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Quantifying Adoption Intensity for Weed-Resistance Management Practices and Its Determinants among U.S. Soybean, Corn, and Cotton Farmers

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Using data envelopment analysis with principal components, we calculate an adoption-intensity index for herbicide-resistance best management practices (BMPs). Empirical results for over 1,100 farmers in twenty-two U.S. states suggest that many farmers could improve their herbicide-resistance BMP adoption. Two-limit truncated regression results show that higher yields and a greater proportion of acres planted with Roundup Ready® seeds motivate weed BMP adoption. While soybean and corn farmers have lower adoption intensity than cotton farmers, farmer educational attainment and greater concern for herbicide effectiveness and for human and environmental safety are found to help increase the adoption of weed BMPs.

Key words: adoption intensity, best management practices, common-weight data envelopment analysis, herbicide-resistance management, polychoric non-negative principal component analysis, weed-resistance management

Introduction

Glyphosate is currently the world's most widely used herbicide (Baylis, 2000; Woodburn, 2000). It is highly effective and provides control of a broad spectrum of weeds yet is also toxicologically and environmentally relatively safe (Duke and Powles, 2008). A 2000 survey of Australian grain farmers who were not using genetically engineered varieties found that they valued glyphosate more highly than other herbicides (Llewellyn et al., 2002). In the United States, glyphosate use is closely connected to adoption of Roundup Ready® (RR) crop varieties genetically engineered to tolerate glyphosate applications. Besides convenience, flexibility, safety, and simplicity of weed management, RR crops provide economic benefits to farmers by reducing herbicide expenditures and increasing yield through improved weed control. These benefits have led to widespread adoption of RR and other herbicide-tolerant crops since their U.S. commercial release in 1996 (Bonny, 2008; Brookes and Barfoot, 2008). In 2013, herbicide-tolerant crops accounted for 93% of soybean planted acres, 85% of corn planted acres, and 82% of cotton planted acres in the U.S. (U.S. Department of Agriculture, National Agricultural Statistics Service, 2013), with the vast majority planted to RR varieties.

This widespread use of glyphosate has been accompaned by the evolution and spread of glyphosate-resistant weeds (Norsworthy et al., 2012), as herbicide resistance often develops in

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fields where herbicides with the same mode of action have been sprayed repeatedly. Since the first glyphosate-resistant weed was reported in Victoria, Australia, in 1996, a total of thirty-one weed species have evolved resistance to glyphosate worldwide, with eleven of these identified since 2010 (Heap, 2014). Fourteen weed species with glyphosate-resistant populations have been confirmed in the United States since glyphosate-resistant rigid ryegrass (*Lolium rigidum*) was documented in 1998 (Heap, 2014). By 2012, glyphosate-resistant weeds had infested 25 million hectares of U.S. cropland.[1]

The evolution and spread of glyphosate-resistant weeds may jeopardize the economic and environmental benefits of herbicide-tolerant crops as farmers shift to more frequent tillage and apply more toxic and/or more expensive herbicides (National Research Council, 2010; Price et al., 2011). In response, weed scientists have developed several best management practices (BMPs) for farmers to slow the evolution and spread of herbicide resistance (e.g., Norsworthy et al., 2012; Shaw, 2012). These BMPs generally increase diversity in weed-management systems and include practices such as alternating herbicides with different modes of action and incorporating cultural (e.g., scouting), mechanical (e.g., tillage), and other non-herbicidal weed control practices (e.g., rotation between RR and non-RR crops). However, because of the heterogeneity in the value of weed-resistance management benefits and in adoption costs, farmers have varying degrees of adoption of the various BMPs. For example, Frisvold, Hurley, and Mitchell (2009) find that U.S. farmers are more likely to adopt BMPs with immediate benefits arising from controlled weed populations and improved yield potential. Also, farmers experiencing resistance problems are inclined to adopt BMPs when traditional means of control become less effective. Human capital requirements and greater variability in agronomic and economic outcomes also influence BMP adoption (Frisvold, Hurley, and Mitchell, 2009). Llewellyn et al. (2007) reach similar conclusions regarding integrated weed-management practices in Australia.

Given the importance of herbicide-resistance BMPs, quantitatively identifying factors that enhance adoption is critical for policy makers. However, measuring farmer adoption of multiple, interrelated practices is recognized as a difficult methodological issue in weed and pest management (e.g., McDonald and Glynn, 1994; Llewellyn et al., 2007). Various methods have been used to try to evaluate farmer adoption of multiple practices and further identify factors associated with BMP adoption in the context of pest management. Many of these studies have either analyzed adoption of each practice separately or assigned a score to each farm based on the number of practices adopted. For example, Hammond et al. (2006) and Frisvold, Hurley, and Mitchell (2009) used the total number of practices adopted as a measure, and Llewellyn et al. (2007) considered farmers who adopt three or more out of a possible six practices as adopters. As some BMPs may be correlated with each other, such a measurement is not able to precisely evaluate a farm's adoption intensity. Furthermore, analyzing each practice separately is impractical when the number of BMPs is extensive.

An alternative method is to generate a composite index, which aggregates information on all practices. An important issue when constructing composite indices is how to weight and aggregate a set of variables measuring individual practice adoption. Many studies have assigned equal weights to each variable, even though some practices are recognized to be of greater importance than others and practices are highly correlated (Frisvold, Hurley, and Mitchell, 2009; Hammond et al., 2006). Nardo et al. (2005) pointed out that applying equal weighting to all variables could result in an unbalanced structure of the composite index. When variables are grouped into subgroups and further aggregated into the composite index, applying equal weighting may imply an unequal weighting of the subgroups as the subgroups with the larger number of variables will have higher weights. In addition, aggregating variables with high degree of correlation using equal weights may bring an element of double counting into the composite index (Nardo et al., 2005).

Some studies have assigned weights based on expert opinion, an approach that may be feasible when there is a well-defined basis for a policy (Nardo et al., 2005). However, this method introduces

[1] See the recent editorial: "A Growing Problem" Nature 510:187 (doi:10.1038/510187a).

social preferences regarding individual dimensions of sustainability that may affect the quality and reliability of the analysis (Gómez-Limón and Riesgo, 2009; Jollands, Lermit, and Patterson, 2004). In addition, this method may cause serious cognitive stress to the experts who are asked to allocate the weights to all variables if too many variables are involved (Nardo et al., 2005).

