BMPs' contribution to future profitability.

Even if the damage function $\delta()$ and resistance-evolution equation $f()$ are such that adoption of BMPs increases the NPV of long-run profits, growers may still not adopt them. Growers must have sufficient information about $\delta()$ and $f()$ to expect that their own adoption of BMPs is profitable in the long run. A potential role of extension is to increase knowledge about $\delta()$ and $f()$. There is more scope for individual growers learning about the effect of practices on current weed damage, $\delta()$, than on the evolution of resistance, $f()$. High variability in production outcomes, however, may make such learning more difficult.

Another factor affecting grower adoption is whether growers perceive weed resistance to be subject to their own control. Pannell and Zilberman (2001) have argued that resistance management is subject to greater individual control than insect pest management, indicating that common pool externalities discouraging resistance management should be less of a problem. If, however, growers perceive that resistance depends on external factors rather than their own actions (i.e., the effect of $\partial f / X_t$ dominates the effect of $\partial f / \boldsymbol{M}_t$), this will discourage BMP adoption. In a study of Ohio farmer perceptions of weed management, Wilson et al. (2008) found growers attributed weed introduction and spread to external natural factors and neighbor behavior. At the same time, they placed less emphasis on the importance of their own actions.

The evolution of resistance may also spur adoption of BMPs. As resistance to an herbicide develops, relying solely on that herbicide becomes less effective at managing weeds. In effect, as $\partial \delta_t / \partial H_t$ approaches zero, growers may be forced to shift to other weed-control methods. Various studies suggest that development of herbicide-resistant weeds in Australia and Canada has spurred greater adoption of BMPs (Llewellyn et al., 2004; Powles, Preston, Jutsum, & Bryan, 1997; Wilson et al., 2008). Thus, one may see use of BMPs not to prevent resistance but as a means of mitigating it.

This simple model suggests testable hypotheses. First, growers will be more likely to adopt BMPs that have immediate benefits in terms of controlling current weed populations. Second, this effect will be stronger for growers with higher potential yields because percent reductions in damage have a higher payoff. In contrast, growers will be less likely to adopt practices that do not provide obvious, short-run benefits. Third, growers experiencing resistance problems may increase BMPs as their traditional means of control becomes less effective. Fourth, implementing complex, interrelated BMPs may require more human capital. So, one may expect more use of BMPs among growers with more education. Greater education helps lower costs of implementing BMPs (C_H). Fifth, greater variability in agronomic and economic outcomes may discourage BMP adoption. Pannell and Zilberman (2001) note the importance of observability and trialability in encouraging adoption of new technologies. In areas with highly variable production outcomes, growers may have more difficulty assessing the effects of and returns to BMP adoption.

Data

Data were collected via a telephone survey conducted by Marketing Horizons for Monsanto in November/December of 2007. The survey was designed to be a random, representative sample of corn, cotton, and soybean growers from the Great Plains eastward. Data collection was restricted to farms with 250 or more acres of the targeted crop. Responses were obtained from 401 cotton growers, 402 corn growers, and 402 soybean growers. While growers were "targeted" to respond to questions about a particular crop, they often also produced other crops. For example, many cotton growers who were asked detailed questions about cotton production also grew corn or soybeans.

The survey included four sections. The first asked questions about operator and farm characteristics. These included operator education and experience, acres operated, percentage of operated land owned, acres of different crops grown, acreage planted with herbicide-tolerant crops, crop-rotation practices, and extent of livestock production. The second section asked growers about their current weed management; adoption of weed-resistance BMPs; herbicides and/or tillage used for pre-plant, pre-emergent, and post-emergent weed control; and timing and frequency of post-emergent weed management. The third section asked growers about their attitudes regarding various weed-management concerns, such as crop yield, crop-yield risk, crop price, crop-price risk, herbicide costs, seed costs, overhead costs, labor and management time, crop safety, operator and worker safety, environmental safety, erosion control, and conve-

Table 1. Frequency of weed resistance best management practice (BMP) adoption (percent of respondents practicing).

BMP	Always	Often	Sometimes	Rarely	Never
Scout before	57%	26%	11%	3%	2%
Scout after	51%	29%	15%	2%	1%
Clean field	60%	14%	13%	5%	8%
Control early	54%	35%	9%	1%	0%
Control escapes	45%	34%	15%	4%	2%
Clean equipment	15%	11%	20%	22%	31%
New seed	87%	7%	3%	1%	2%
Different modes	18%	21%	33%	15%	13%
Supplemental tillage	11%	10%	26%	21%	32%
Use label rate	74%	19%	4%	1%	0%

nience. The fourth section asked growers about the cost of their weed-management program and the value of the benefits they derived using a RR weed-management program.

