Quantifying Farmer Adoption Intensity for Weed Resistance Management Practices and Its Determinants

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Abstract

Given the importance of adopting weed resistance management BMPs, it is important to develop methods to compare BMP adoption among farms and to identify factors that affect BMP adoption. Because of the relatively large number of BMPs and interactions among them, a composite index that integrates and aggregates over all practices is a necessary measure. We use data envelope analysis (DEA) to develop a measure of farmer adoption intensity for a set of interrelated BMPs. In addition, we use polychoric principal component analysis before applying the common-weight DEA method of Despotis to remove correlation among variables and transform categorical variables to continuous ones that fit better in DEA. We applied the method to survey data from soybean growers from ten states in the central and southern U.S. The empirical results suggest that most growers adopt most of the practices, but that there is room for improvement. In addition, we found a significant negative effect on BMP adoption intensity scores for growers who more highly valued the RR trait in soybeans and positive effects for growers who were concerned about herbicide resistant weeds and cost and crop safety when making herbicide decisions.

Introduction

Herbicide-tolerant (HT) crops provide economic benefits to growers such as reduced herbicide costs and increased yield due to improved weed control. These benefits, when combined with benefits such as simplicity of weed management, convenience, flexibility and safety, have led to widespread grower adoption of HT crops since commercial introduction in 1996 (Carpenter and Giannessi 1999; Marra et al. 2002; 2004; Bonny 2008; Brookes and Barfoot 2008; Piggott and Marra 2008; Sydorovych and Marra 2008). In 2011, HT crops accounted for 94% of soybean planted acres, 73% of cotton planted acres, and 72% of corn planted acres in the U.S (USDA-NASS 2012; Figure 1). The vast majority of this acreage was planted with Roundup Ready® (RR) varieties that can tolerate applications of glyphosate.

Accompanying this widespread adoption of HT crops has been the evolution and spread of weed resistance to herbicides, including glyphosate resistance (Norsworthy et al. 2012). By 2008, nine weed species with glyphosate resistant populations were documented in 19 states, including major corn, cotton, and soybean producing states (Hurley et al. 2009b). The development and spread of glyphosate resistance jeopardizes both the economic and environmental benefits of HT crops as farmers shift to more frequent tillage and applying more toxic and/or more expensive herbicides. News outlets have covered the problem, including an ABC News prime time story “Super Weed Can’t Be Killed” in 2009.[1] The U.S. House of Representatives’ Committee on Oversight and Government Reform held hearings in 2010 on the

[1] ABC News prime time story “Super Weed Can’t Be Killed” October 26, 2009. Online: http://abcnews.go.com/WNT/video?id=8767877.

problem.[2] More recently, the National Academy of Sciences recently convened a national summit on strategies to manage herbicide resistant weeds.[3]

Weed scientists have developed several best management practices (BMPs) to help slow the development of herbicide resistance among weed populations (see Norsworthy et al. (2012) for a full description or the summary of Shaw (2012)). However, due to heterogeneity in the value of weed resistance management benefits and in adoption costs, farmers have varying degrees of adoption of the different BMPs. For example, Frisvold et al. (2009) find that growers are more likely to adopt BMPs with immediate benefits from controlling current weed populations and higher potential yields, while growers experiencing resistance problems tend to adopt BMPs as their traditional means of control are less effective. Moreover, human capital requirements and greater variability in agronomic and economic outcomes also influence BMP adoption (Frisvold et al. 2009).

Given the importance of adopting weed resistance management BMPs, developing methods to compare BMP adoption among farms and to identify factors that affect BMP adoption would be useful. Because of the relatively large number of BMPs and interactions among them, a composite index that integrates and aggregates over all practices could be particularly helpful as a measure of weed resistance management BMP adoption intensity. At the farm-level, this composite indicator would measure each farm's BMP adoption intensity relative to its peers. At the aggregate level, the properties of the distribution of all the composite indicators describe how a farm population is performing as a whole and this performance can be tracked over time, particularly in response to policies, programs, or other changes.