This study combines data envelopment analysis and principal component analysis to create a composite index that endogenously solves for practice weights without resorting to exogenous information or subjective preferences. The method can correct for overlapping information of correlated variables, compare individuals under a common basis, and can be applied to large datasets containing both discrete and continuous variables measuring practice adoption. Furthermore, we use regression analysis to investigate factors affecting BMP adoption intensity. More specifically, we analyze adoption of weed-resistance management BMPs among U.S. soybean, corn, and cotton farmers, since the first commercially successful herbicide-tolerant varieties were developed for these crops and have become popular among farmers.

Data

The data for this analysis are the same weed-resistance management BMP adoption data analyzed by Frisvold, Hurley, and Mitchell (2009). Telephone interviews of U.S. farmers planting at least 250 acres of soybeans, corn, or cotton were conducted in November and December of 2007 in twenty-two different U.S. states. The survey covered a representative random sample of soybean, corn, and cotton farmers. The final data contain responses from 402 soybean farmers, 402 corn farmers, and 401 cotton farmers.

In terms of weed-resistance management BMPs, farmers were asked specifically for the adoption of the following practices:

1. Scouting fields before herbicide applications;
2. Scouting fields after herbicide applications;
3. Starting with a clean field, using either a burndown herbicide application or tillage;
4. Controling weeds early when they are relatively small;
5. Controling weed escapes and prevent weeds from setting seeds;
6. Cleaning equipment before moving from field to field to minimize spread of weed seed;
7. Using new commercial seed 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 recommended application rate from the herbicide label.

Potential responses for how often each BMP was used were “always,” “often,” “sometimes,” “rarely,” and “never.”

In addition to these BMPs analyzed by Frisvold, Hurley, and Mitchell (2009), three variables were constructed for other important weed-management practices to include in this analysis. Because rotation between RR crops and non-RR crops helps reduce the risk of glyphosate resistance, the percentage of the area planted with RR varieties in 2007 following a non-RR crop planted in 2006 (*%RRPostNonRR*) was included as a BMP. In addition, the percentages of the total soybean-, corn-, and cotton-planted area receiving pre-plant burndown herbicides (*%Burndown*) and pre-emergent residual herbicides (*%Residual*) were also included as BMPs.

Table 1. Statistical Description of the Weed-Resistance Management BMP Adoption Data for Farmers Growing Soybeans, Corn, and Cotton ($n = 1,143$)

	Frequency of Adoption (% of Respondents)				
Practice	**Never**	**Rarely**	**Sometimes**	**Often**	**Always**
Scout fields before herbicide application	2.4	2.7	11.4	26.5	57.0
Scout fields after herbicide application	1.5	2.4	15.0	29.7	51.5
Start with clean field, using burndown herbicide application or tillage	7.3	4.7	12.8	14.6	60.6
Control weeds early when small	0.5	1.2	8.5	35.1	54.7
Control weed escapes and prevent weeds from setting seeds	1.8	3.9	15.2	34.0	45.0
Clean equipment before moving between fields	31.5	22.6	20.4	10.8	14.8
Use new commercial seed free from weed seed	1.7	0.7	3.2	6.9	87.5
Use multiple herbicides with different modes of action during season	12.2	15.2	33.9	20.5	18.3
Use tillage to supplement weed control provided by herbicides	31.1	21.3	26.6	10.0	11.0
Use recommended application rate from herbicide label	0.4	0.9	4.5	19.8	74.4

Variable	**Mean**	**St. Dev.**	**Min.**	**Max.**
Percent Roundup Ready area planted after a non-Roundup Ready crop	32.8	41.4	0.0	100.0
Percent planted area treated with a burndown herbicide application	36.4	43.9	0.0	100.0
Percent planted area treated with a residual herbicide application	40.0	45.7	0.0	100.0

Table 1 summarizes farmer responses regarding adoption of these thirteen practices. Data for 379 soybean farmers, 377 corn farmers, and 387 cotton farmers remained after removing those with incomplete or unusable responses. Responses of "never," "rarely," "sometimes," "often," and "always" were coded as 0, 1, 2, 3, and 4, respectively.

The three least-adopted practices were cleaning equipment before moving between fields, using supplemental tillage, and using multiple herbicide modes of action. Variations exist among farmers of different crops. Compared to soybean and corn farmers, relatively more cotton farmers always scouted fields before and after an herbicide application, started with a clean field by using a burndown herbicide application or tillage, and cleaned equipment before moving between fields to minimize weed seed spread. Application of pre-plant burndown herbicides, which averaged 36% among all farmers, was quite different for farmers of the three crops—cotton farmers applied pre-plant burndown herbicides on 56% of their crop versus 35% for soybean and 18% for corn. On average, 40% of total planted area was treated with pre-emergent residual herbicides for all farmers, but soybean farmers treated a smaller percentage of their crop, 22%, compared to 51% for corn and 48% for cotton. Summaries of the thirteen practices for each group of crop farmers are listed in appendix tables A1–A3.

Analytical Methodology

Data envelopment analysis (DEA) has been widely used to create composite indices in a variety of contexts, including measuring human development (Despotis, 2005), quality of life (Hashimoto and Ishikawa, 1993), and farm sustainability (Reig-Martínez, Gómez-Limón, and Picazo-Tadeo, 2011; Dong, Mitchell, and Colquhoun, 2015).

Two problems emerge, however, when applying DEA to BMP adoption data. First, adoption of related BMPs is often highly correlated. For example, practices such as scouting for weeds after an herbicide application and controlling weed escapes are commonly correlated. Correlation among variables reduces the discrimination power of DEA and introduces bias (Nunamaker, 1985; Dyson et al., 2001). Second, BMP adoption surveys commonly offer respondents categories to indicate the degree of adoption, for example, asking how frequently a particular practice is used (e.g., always, often, sometimes, rarely, never) or asking whether or not it is used (e.g., yes, no). The resulting categorical measures of adoption create problems for DEA, such as nonconstant marginal effects for practice adoption and illogical convex combinations of practices (Kolenikov and Angeles, 2009; Rigdon and Ferguson, 1991; Banker and Morey, 1986).