For this study, weed-resistance management practices were categorized into 10 separate BMPs:

1. Scouting fields before applying herbicides
2. Scouting fields after herbicide applications
3. Start with a clean field, using either a burndown herbicide application or tillage
4. Controlling weeds early when they are relatively small
5. Controlling weed escapes and preventing weeds from setting seeds
6. Cleaning equipment before moving from field to field to minimize spread of weed seed
7. Using new commercial seed that is as free from weed seed as possible
8. Using multiple herbicides with different modes of action
9. Using tillage to supplement herbicide applications
10. Using the herbicide-label recommended application rate

Growers could choose among five responses when asked how frequently they adopted a BMP: (1) always, (2) often, (3) sometimes, (4) rarely, and (5) never. (Growers could respond, “don’t know,” but these accounted for 0.3% of responses). Six BMPs were always practiced by a majority of growers (Table 1). There were three BMPs, however, that a significant share of growers never practiced. These included cleaning equipment before moving between fields (31%), using multiple herbicides with different modes of action (13%), and using supplemental tillage (32%).

Table 2. Frequency of weed resistance BMP adoption (percent of respondents).

BMP	Often or always	Sometimes	Rarely or never
Scout before	83%	11%	5%
Scout after	81%	15%	4%
Clean field	75%	13%	12%
Control early	89%	9%	2%
Control escapes	79%	15%	6%
Clean equipment	25%	20%	54%
New seed	94%	3%	2%
Different modes	39%	33%	28%
Supplemental tillage	21%	26%	53%
Use label rate	93%	4%	1%

Table 2 combines the share of BMPs practiced often or always, then rarely or never for the same data. There are seven practices that 75% of growers practice frequently (often or always; Table 2): use new seed (94%), follow label rate (93%), start with a clean field (75%), scout before (83%), scout after (81%), control weeds early (89%), and control weed escapes (79%). Again, one can see that the remaining three BMPs—using multiple herbicides with different modes of action, cleaning equipment, and supplemental tillage —were practiced less frequently (Table 2).

Adoption patterns were remarkably similar across producer groups. Seven of the BMPs were practiced by 71% or more of corn, cotton, or soybean producers (Figures 1a, 1b, 1c). Moreover, these were the same seven practices. All three of the producer groups used multiple herbicides with different modes of action, cleaned equipment, or practiced supplemental tillage much less frequently. Less than half of any of these producers practiced these three BMPs often or always. More corn producers used multiple herbicides with different modes

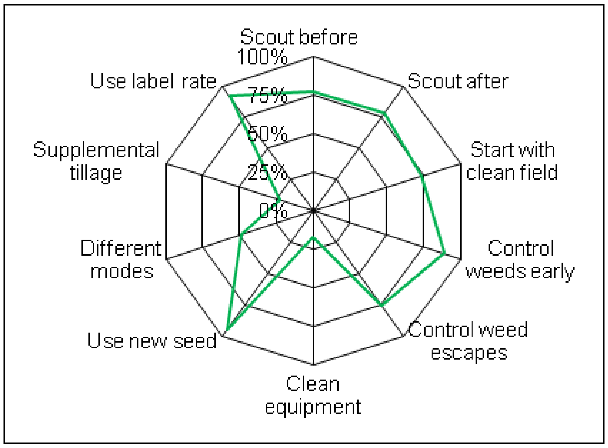

Figure 1a. Percent of corn growers adopting BMPs often or always.

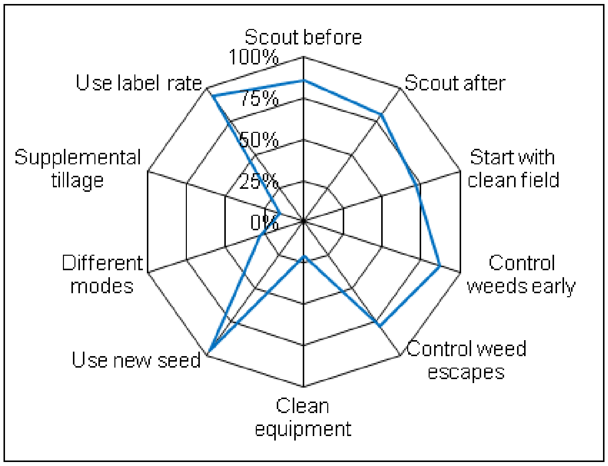

Figure 1b. Percent of soybean growers adopting BMPs often or always.