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[2] U.S. House of Representatives' Committee on Oversight and Government Reform, Domestic Policy subcommittee "Are Superweeds and Outgrowth of USDA Biotech Policy?" on July 28, 2010. Online: http://democrats.oversight.house.gov/index.php?option=com_jcalpro&extmode=view&extid=197.

[3] National Summit on Strategies to Manage Herbicide-Resistant Weeds hosted by the National Academy of Sciences, May 10, 2012, Washington, DC. Online: http://nas-sites.org/hr-weeds-summit/.

Data envelopment analysis (DEA) is a widely used mathematical programming technique to generate a composite index (e.g., Singh et al. 2009; Van Passel and Meul 2012; OECD 2008; Hatefi and Torabi 2010). However, when applying a DEA approach to data on weed resistance management BMP adoption, problems arise. First, adoption of BMPs is often highly correlated. For example, growers tend to adopt certain practices together, such as scouting for weeds after application of herbicides and controlling weed escapes. Correlation among variables reduces the discrimination power of DEA and introduces bias (Nunamaker 1985; Dyson et al. 2001). Second, data collected to describe weed BMP adoption are often categorical variables, which created problems for DEA (Kolenikov and Angeles 2009; Rigdon and Ferguson 1991). As a result, following the method of Dong et al. (2012), we use principal component analysis (PCA) to transform categorical variables measuring weed BMP adoption into continuous variables and to reduce the correlations among these variables before applying DEA. As RR soybeans were one of the first HT crops commercialized and the most popular among growers (Figure 1), we analyze adoption of weed resistance management BMPs among U.S. soybean growers based on survey data, and then identify factors that affect the BMP adoption intensity of soybean growers using regression analysis.

Data and Methodology

Data

Telephone interviews of U.S. growers who planted 250 or more acres of soybeans in a ten state region (Arkansas, Illinois, Indiana, Iowa, Minnesota, Missouri, Nebraska, North Dakota, Ohio, and South Dakota) were conducted in November and December of 2007. The telephone survey was designed to be a representative random sample of soybean growers from this region, with the final data containing responses from 402 soybean growers (Frisvold et al. 2009).

Farmers were asked questions about themselves and their farming operations, including operator education and experience, acres operated, percentage of operated land owned, total acres of crops grown, acreage planted with herbicide tolerant soybeans, crop rotation practices, and extent of livestock production. In addition, the survey asked about their tillage and weed control practices, including adoption of various weed resistance management BMPs, as well as costs for weed management, and benefits from planting RR varieties. The survey also asked growers their attitudes regarding various weed management concerns when selecting herbicides, 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 convenience.

In terms of weed resistance management BMPs, growers were specifically asked for their adoption levels for the following ten practices:

1. Scouting fields before herbicide applications,
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 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.

For each of these ten BMPs, available responses for how often each BMP was used were "always", "often", "sometimes", "rarely", and "never." Table 1 summarizes grower responses regarding adoption of these BMPs for the 376 growers remaining after dropping those with incomplete or otherwise unusable responses.

Of these 376 growers, about 91% growers report "always" using new commercial seed that is as free from weed seed as possible, while only 7.5% growers report "always" using tillage to supplement weed control provided by herbicide applications. Most growers use the recommended application rate from the herbicide label, with 74% reporting "always" and 21% reporting "often". Clean equipment before moving between fields to minimize weed seed spread is a less often adopted practice with 1 in 5 doing so "always" or "often". We give the responses of "never", "rarely", "sometimes", "often", and "always" values of 0, 1, 2, 3, and 4, respectively, for the empirical analysis here.

Besides these ten BMPs, other weed control practices were also included in the evaluation. The percentage of soybean acres planted with RR varieties in 2007 (*%RR*) and the percentage of these RR soybean acres that were planted following a non-RR crop planted in 2006 (*%RRPostNonRR*) were also included, as HT crops have become a key part of weed control. In addition, the percentage of soybeans (both RR and conventional combined) that were planted in a no-till system (*%NoTill*) and in a minimum-till system (*%MinTill*) in 2007 were also included, as tillage is a form of weed control. Also, the percentage of soybean acres (both RR and conventional combined) receiving pre-plant burndown herbicides (*%Burndown*) and pre-emergent residual herbicides (%*Residual*) were included. Table 1 also reports statistical descriptions of survey responses for these variables.