To overcome these problems, we follow the approach of Dong, Mitchell, and Colquhoun (2015) and use principal component analysis (PCA) before the DEA to transform the categorical adoption variables into continuous variables and reduce the correlations among these variables. Because the traditional PCA may generate negative principal components, which are problematic for the DEA, we use polychoric non-negative PCA based on the polychoric correlation coefficient to ensure that all the principal component weights are non-negative (Dong, Mitchell, and Colquhoun, 2015).

Polychoric Non-negative PCA

Let $\boldsymbol{X} \in R^{V\times K}$ be the matrix of the original adoption data composed of variables with V rows and K columns, where $v = 1$ to V indexes the variables measuring practice adoption, $k = 1$ to K indexes farmers, and each element x_{vk} is the observation of variable v for farmer k. Divide each observation x_{vk} by each variable's standard deviation σ_v to form the normalized data matrix $\tilde{\boldsymbol{X}} \in R^{V\times K}$ with elements $\tilde{x}_v = x_{vk}/\sigma_v$. Non-negative polychoric PCA solves for the weight matrix $\boldsymbol{U} \in R^{V\times I}$ used to calculate $\boldsymbol{Y} = \boldsymbol{U}^{\boldsymbol{T}}\tilde{\boldsymbol{X}}$, where $\boldsymbol{U} \geq 0$ is the principal vectors constrained so that all elements are positive and $\boldsymbol{Y} \in R^{I\times K}$ is the matrix of the $I \leq V$ principal components retained for subsequent DEA. Each element of $\boldsymbol{Y}$ is $y_{ik} = \sum_{v=1}^{V} u_{vi}\tilde{x}_{vk}$, where $u_{vi} \in \boldsymbol{U}$ is the weight for variable v for principal component i, and $i = 1$ to $I \leq V$ indexes retained principal components. Non-negative polychoric PCA ensures that each y_{ik} is continuous and non-negative and that all of the principal components are uncorrelated with one another. Dong, Mitchell, and Colquhoun (2015) describe the optimization process for finding the weight matrix $\boldsymbol{U}$ in more detail.

Data Envelopment Analysis with Common Weights

Following Dong, Mitchell, and Colquhoun (2015), we use the common-weight DEA approach, originally proposed by Despotis (2005), because it has more discriminating power than basic DEA. Common-weight DEA solves the following mathematical programming model:

$$\begin{gathered} \text{Minimize } h(d_k, \omega_i, z) = t\frac{1}{K}\sum_{k=1}^{K} d_k + (1-t)z \\ \text{subject to } S_k^b - \sum_{i=1}^{I}\omega_i y_{ik} = d_k,\ d_k \geq 0,\ z - d_k \geq 0\ \forall\, k,\ \omega_i \geq \varepsilon\ \forall\, i,\ z \geq 0. \end{gathered} \tag{1}$$

For farmer k, $d_k = S_k^b - \sum_{i=1}^{I}\omega_i y_{ik}$ is the deviation of the common-weight DEA adoption-intensity score $\sum_{i=1}^{I}\omega_i y_{ik}$ from the basic DEA adoption-intensity score, S_k^b; y_{ik} is the value of the ith principal component for farmer k, and ω_i is the common weight for the ith principal component. The common weight ω_i must be strictly positive ($\omega_i \geq \varepsilon$), where ε is the infinitesimal. The deviation d_k must be non-negative ($d_k \geq 0$) and cannot exceed z, the maximum deviation over all farmers ($z - d_k \geq 0$), which also must be non-negative ($z \geq 0$). Finally, the parameter $0 \leq t \leq 1$ determines the weight for the average and maximum deviations in the objective function.

For this analysis, t is varied from 0 to 1 with a step size of 0.01 and model (1) is solved, with each value of t giving the adoption-intensity score $S_{kt} = \sum_{i=1}^{I} \omega_{it} y_{ik}$ for each farmer k. The final BMP adoption-intensity score for each farmer k is then the average of these scores over all values of t:

$$\overline{S}_k = \frac{1}{T}\sum_{t=0}^{1} S_{kt} = \frac{1}{T}\sum_{t=0}^{1}\sum_{i=1}^{I} \omega_{it} y_{ik} = \sum_{i=1}^{I} \overline{\omega}_i y_{ik}, \tag{2}$$

where T is the total number of different values used for t (e.g., $T = 101$ with $t = 0$ to 1 and a step size of 0.01) and $\overline{\omega}_i = \frac{1}{T}\sum_{t=0}^{1} \omega_{it}$ is the average weight for the ith principal component over all values of t. In terms of interpretation, each farmer's score $0 \leq \overline{S}_k \leq 1$ is a measure indicating how intensely farmer k has adopted the BMPs relative to the farmers in the group, with scores of 1.0 implying that farmer k is on the frontier (i.e., among those most intensely adopting the BMPs).

Substitute $y_{ik} = \sum_{v=1}^{V} u_{vi}\tilde{x}_{vk}$ and $\tilde{x}_{vk} = x_{vk}/\sigma_v$ into equation (2):

$$\overline{S}_k = \sum_{v=1}^{V}\sum_{i=1}^{I} (\overline{\omega}_i u_{vi}/\sigma_v) x_{vk} = \sum_{v=1}^{V} w_v x_{vk}, \tag{3}$$

where $w_v = \sum_{i=1}^{I} \overline{\omega}_i u_{vi}/\sigma v$ is the weight for each original variable, which depends on the PCA weights, the DEA weights, and the standard deviation of the original variable. This expression for w_v indicates how changing adoption of a specific practice x_{vk} changes a farmer's adoption-intensity score, holding adoption for all other practices for all other farmers constant.

This combined PCA-DEA approach provides a theoretical and empirical basis for deriving endogenous weights for each practice, rather than some type of subjective weights for each practice. Based on these weights, a composite index of BMP adoption intensity is calculated for each farmer.