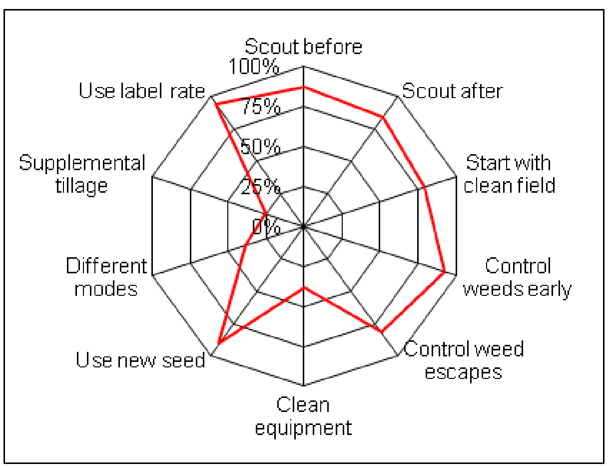

Figure 1c. Percent of cotton growers adopting BMPs often or always.

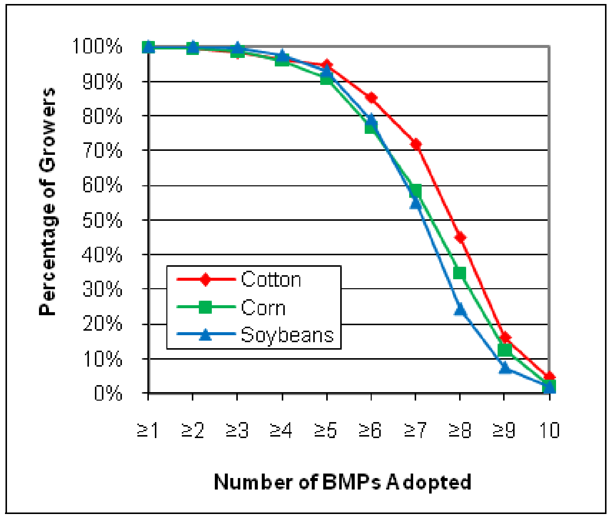

Figure 2. Percentage of growers often or always adopting BMPs by total number of BMPs adopted and targeted crop.

of action often or always (49%) than either cotton (38%) or soybean (28%) growers.

Cotton growers were more likely to practice more BMPs often or always than were corn or soybean growers (Figure 2). More than 70% of cotton growers practice seven or more BMPs often or always, compared to 58% of corn producers and 55% of soybean producers. About 45% of cotton growers practiced eight or more BMPs often or always compared to 35% for corn growers and 24% for soybean growers. About 95% of cotton growers often or always adopted five or more BMPs.

Methods

Integrated weed management (IWM) involves adoption of multiple, interrelated practices. For empirical research, this raises questions about how one measures adoption when "adoption" involves making selections from a suite of different practices. Some studies consider adoption of individual practices, while others attempt to develop indexes characterizing the intensity of adoption. Hollingsworth and Coli (2001) developed a scoring system based on a weighted sum of practices adopted. Hammond et al. (2006) used an index that was an unweighted count of the total number of practices adopted. Llewellyn et al. (2007) considered those growers who adopted three or more practices (out of a possible six) as IWM adopters.

We analyzed data concerning BMP adoption in two ways. First, multivariate count-data analysis was used to identify which factors explained the total number of BMPs a grower adopted frequently (often or always).

For example, which factors help predict whether a grower will adopt eight practices frequently as opposed to seven? Here ,the dependent variable is similar to the unweighted index approach of Hammond et al. (2006). Next, multivariate ordered-probit regressions were estimated to identify factors that help explain how frequently a grower practiced a particular, single BMP.

For the multivariate regression analyses, in addition to the Marketing Horizons survey data, county-specific variables were created using data from the USDA NASS. These included the coefficient of variation (CV) of county crop yields of the targeted crop. CV is the standard deviation of yields divided by the mean of yields over 10 years. The yield CV was included to test the hypothesis that growers in counties with greater yield risk had different patterns of BMP adoption. Growers were asked what they expected their target crop yields would total. An index was created that was the ratio of growers' expected yields to their counties' average yields. This variable was included to test the hypothesis that growers with higher-than-average yields (perhaps better managers or growers farming under conditions that are more favorable) were more likely to adopt BMPs more frequently.