Table 1 shows that almost all growers plant RR soybeans, with about half of these RR acres planted following a RR crop planted the previous year. Slightly less than half of the soybean growers plant their soybean in a no-till system and about a quarter in a minimum tillage system. Finally, about a third of the soybean growers use a pre-plant burndown herbicide and about a fifth use a residual herbicide.

The data summarized in Table 1 serve as the adoption data for weed resistance management BMPs. These data are used to develop a single composite index measuring each grower's BMP adoption intensity, first using both polychoric and traditional principal component analysis to address problems with correlation and the categorical nature of some of the adoption variables, and then using both conventional and common-weight data envelope analysis.

Methodology

Data envelope analysis (DEA) is a widely used technique based on mathematical programming to benchmark the performance of individual decision making units (DMUs) against a "best practices" frontier (Cooper et al. 2007). Unlike parametric approaches, DEA does not assume a specific functional form for the frontier or a specific distribution for the distance from the frontier. DEA is well-suited for constructing a relative measure of BMP adoption intensity by integrating across the many BMPs to generate a single composite index for each DMU.

Two problems emerge when applying a traditional DEA approach to BMP adoption data: correlations exist among measures of practice adoption and many of the measures of practice adoption are categorical variables. Both problems influence DEA by reducing its discriminating power and introducing bias. To address these problems before applying DEA, we first use PCA to reduce the correlation among variables and to transform categorical variables into continuous variables.

PCA transforms a set of variables to a new set of uncorrelated principal components, with the first few principal components retaining most of the variation present in the original variables (Jolliffe 2002; Duong and Duong 2008). PCA is one of the most commonly used selection algorithms to reduce data dimensions, remove noise, and extract meaningful features before further analysis (Jolliffe 2002; Han 2010). Traditional PCA assumes the variables follow a normal (Gaussian) distribution, at least approximately. Discrete and categorical data violate this distributional assumption and thus bias estimation results from maximum likelihood factor analysis procedures (Kolenikov and Angeles2009; Rigdon and Ferguson 1991). To address this problem, we follow Dong et al. (2012) and use polychoric and polyserial PCA before using DEA (Kolenikov and Angeles 2009; Rigdon and Ferguson 1991; Babakus 1985; Olsson 1979).

Polychoric PCA

Traditional PCA assumes that the variables approximately follow a normal (Gaussian) distribution. The discrete data used here to measure adoption of several BMPs (Table 1) violate this assumption (Kolenikov and Angeles 2009), so that estimation results using maximum likelihood factor analysis procedures will be biased (Rigdon and Ferguson 1991). Hence, we use the polychoric correlation coefficient (Pearson 1901; Pearson and Pearson 1922) calculated for ordinal transformations of bivariate normal variables to produce an unbiased estimate of the correlation between the original bivariate normal variables (Babakus 1985; Olsson 1979).

Conceptually, the method works as follows. Let y_1 and y_2 be two ordinal variables with m_1 and m_2 respective categories, each derived by discretizing the latent continuous variables y_1^* and y_2^* according to a set of thresholds $b_{l,1},...,b_{l,m_l-1}$ for l = 1, 2:

$$y_l = \begin{cases} r & \text{if } b_{l,r-1} < y_l^* < b_{l,r}, \text{ for } r = 1, \ldots, m_{l-1} \\ 0 & \text{otherwise} \end{cases} . \quad (1)$$

The polychoric correlation is the correlation coefficient for the latent continuous variables y_1^* and y_2^* implied by the observed ordinal variables y_1 and y_2. Assuming a distribution for the latent variables y_1^* and y_2^* gives the likelihood function for the polychoric correlation coefficient, which can then be estimated using the observed y_1 and y_2. Typically a bivariate normal distribution is used, assuming means of zero and standard deviations of one for the latent variables (Olsson 1979). If one of the observed variables discrete and the other is continuous, then the polyserial correlation is calculated, which assumes only the discrete variable has an underlying latent variable. Based on these assumptions, the correlation is determined using maximum likelihood estimation. Combining pairwise estimates of the polychoric or polyserial correlations gives the overall correlation matrix for the observed data and then PCA is conducted using this correlation matrix (Kolenikov and Angeles 2009).