Two-Limit Truncated Regression

To investigate exogenous factors affecting farmer BMP adoption-intensity scores, we use truncated regression and bootstrapping techniques. The regression model is

$$\overline{S}_k = \beta_0 + \sum_{n=1}^{N} \beta_n Z_{nk} + e_k, \tag{4}$$

where Z_{nk} is the nth independent variable for farmer k, β_n is the coefficient to estimate for $n = 1$ to N, and e_k is the corresponding error term. The dependent variable $\overline{S}_k$ is the adoption-intensity score and bounded between 0 and 1, so a two-limit truncated regression is used. Following Simar and Wilson (2007), we use a bootstrap procedure with 1,000 replications to estimate bias-corrected standard errors consistent with the data-generating process.

Table 2 summarizes the variables used as independent variables in the regression. Farmer educational attainment (*Education*) and years of farming experience (*Experience*) capture the effects of different types of human capital. In addition, variables for different measures of operation characteristics were also used. The acres of the target crop planted (*CropArea*) is a measure of farm size. Because herbicide-resistant weeds have potential long-term impacts on land productivity and value, the percentage of land owned (*%Own*) is included in the regression. Similarly, the percentage of herbicide applications made by custom applicators (*%CustomApp*) is included because custom applicators potentially have access to broader information sets but also have different incentives.

The variation of county's average yield for the previous ten years (*YieldCV*) measures the geographic variation in systemic yield risk, and the percentage difference between a farmer's

Table 2. Statistical Description of Variables Used to Analyze Adoption-Intensity Scores

Variable	Description	Mean (St. Dev.)
Education	Operator has college or advanced degree (Yes=1, No=0)	0.34
		(0.48)
Experience	Years managing farming operation	29.56
		(12.15)
CropArea	Acres of target crop plant in 2007	1425.51
		(1,202.93)
%Own	% of operated land owned by farmer	41.00
		(32.27)
%CustomApp	% of herbicide applications made by custom applicator	28.67
		(42.35)
YieldCV	Coefficient of variation for county average yield	0.18
		(0.09)
YieldDiff	% farm average yield deviates from county average	22.48
		(51.26)
Livestock	Raise commercial livestock (Yes=1, No=0)	0.36
		(0.48)
CropDiversity	Herfindahl index of crop diversity	0.61
		(0.22)
ValueRR	Reported additional value ($US/acre) from planting RR crop in 2007	26.24
		(33.29)
ResistanceConcern	Mentioned concern with herbicide-resistant weeds (Yes=1, No=0)	0.51
		(0.50)
%RR	% of acres were planted in Roundup Ready	0.82
		(0.34)
Soybeans	Planting soybeans (1 if soybeans planted; 0 otherwise)	0.33
		(0.47)
Corn	Planting corn (1 if corn planted; 0 otherwise)	0.33
		(0.47)
Cotton	Planting cotton (1 if cotton planted; 0 otherwise)	0.34
		(0.48)

reported expected yield and the county-average yield (*YieldDiff*) measures farm's relative land quality. A Herfindahl index (HHI) of each farm's crop diversity (*CropDiversity*) and an indicator variable for farm livestock production (*Livestock*) are included to reflect enterprise diversity. The HHI ranges from 0.25 if the farmer splits crop land equally among corn, cotton, soybean, and other crops and 1.0 if the farmer plants all crop land to a single crop. Crop indicator variables (*Soybeans*, *Corn*, *Cotton*) were used to capture any crop-specific fixed effects. The *ValueRR* variable is the additional value per hectare each farmer reported deriving from planting RR crops instead of conventional crops. Because planting a RR crop may also affect weed BMP adoption, we include the percentage of total acres planted to RR crops (*%RR*).

At the end of the telephone survey, respondents were asked an open-ended question about their most important concerns regarding weed management. An indicator variable was constructed from these responses to denote whether or not the farmer mentioned herbicide-resistant weeds: *ResistanceConcern* equals 1 if the farmer mentioned resistance and 0 otherwise. The survey did not mention or ask about herbicide resistance, so this response variable is unprompted. Finally, indicator variables for the state where the farm is located were used to capture state-level fixed effects, with farmers in Missouri used as the base for comparison. Table 3 summarizes the state data.

Table 3. Statistical Description of State Indicator Variables Used to Analyze Adoption-Intensity Scores

Variable	Description	Mean (St. Dev.)
AL	Alabama	0.022
		(0.15)
AR	Arkansas	0.041
		(0.20)
GA	Georgia	0.028
		(0.17)
IL	Illinois	0.120
		(0.32)
IN	Indiana	0.065
		(0.25)
IA	Iowa	0.121
		(0.33)
KS	Kansas	0.014
		(0.12)
LAMS	Louisiana or Mississippi	0.022
		(0.15)
MN	Minnesota	0.083
		(0.28)
MO	Missouri	0.062
		(0.24)
NCSCVA	North Carolina, South Carolina or Virginia	0.030
		(0.17)
NE	Nebraska	0.065
		(0.25)
ND	North Dakota	0.020
		(0.14)
OH	Ohio	0.043
		(0.20)
SD	South Dakota	0.046
		(0.21)
TN	Tennessee	0.020
		(0.14)
TXOK	Texas or Oklahoma	0.175
		(0.38)
WI	Wisconsin	0.020
		(0.14)

Notes: Equals 1 if farmer operates in the indicated state(s) and 0 otherwise.