The number of BMPs a grower adopts often or always can only be an integer from 0, 1, 2, … up to 10. This means a Poisson (or other count data) model is more appropriate than standard linear regression, which can yield parameter estimates that are inefficient, biased, or both and can yield nonsensical predicted values (Greene, 1997; King, 1988). A Poisson regression assumes that the mean and variance of the dependent variable are equal. This assumption can overestimate the statistical significance of regression parameter estimates when there is over-dispersion (variance greater than the mean) or underestimate their statistical significance when there is under-dispersion (variance less than the mean). However, estimation here followed McCullagh and Nelder (1989), who fit a Poisson regression that relaxes this restriction. McCullagh and Nelder use the Pearson chi-square method to estimate a scale parameter s, such that $s = 1$ if the mean and variance are equal, $s > 1$ if the variance exceeds the mean (over-dispersion), and $s < 1$if the variance is less than the mean (under-dispersion). We also estimate a generalized negative binomial regression as an alternative to a Poisson regression because it also allows for separate estimation of mean and variance (Cameron & Trivedi, 1998; Greene, 1997).

Next, ordered-probit regressions were estimated separately for each of the 10 BMPs. When asked how frequently they adopted a given BMP, respondents could answer 1-always, 2-often, 3-sometimes, 4-rarely, or 5-never. In addition, respondents could answer "don't know," but few responded this way, so we deleted these few observations from the regression analysis.

Table 3. Descriptive statistics for variables used in regressions.

	Means	St. dev.
Number of BMPs practiced often or always	6.838	1.540
Corn producer (=1 if targeted producer; = 0 otherwise)	0.342	
Soybean producer (=1 if targeted producer; = 0 otherwise)	0.355	
Cotton producer (=1 if targeted producer; = 0 otherwise)	0.303	
Years of education	14.042	1.816
Years farming	29.799	12.116
Crop acreage (acres)	1422	1196
Percent of land owned	41.611	32.060
Raises livestock (=1 if yes; = 0 otherwise)	0.368	
Percent RR (percent of targeted crop planted to RR varieties)	87.026	28.275
Yield difference (percent difference of grower's expected targeted crop yield compared to county 10-year average)	29.559	44.120
Yield CV (county 10-year coefficient of variation of targeted of yield of grower's targeted crop)	0.177	0.084
Resistance concern (=1 if yes if grower indicated weed resistance was a concern; = 0 otherwise)	0.516	
Herfindahl index (Measure of crop specialization = 1 for complete specialization; minimum value of 0.25)	0.536	0.160
Custom applications (percent of herbicide applications to targeted crop made by custom applicators)	28.577	41.871
County resistance (=1 if weed resistance reported in county; = 0 otherwise)	0.126	
CRD resistance (percent of counties in 'crop reporting' with reports of weed resistance)	8.932	20.679
Number of observations	1,006	

Source: Marketing Horizons Survey and NASS county-level yield data.

Table 4. Count data regression results for the number of weed BMPs adopted often or always.