The survey also contained thirteen questions asking farmers about the importance of various herbicide characteristics and concerns when selecting herbicides. Respondents were asked to rank each characteristic or concern as "not at all important," "not too important," "neither important nor unimportant," "somewhat important," or "very important" when selecting herbicides for weed control in the three crops, with responses coded as 0, 1, 2, 3, and 4, respectively. Table 4 summarizes farmer responses to these thirteen questions. Because responses were highly correlated and categorical, we used polychoric PCA to reduce data dimensions and to create variables for use in the two-limit truncated regression. Based on an eigenvalue-one criterion, three principal components were retained, which accounted for 58% of total variance. The first principal component is accounted for by questions 9 to 13 and is associated with concern for human and environmental safety. The

Table 4. Statistical Description of Variables Measuring Farmer Concerns When Choosing Herbicides, Which Are Used to Analyze Adoption-Intensity Scores

	Frequency (% of Respondents)				
Concerns When Choosing Herbicides	Not at All Important	Not Too Important	Neither Important nor Unimportant	Somewhat Important	Very Important
1. Cost of herbicide application	0.27	0.8	1.42	30.22	67.29
2. Reducing yield loss due to weed competition	0	0	0.09	4.44	95.47
3. Consistency of herbicide effectiveness controlling weeds	0	0	0	3.64	96.36
4. Reducing number of herbicide applications	0.09	0.98	1.33	31.47	66.13
5. Crop safety	0.09	0.36	0.09	7.64	91.82
6. Having a clean field	0	0.09	0.53	17.07	82.31
7. Time needed to apply the herbicide	0.71	2.4	3.38	43.64	49.87
8. Flexibility of application timing	0.09	0.44	0.53	34.04	64.89
9. Personal, family, and employee health	0.36	0.44	0.27	4.71	94.22
10. Public health	1.16	0.98	0.89	15.2	81.78
11. Effect of herbicide on wildlife	3.02	3.56	4.18	37.07	52.18
12. Effect of herbicide on water quality	1.24	2.04	1.33	19.56	75.82
13. Erosion control	2.4	3.56	2.67	24.27	67.11

second principal component is accounted for by questions 2 and 3 and is associated with concern for effective weed control. The third is accounted for by questions 4 and 7 and is associated with concern for managerial time. These three principal components are included as explanatory variables in the regression of weed BMP adoption-intensity scores.

Results and Discussion

Weed BMP Adoption Intensities

We applied this PCA-DEA approach to the thirteen variables from the soybean, corn, and cotton farmer survey summarized in table 1. We first conducted polychoric non-negative PCA on the normalized weed BMP adoption data to reduce correlations among the adoption variables and to convert categorical variables to be continuous. Because thirteen variables are not excessive for DEA, the primary purpose of the PCA for this analysis is to remove correlations among variables and to generate nondiscrete positive principal components. As a result, twelve principal components were retained, accounting for 95% of the total variance in the original data. We next conducted common-weight DEA for the twelve non-negative principal components by solving model (1) with t ranging from 0.00 to 1.00 with a step size of 0.01.

Table 5 lists the average and the minimum weed BMP adoption-intensity scores as well as scores at the three quartiles. Across all farmers, the lowest adoption-intensity score is 0.450 and the average

Table 5. Statistics Describing Weed BMP Adoption-Intensity Scores for Farmers Growing Soybeans, Corn, and Cotton

Average	0.897
Standard Deviation	0.104
Minimum	0.450
25% Quartile	0.843
50% Quartile	0.926
75% Quartile	0.983

Table 6. Statistics Describing Weed BMP Adoption-Intensity Scores for Farmers Growing Soybeans, Corn, and Cotton

Practice	Final Weights
Scout fields before herbicide application	0.0121
Scout fields after herbicide application	0.0048
Start with clean field, using burndown herbicide application or tillage	0.0007
Control weeds early when small	0.0580
Control weed escapes and prevent weeds from setting seeds	0.0012
Clean equipment before moving between fields	0.0017
Use new commercial seed free from weed seed	0.0819
Use multiple herbicides with different modes of action during season	0.0002
Use tillage to supplement weed control provided by herbicides	0.0000
Use recommended application rate from herbicide label	0.0878
Percent Roundup Ready area planted following a non- Roundup Ready crop	0.0000
Percent planted area treated with a burndown herbicide application	0.0065
Percent planted area treated with a residual herbicide application	0.0000

is 0.897. In terms of quartiles, 25% of farmers had adoption-intensity scores exceeding 0.983, half exceeding 0.926 and 75% exceeding 0.843. These results imply that most farmers performed similarly in terms of adopting the weed-resistance management BMPs analyzed here, but there was still potential for many farmers to improve. For example, 25% of farmers had adoption-intensity scores of less than 0.843, suggesting that these farmers could increase their BMP adoption by at least 15 percentage points relative to the best farmers who defined the DEA frontier.

Figure 1 presents the histogram of the adoption-intensity scores for all the farmers. Results show that 41% of farmers had adoption-intensity scores exceeding 0.95, but 8% had BMP adoption-intensity scores of less than 0.75. To show the dispersion of scores across crops, figure 2 separately presents the BMP adoption scores for soybeans, corn, and cotton farmers. Compared to cotton farmers, relatively more corn and soybean farmers were in the middle of the score distribution and relatively fewer in the upper and lower tails. These results indicate that farmers were heterogeneous in terms of adopting weed-management BMPs across and within crop groups, so that regression analysis could potentially identify factors associated with this heterogeneity.

Table 6 reports the weight for each BMP as calculated by equation (3), indicating the importance of each practice for farmer adoption-intensity scores. The weights in table 6 are endogenous and depend on the practice adoption of all farmers, so that, conceptually, these weights would change if a single farmer changed adoption of a practice. Thus, interpretation of these weights as marginal effects—how much adoption of a practice contributes to the total score—depends on the practice adoption of all other farmers. Therefore, the standard *ceteris paribus* qualification is somewhat

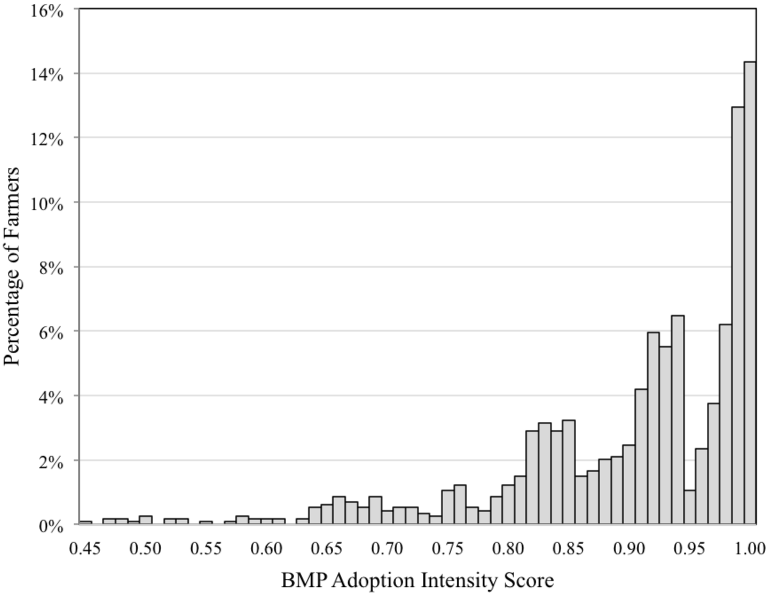

Figure 1. Histogram of Weed-Resistance Management BMPs Adoption-Intensity Scores for All Farmers

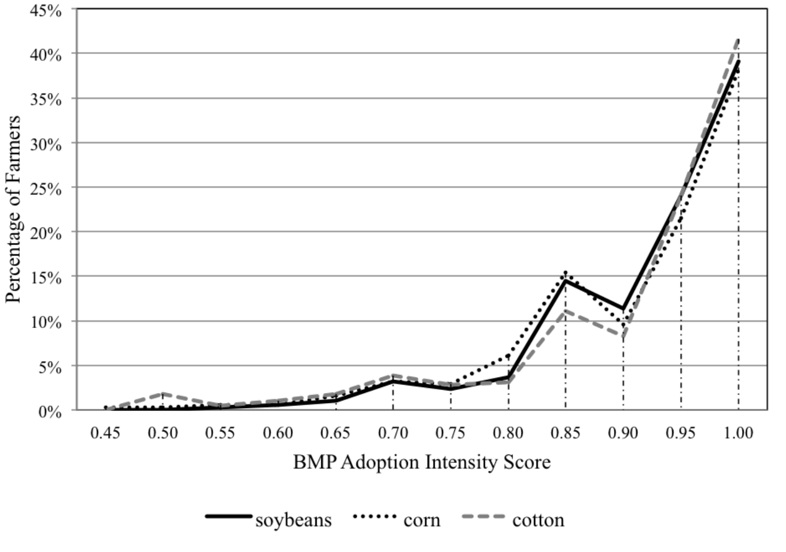

Figure 2. Weed-Resistance Management BMPs Adoption-Intensity Scores for Corn, Soybean and Cotton Farmers

different than in other types of analysis. To gain some sense of the impact, see Dong et al. (2015), who explore how a small subset of farmers changing their practice adoption changes the scores of the other farmers.

In table 6, using the recommended application rate on the herbicide label is the main practice affecting the weed-resistance management practice adoption-intensity score, followed by using new commercial seed as free from weed seed as possible. In terms of interpretation, these weights are the increase in a farmer's adoption-intensity score for increasing adoption of the practice by one unit (e.g., switching from "often" to "always"). As table 1 shows, these two practices have the greatest percentage of "always" being used by the surveyed farmers. As a result, the PCA-DEA method gives them relatively large weights because they are the practices that help differentiate the few farmers who do not use them from the majority of farmers. The weights also depend on the standard deviations of practice adoption, so controlling weeds early when they are small also receives a relatively large weight, since most farmers report using this practice "often" or "always." Finally, the percentage of the planted area treated with a burndown herbicide application also has a relatively large weight. Specifically, a ten-percentage-point increase in the area treated with a burndown herbicide would increase a farmer's adoption-intensity score by 0.0650.

These weights also indicate the practices for which nonadoption has the largest negative impact on a farmer's adoption-intensity score. Farmers who do not use recommended herbicide application rates, plant weed-free commercial seed, do not control weeds early when they are small, or do not scout fields before herbicide application have the lowest adoption-intensity scores. Increasing adoption of these practices among nonadopting farmers would have the largest positive impact on the distribution of scores in figure 1, indicating good targets for outreach and/or incentive programs.

Determinants of BMP Adoption Intensity

Two-limit truncated regression results are summarized in table 7. Interestingly, regression results find no significant effect on weed BMP adoption-intensity scores for several variables, such as the percentage of operated land owned by the farmer (*%Own*), whether the farmer mentioned concern about herbicide-resistant weeds (*ResistanceConcern*), and the farmer's years of farming experience (*Experience*). One possible reason for the insignificant effect for these variables may be that some of the farmers are not aware of the herbicide-resistance BMPs and thus do not adopt them, suggesting that educating farmers about herbicide-resistance BMPs is important.

The percentage difference between a farmer's reported expected yield and the county's average yield (*YieldDiff*) is positively associated with weed BMP adoption, which is consistent with the notion that farmers with better-quality land adopt more weed BMPs in an effort to preserve the productivity of that land. The significant negative, though relatively small, effect for *CropArea* conforms to the more intense time constraints faced by larger farms that preclude opportunities for BMPs adoption since many BMPs require additional labor or management times. Farmer education is positively associated with weed BMP adoption, possibly because they better understand their importance or are better able to manage more complex production systems. In addition, the proportion of RR acres (*%RR*) was positively associated with weed BMP adoption, which is consistent with a linkage between RR crops and weed resistance to glyphosate and the idea that farmers planting more RR seeds are more careful in weed-resistance management. Only one state effect was significant, showing that, compared with farmers in Missouri, those in Texas and Oklahoma had higher weed BMP adoption intensities. The negative effects for the corn and soybean indicator variables in table 7 imply that corn and soybean farmers adopted weed BMPs at a lower intensity relative to their peers growing cotton, with scores on average about 0.04 lower. Figure 2 shows the distribution of these score differences by crop to provide a more nuanced description. The three curves are fairly similar, but there are more cotton farmers than corn and soybean farmers among farmers with very high or very low scores. Farmers with scores in the middle, ranging from 0.75 to 0.95, show the reverse, with more corn and soybean farmers than cotton farmers in this range.