	State effects				No state effects			
	Poisson		Negative binomial		Poisson		Negative binomial	
Variable	Coeff.	Signif.	Coeff.	Signif.	Coeff.	Signif.	Coeff.	Signif.
Intercept	**1.798**	**0.000**	**1.797**	**0.000**	**1.797**	**0.000**	**1.796**	**0.000**
Soybean	-0.009	0.640	-0.01	0.623	-0.016	0.393	-0.015	0.396
Cotton	***0.080***	***0.100***	0.079	0.111	**0.074**	**0.002**	**0.073**	**0.003**
Raise livestock	-0.002	0.913	-0.002	0.89	-0.006	0.686	-0.006	0.696
Resist concern	0.005	0.756	0.006	0.704	0.006	0.69	0.006	0.667
County weed resistance	0.047	0.172	0.048	0.169	0.050	0.142	0.050	0.147
Education	**0.011**	**0.010**	**0.011**	**0.010**	**0.012**	**0.003**	**0.012**	**0.003**
Years farming	***-0.001***	***0.059***	***-0.001***	***0.058***	-0.000	0.143	-0.000	0.15
Crop acres	0.0000	0.148	0.00001	0.134	***0.00001***	***0.085***	***0.00001***	***0.084***
% land owned	0.000	0.304	0.000	0.27	0.000	0.252	0.000	0.239
RR acres	0.000	0.53	0.000	0.522	0.000	0.532	0.000	0.514
Yield diff	**0.0000**	**0.037**	**0.0000**	**0.035**	***0.0000***	***0.054***	**0.0000**	**0.048**
Yield CV	**-0.358**	**0.006**	**-0.366**	**0.006**	**-0.314**	**0.007**	**-0.319**	**0.007**
Herfindahl	0.074	0.124	0.073	0.135	0.056	0.22	0.056	0.229
% custom ap.	0.000	0.489	0.000	0.519	0.000	0.580	0.000	0.588
CRD weed Rst	**-0.002**	**0.016**	**-0.002**	**0.015**	***-0.001***	***0.053***	***-0.001***	***0.057***
IL*	**0.057**	**0.040**	**0.058**	**0.038**				
IN	**0.078**	**0.042**	**0.078**	**0.043**				
KS	**0.179**	**0.001**	**0.182**	**0.001**				
s (Scale)	0.332		0.043		0.335		0.043	
Likelihood ratio test statistic	91.302	0.000	90.689	0.000	61.875	0.000	61.168	0.000
d.f.	32		32		15		15	

** Only significant state effects reported. Boldface denotes significance at 5% level. Boldface with italics denotes significant at 10% level.*

The set of covariates used in the regression models included (1) dummy variables for target crop grown and whether a grower sold livestock; (2) years of grower education and farming experience; (3) total crop acres and percent of cropland owned; (4) the percentage of target crop planted to RR seed varieties in the previous year; (5) percent of herbicide applications carried out by a custom applicator; (6) a Herfindahl index based on the proportion of the crop acreage planted to corn, cotton, soybean, and other crops, which increases as a grower becomes more specialized; (7) a dummy variable indicating that the grower listed weed resistance as a concern in an open-ended question about weed management concerns—growers were not asked directly if resistance was a concern; (8) grower expected yield as a percent of county average yield and the coefficient of variation of target crop yield in the grower's county; and (9) measures of reported herbicide resistance. Two measures of reported herbicide resistance were constructed based on proprietary data obtained from Monsanto. These were (a) a dummy variable indicating weed resistance to herbicides has been reported in a grower's county and (b) the percentage of counties in a grower's crop reporting district where weed resistance has been reported.

Table 3 reports descriptive statistics for variables used in the regressions. The sample included 1,006 observations after deleting those observations with missing data. Adoption rates of RR varieties are high, with an average of 87% of the acres of targeted crops planted to those varieties. Grower yield expectations also seem high relative to county averages. On average, growers expected their yields to exceed their county's 10-year average by 29%. This may reflect optimism on the part of producers, but recall that (a) growers were surveyed about their primary crop, and (b) our sample includes larger producers, only those growing 250 or more acres of the targeted crop. So, it might not be too surprising that relatively large growers, specializing in production of a crop expect higher-than-average yields. Or, growers' responses may reflect their potential yield, perhaps reflecting the highest yield they obtained in recent years.

Results—Count-Data Analysis

Table 4 reports count-data regression results where the dependent variable is the total number of weed BMPs that a grower reported using either often or always. Table 4 reports results for generalized Poisson and negative binomial regressions with and without state fixed effects. The Poisson and negative binomial specifications yield similar results, with both models suggesting under-dispersion. Based on the likelihood statistics, we can reject the hypothesis of no state-level effects. However, only three states individually had statistically significant effects. The default state is Iowa, and the regression coefficients for Illinois, Indiana, and Kansas were all positive and significant. This suggests that, compared to Iowa, growers in these states tend to practice more BMPs often or always, while growers in other states tend to practice about the same number of weed BMPs as Iowa's growers.

A number of variables were significant across all specifications. The number of BMPs adopted

- increased with a grower's level of education,
- increased for growers with expected yields greater than the county average yield,
- was lower in counties with more variable yields (measured by the county yield CV), and
- was lower in crop- reporting districts reporting more resistance problems.

In regressions with state effects, the number of years of farming experience was negatively associated with the number of BMPs adopted, suggesting that younger farmers tend to adopt more BMPs. Separate models estimated by target crop did not perform well and so are not reported here—for the separate corn and soybean models, the null hypothesis of all zero coefficients (except for the constant) could not be rejected at the 5% level of significance.

In sum, younger, more educated growers who expect to obtain higher-than-average yields practiced a greater number of BMPs often or always. Growers in regions with greater percentage yield variability practiced fewer BMPs. The relationship between local resistance episodes and grower BMP adoption was mixed. Growers in crop-reporting districts with more counties reporting resistance practiced fewer BMPs. Yet, growers farming in counties reporting resistance, tended to adopt more BMPs. This latter relationship was not significant, however.

Cotton growers and larger operators appeared to adopt more BMPs, but this affect was attenuated by including state-specific effects. The attenuating effect of state variables may come from the fact that there was no overlap of growers in surveyed cotton and corn states and only a small overlap between surveyed cotton and soybean growers. Hence, there is a relatively high correlation between the state dummy variables and the cotton grower dummy variable.

Ordered-Probit Results

Table 5 reports results for separate ordered-probit regression for each of the 10 BMPs. The dependent variable is the frequency of practicing a given BMP, where growers could choose between frequencies of never, rarely, sometimes, often, or always. Table 5 reports the effects of explanatory variables that were significant at the 5% and 10% levels. A positive sign (+) indicates an increase in the probability of practicing the BMP more frequently, while a negative minus sign (–) indicates the variable decreased the frequency of adopting the BMP.

Table 6 summarizes results of the ordered-probit regressions by explanatory variable. It reports the variables that had significant effects (at the 10% level) on adoption of each weed-resistance BMP. Results are summarized with and without state effects, with the data pooled across all growers.

In the count-data regressions, targeted cotton producers were more likely to adopt more BMPs often or always, but including state-specific effects attenuated this cotton-grower effect. This pattern repeats itself with frequency of adoption of individual BMPs. Targeted cotton producers appear to have a higher probability of more frequent adoption of a number of individual BMPs in the ordered probits. However, once we include state effects, the statistical significance of these relationships declines. In both ordered probits, soybean producers use multiple herbicides with different modes of action less frequently. In the count-data regression, a negative association existed between being a soybean producer and the number of BMPs adopted often or always, but the association was not significant.

The probit regressions also show that growers who expect yields higher than the county average are more likely to use multiple herbicides with different modes of action. In contrast, growers in counties with greater yield variability less frequently used herbicides with dif-

Table 5. Ordered-probit regressions for frequency of weed-resistance BMP adoption.

Explanatory variables	Scout before	Scout after	Clean field	Control early	Control escapes	Clean equipment	Use new seed	Different modes of action	Supplemental tillage	Follow label rate
Education		+[a]				–[b]		+[a]	–[b]	
Years farming				+[a]	–[b]			–[a]	–[a]	
Crop acres										
Percent land owned	+[b]		–[b]							
Roundup Ready acres							+[a]	–[b]		+[b]
Yield difference	+[b]	+[b]			+[a]		+[b]	+[a]		
Yield CV	–[b]	–[b]			–[a]			–[a]	–[a]	
Herfindahl index										
Custom application		–[b]	–[b]		–[a]					
Crop rep. dist. resistance				–[b]	–[a]					
County weed resistance								+[a]		
Resistance is a concern						–[a]	+[b]		–[a]	–[a]
Soybean								–[a]	–[a]	
Cotton	+[a]					+[b]				
Raises livestock		–[a]						+[b]		
AL									–[b]	
AR				+[a]					+[b]	
GA	–[b]			+[b]						
IL									+[a]	
IN					–[a]	+[a]	+[b]			
KS	+[a]	+[a]	+[a]			+[a]				
LA/MS				+[a]			–[b]			
MN			–[a]		–[a]	+[a]				+[a]
MO			+[b]				+[a]			
NE					–[a]	+[a]				+[b]
NC/SC/VA				+[a]						+[b]
ND					–[a]	+[a]				
OH					–[b]	+[b]				+[a]
SD			–[a]	+[a]		+[b]		–[a]		
TN			+[b]	+[a]						
TX/OK						+[a]	–[a]	–[b]	+[a]	
WI			–[b]					+[a]		
Likelihood P*	0.008	0.000	0.000	0.005	0.000	0.000	0.000	0.000	0.000	0.076

Adoption frequency categories: never, rarely, sometimes, often, always; + denotes variable had a positive and significant impact on frequency of adoption; – denotes variable had a negative and significant impact on frequency of adoption

[a] regression coefficient significant at 5% level; [b] coefficient significant at 10% level

** P-value of likelihood ratio test of null hypothesis that regression coefficients of all explanatory variables = 0* ferent modes of action, practiced weed scouting, and controlled weed escapes. The positive impact of expected yield and the negative impact of yield variability are consistent with the count-data regressions.