Table 7. Bootstrapped Two-Limit Truncated Regression Results for Determinants of BMP Adoption-Intensity Scores

		Bias-Corrected 90% Confidence Interval	
	Coefficient	Lower Bound	Upper Bound
Intercept	0.4540	0.2839	0.6150
Education	0.0234*	0.0109	0.0343
Experience	0.0003	−0.0002	0.0008
CropArea	-5.1×10^{-6}*	-1.1×10^{-5}	-2.7×10^{-8}
%Own	0.0057	−0.0106	0.0253
%CustomApp	-2.3×10^{-5}	−0.0002	0.0001
YieldCV	−0.1025	−0.2174	0.0085
YieldDiff	0.0002*	4.7×10^{-4}	0.0003
Livestock	0.0032	−0.0078	0.0142
CropDiversity	−0.0354	−0.0731	0.0018
ValueRR	-3.6×10^{-5}	−0.0002	0.0002
ResistanceConcern	0.0072	−0.0022	0.0191
%RR	0.0395*	0.0122	0.0690
Soybeans	−0.0443*	−0.0740	−0.0141
Corn	−0.0442*	−0.0786	−0.0118
TXOK[a]	−0.0530*	−0.0855	−0.0214
1st Principal Component[b]	0.0103*	0.0070	0.0135
2nd Principal Component[b]	0.0087*	0.0034	0.0138
3rd Principal Component[b]	−0.0022	−0.0074	0.0025

Notes: Single asterisk (*) indicates significance at the 10% level.
[a]Only statistically significant state effects are listed.
[b]Using variable numbers in table 6, the first principal component was accounted for by questions 9 to 13 and associated with concern for human and environmental safety; the second by questions 2 and 3 and associated with concern for effective weed control; and the third by questions 4 and 7 and associated with concern for managerial time.

In table 7, the results for the first principal component, associated with greater concern for human health and environmental impacts when choosing herbicides, were positive and significant, suggesting that concerns about the human and environmental health effects of herbicides are positively associated with higher weed BMP adoption intensities. The second principal component, associated with concern for effective weed control, also had a positive and significant effect, implying that concerns about weed control effectiveness are also positively associated with weed BMP adoption intensities, which would be consistent with attempts to preserve the longer-term effectiveness of herbicides.

In summary, the results in table 7 show significant positive associations between the intensity of adoption of weed-resistance management practices and above-average yields, proportion of Roundup Ready® crop acres, education, less crop acreage, and concerns about herbicide effectiveness and human and environmental health when choosing herbicides. Furthermore, cotton farmers on average have higher adoption-intensity scores than corn and soybean farmers, but, as figure 2 shows, this difference varies depending on the adoption-intensity score. Finally, we found little evidence of significant difference among the states.

These results are also suggestive of the types of farmers to target in order to increase the general level of adoption of weed-resistance management practices. Specific targets would be less educated farmers with average to below-average yields who still plant a substantial portion of non-Roundup Ready® seed as well as corn and soybean farmers (as opposed to cotton famers). In addition, farmer concerns affect adoption behavior, and these concerns can be influenced by outreach and advertising programs and thus have indirect effects on adoption of weed-resistance management BMPs. Specifically, these results suggest that efforts to increase concern for the human and environmental health impacts of herbicides would help increase weed BMP adoption, as would efforts to increase farmer interest in achieving or maintaining more effective weed control.

Comparisons and Conclusions

The emergence and spread of glyphosate-resistant weeds is jeopardizing the economic and environmental benefits of herbicide-tolerant crops. Weed scientists have developed several best management practices (BMPs) to slow the evolution and spread of herbicide-resistant weeds (e.g., Norsworthy et al., 2012; Shaw, 2012), and increasing farmer adoption of weed-resistance management BMPs is an important priority for several stakeholders. Identifying factors that enhance BMP adoption is critical for developing effective policies, but measuring adoption of multiple, interrelated practices is recognized as a difficult methodological issue in weed and pest management (e.g., McDonald and Glynn, 1994; Llewellyn et al., 2007). Various methods have been used to evaluate adoption of multiple practices and identify factors associated with their adoption in the context of pest management. Here we introduce another method.

This study uses a common-weight DEA score to measure BMP adoption intensity, first using non-negative principal component analysis to pre-process the adoption data to remove correlation. Two-limit truncated regression is then used to identify the effect of exogenous factors on this score. This method provides an alternative to more standard methods by endogenously solving for the weights for each practice, in contrast to methods assigning equal or subjective weights. This method not only ranks farms in terms of weed BMP adoption intensity and generates a composite index as a score for each farm but also indicates the importance of each practice in determining this composite score. An advantage of the method is the convenience of a single index measure of BMP adoption intensity that integrates across multiple interrelated practices and can be analyzed using regression. For some sense of the differences and other advantages of this method, we compare our results to those of Frisvold, Hurley, and Mitchell (2009), who analyzed these same data.

Frisvold, Hurley, and Mitchell (2009) used a count-data regression to identify the factors affecting the total number of weed resistance BMPs used "often" or "always." The count-data model implies equal weight for each practice and becomes unusable when there are continuous variables among the data measuring BMP adoption. In contrast, our analysis used DEA to develop a composite index of BMP adoption intensity using the full range of farmer responses (i.e., not just a binary variable for using each practice often or always) and added three more practices measured with continuous variables (the variables in the bottom portion of table 1).

Frisvold, Hurley, and Mitchell (2009) also conducted an ordered-probit regression to evaluate effects of covariates on the adoption of each BMP individually (i.e., not a multivariate ordered-probit). This method is practical when there are few practices, but with ten practices and fifteen covariates, interpreting the 150 coefficients becomes difficult, even without the state effects for each practice (see tables 5 and 6 in Frisvold, Hurley, and Mitchell, 2009). In contrast, the method used here works on large datasets containing both discrete and continuous variables for BMP adoption and is fairly intuitive to interpret.

Despite using slightly different sets of BMPs and different measures of BMP adoption, some of the same variables had statistically significant effects with the same signs in both analyses. Specifically, more educated farmers with above-average yields used more weed-resistance management BMPs, as did cotton farmers compared to corn and soybean farmers. However, the number of acres operated had opposite effects in the two studies (though the impact was quite small in our results). On the other hand, the principal components we used for grower concern for human and environmental health and for herbicide effectiveness both had positive and significant impacts on BMP adoption intensity, but Frisvold, Hurley, and Mitchell (2009) did not include these as covariates. Similarly, they found that having herbicide-resistant weeds in a farmer's crop-reporting district had a negative and significant effect on the number of BMPs adopted, but our analysis did not use this covariate because of endogeneity concern.

Our results suggest that the pertinent factors driving farmer adoption of weed-resistance management practices include not only farmer and operation characteristics such as educational attainment, the intensity of Roundup Ready® crop use, and average yield but also farmer attitudes and concerns when choosing herbicides. More specifically, our results suggest that farmers with below-average yields and below-average adoption rates of Roundup Ready® crops use fewer weed-resistance management practices compared to cotton farmers. In addition, farmers with concerns about herbicide resistance do not adopt BMPs, possibly because they do not know the BMPs. As a result, educational outreach programs and/or incentive programs targeted at increasing farmer use of weed-resistance management practices should focus more on farmers who do not know much about BMPs and corn and soybean farmers with less education, below-average yields, and who plant relatively smaller amounts of Roundup Ready® crops. Because farmer concerns also impact behavior, outreach and promotion programs to increase farmer concern for the human health and environmental impacts of herbicides and farmer interest in maintaining effective weed control would help increase weed BMP adoption.

This analysis is based on a survey conducted in 2007; given the rapid spread of herbicide-resistant weed since then, farmer awareness and concern about herbicide-resistant weeds and their management practices have likely changed. Repeating this survey would likely find shifts in weed BMP adoption, as well as more and different variables with significant effects on farmer weed BMP adoption intensities. Such a study could prove particularly enlightening, especially if the same farmers were surveyed a second time.

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Appendix

Table A1. Statistical Description of the Weed-Resistance Management BMP Adoption Data for Farmers Growing Soybeans ($n = 379$)

	Frequency of Adoption (% of Respondents)				
Practice	**Never**	**Rarely**	**Sometimes**	**Often**	**Always**
Scout fields before herbicide application	1.1	1.6	10.3	31.7	55.4
Scout fields after herbicide application	1.3	2.9	14.5	32.5	48.8
Start with clean field, using burndown herbicide application or tillage	9.8	5.5	12.9	15.3	56.5
Control weeds early when small	0.3	1.3	10.6	36.9	50.9
Control weed escapes and prevent weeds from setting seeds	2.4	3.7	14.0	31.7	48.3
Clean equipment before moving between fields	34.8	26.1	18.5	10.0	10.6
Use new commercial seed free from weed seed	1.1	0.3	1.9	5.5	91.3
Use multiple herbicides with different modes of action during season	18.5	20.1	33.3	14.5	13.7
Use tillage to supplement weed control provided by herbicides	37.2	23.0	24.5	7.7	7.7
Use recommended application rate from herbicide label	0.5	0.3	3.7	21.1	74.4

Variable	Mean	St. Dev.	Min.	Max.
%RRPostNonRR	51.0	43.6	0.0	100.0
%Burndown	34.7	43.7	0.0	100.0
%Residual	21.9	38.1	0.0	100.0

Table A2. Statistical Description of the Weed-Resistance Management BMP Adoption Data for Farmers Growing Corn ($n = 377$)

	Frequency of Adoption (% of Respondents)				
Practice	**Never**	**Rarely**	**Sometimes**	**Often**	**Always**
Scout fields before herbicide application	4.2	4.2	14.3	25.2	52.0
Scout fields after herbicide application	1.9	1.9	17.5	32.6	46.2
Start with clean field, using burndown herbicide application or tillage	8.2	5.6	12.2	15.9	58.1
Control weeds early when small	1.1	1.9	7.7	32.9	56.5
Control weed escapes and prevent weeds from setting seeds	1.9	6.4	16.7	32.6	42.4
Clean equipment before moving between fields	35.8	25.7	20.7	8.2	9.6
Use new commercial seed free from weed seed	1.3	0.3	3.2	5.8	89.4
Use multiple herbicides with different modes of action during season	6.6	12.2	31.6	27.3	22.3
Use tillage to supplement weed control provided by herbicides	30.0	22.3	25.7	10.1	11.9
Use recommended application rate from herbicide label	0.8	0.8	5.6	20.7	72.2

Variable	**Mean**	**St. Dev.**	**Min.**	**Max.**
%RRPostNonRR	29.0	40.4	0.0	100.0
%Burndown	17.9	32.9	0.0	100.0
%Residual	50.6	45.0	0.0	100.0

Table A3. Statistical Description of the Weed-Resistance Management BMP Adoption Data for Farmers Growing Cotton ($n = 387$)

	Frequency of Adoption (% of Respondents)				
Practice	**Never**	**Rarely**	**Sometimes**	**Often**	**Always**
Scout fields before herbicide application	2.1	2.3	9.6	22.7	63.3
Scout fields after herbicide application	1.3	2.3	12.9	24.0	59.4
Start with clean field, using burndown herbicide application or tillage	3.9	3.1	13.2	12.7	67.2
Control weeds early when small	0.3	0.5	7.2	35.4	56.6
Control weed escapes and prevent weeds from setting seeds	1.3	1.8	15.0	37.7	44.2
Clean equipment before moving between fields	24.0	16.0	22.0	14.0	24.0
Use new commercial seed free from weed seed	2.6	1.6	4.7	9.3	81.9
Use multiple herbicides with different modes of action during season	11.4	13.4	36.7	19.6	18.9
Use tillage to supplement weed control provided by herbicides	26.4	18.6	29.5	12.1	13.4
Use recommended application rate from herbicide label	0.0	1.6	4.4	17.6	76.5

Variable	**Mean**	**St. Dev.**	**Min.**	**Max.**
%RRPostNonRR	18.8	32.8	0.0	100.0
%Burndown	56.1	45.3	0.0	100.0
%Residual	47.5	47.8	0.0	100.0