Table 6. Significant variables from ordered-probit regressions and their effect on the frequency of adopting weed resistance BMPs.

Explanatory variable	Ordered probit—No state effects		Ordered probit—State effects	
Soybean	Control early (–)	Diff. modes (–)	Diff. modes (–)	Suppl. tillage (–)
Cotton	Scout before (+)	Clean equip. (+)	Scout before (+)	Clean equip.(+)
	Scout after (+)	New Seed (–)		
	Suppl. tillage (+)			
Education	Scout after (+)		Scout after (+)	Clean equip. (–)
			Diff. modes (+)	Suppl. tillage (–)
Years farming	Control early (+)	Diff. modes (-)	Control early (+)	Diff. modes (–)
			Control esc. (–)	Suppl. tillage (–)
Crop acres	Scout before (+)			
% land owned	Scout before (+)		Scout before (+)	Clean field (–)
Roundup Ready acres	New Seed (+)	Label rate (+)	New Seed (+)	Label rate (+)
	Diff. modes (–)	Clean field (–)	Diff. modes (–)	
	Suppl. tillage (–)			
Yield difference	Control esc. (+)	Diff. modes (+)	Scout before (+)	New Seed (+)
			Scout after (+)	Diff. modes (+)
County yield CV	Scout after (–)	Control esc. (–)	Scout before (–)	Control esc. (–)
	Diff. modes (–)		Scout after (–)	Diff. modes (–)
			Suppl. tillage (–)	
Herfindahl index	Clean field (–)	Suppl. till. (+)		
Custom applications	Scout after (–)	Control esc. (–)	Clean field (–)	Control esc. (–)
Resistance in CRD	Control esc. (–)	Diff. modes (–)	Control early (–)	Control esc. (–)
Resistance in county	Diff. modes (+)		Diff. modes (+)	
Resistance a concern	Clean field (+)	Diff. modes (+)	Clean equip. (–)	Suppl. tillage (–)
	Clean equip.(–)	Suppl. till. (–)	New Seed (+)	Label rate (–)
	New Seed (+)			
Raised livestock	Scout after (–)		Scout after (–)	
	Diff. modes (+)			

A higher percentage of acreage planted to RR seed varieties was associated with greater use of new seed and less-frequent use of multiple herbicides with different modes of action. RR acreage was associated with more frequently following herbicide-label rates. Growers expressing a concern about resistance in the open-ended questions used supplemental tillage and cleaned equipment less frequently, but used new commercial seed more frequently. Growers operating in a county with reports of weed resistance more frequently used multiple herbicides with different modes of action.

Conclusions

Although cotton growers adopted BMPs somewhat more frequently, BMP adoption patterns were remarkably similar across crops. For all three crops, adoption rates of the same three BMPs were low. These were cleaning equipment, using multiple herbicides with different modes of action, and supplemental tillage. The other seven BMPs were practiced frequently (often or always) by all three grower types.

Generalized Poisson and negative binomial regression results suggest that factors significantly and positively associated with adopting more BMPs include (a) having more education; (b) having less experience (perhaps being younger?); (c) growing cotton; (d) expecting higher yields relative to the county average; and (e) farming in counties with a lower yield coefficient of variation. In the ordered probits, farming in a county with a larger coefficient of variation of target crop yield *reduced* the probability of frequent adoption of several BMPs. Highly variable production outcomes may hinder the observability and trialability of BMPs (Pannell & Zilberman, 2001). With greater yield variability, it may be more difficult for growers to assess outcomes or benefits of BMP adoption. In contrast, the ratio of a grower's expected yield to the county average yield *increased* the probability of frequent adoption of BMPs. There may be some form of a "good manager" effect at work, where growers with higher yields (or at least higher expected yields) than their neighbors tend to adopt more BMPs more frequently. If BMPs increase current returns by minimizing percent yield loss to weeds, gains from damage reduction would be greater for growers with higher yields.

The survey data suggests that most growers are frequently adopting most BMPs. Extension efforts may thus be more effective by targeting a minority of growers (and a few practices). In particular, counties with a high coefficient of variation of crop yield would be areas to look for low BMP adoption.

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