In PCA, both positive and negative weights are used to calculate principal components in linear combination of variables, which can imply negative principal components. However, because DEA inputs and outputs must be positive to have real economic meanings, additional transformations are used so that the data consist of only positive principal components. Following Adler and Golany (2002), the principal components used for the analysis are:

$$\tilde{X}_{ik} = X_{ik} + \left|\min\{\mathbf{X}_i\}\right| + 1, \quad (2)$$

where X_{ik} and $\tilde{X}_{ik}$ are, respectively, the original and transformed elements of the i^{th} principal component for farm k, $|\cdot|$ is the absolute value, and $\min\{\mathbf{X}_i\}$ is the minimum observed element of $\mathbf{X}_i$, the $1 \times K$ vector of observed values for farms $k = 1$ to K of the i^{th} principal component.

Data Envelopment Analysis

Conventional DEA often evaluates several DMUs as efficient, i.e., "on the frontier." In order to improve the discriminating power of DEA and obtain a complete ranking of all DMUs, we use the common-weight DEA approach described by Despotis (2002, 2005). More specifically, in this context, conventional DEA determines the BMP adoption intensity score S_k for each farm k as a weighted average of its principal components, or $S_k = \sum_{i=1}^{I} \omega_{ik} \tilde{X}_{ik}$, where ω_{ik} is the weight for i^{th} principal component for farm k and $\tilde{X}_{ik}$ is the i^{th} principal component for farm k transformed using equation (2). Note that $0 \le S_k \le 1$, because S_k measures the distance of each farm k from the origin as the proportion of the radial distance from the origin to the outer envelope defined by the data for all farms. Conventional DEA chooses farm-specific weights for the principal components by maximizing the adoption intensity score for each farm individually, while common-weight DEA chooses these weights for each principal component to be equal for all farms. In other words, common-weight DEA finds ω_i $\forall$ k, while conventional DEA finds ω_{ik} $\forall$ k and $\forall$ i (Despotis 2002). Following Despotis (2002; 2005), we specify the model so that the maximum adoption intensity score for a farm under the common-weight DEA approach is the adoption intensity score for the farm under the conventional DEA approach.

More formally, conventional DEA finds the adoption intensity score S_k for each farm k by solving the following mathematical programming model for each farm independently:

$$\text{Maximize } S_k(\omega_{ik}) = \sum_{i=1}^{I} \omega_{ik} \tilde{X}_{ik}, \text{ subject to } \sum_{i=1}^{I} \omega_{ij} \tilde{X}_{ij} \le 1,\ \omega_{ij} \ge \varepsilon \quad \forall j . \qquad (3)$$

The weights are strictly positive ($\omega_{ik} \ge \varepsilon$), where ε is the infinitesimal. Note that model (3) is equivalent to an input-oriented, constant returns to scale DEA model with I outputs and a single dummy input of 1 for all farms (Hatefi and Torabi 2010).

The common-weight DEA approach of Despotis (2002, 2005) solves the following mathematical programming model, using the same weight for each principal component ($\omega_i \ \forall i$):

$$\begin{aligned}
&\text{Minimize } \ h(d_k, \omega_i, z) = t\frac{1}{K}\sum_{k=1}^{K} d_k + (1-t)z \\
&\text{subject to } \ S_k - \sum_{i=1}^{I} \omega_i \tilde{X}_{ik} = d_k, \ d_k \geq 0, \text{ and } \ z - d_k \geq 0 \ \forall k, \\
&\qquad\qquad\quad \omega_i \geq \varepsilon \ \forall i, \ \ z \geq 0.
\end{aligned} \tag{4}$$

First examining the constraints, S_k is the conventional DEA score obtained by solving model (3) for farm k and $d_k = S_k - \sum_{i=1}^{I} \omega_i \tilde{X}_{ik}$ is the deviation of the common-weight DEA score $\sum_{i=1}^{I} \omega_i \tilde{X}_{ik}$ for farm k from its conventional DEA score S_k. This deviation d_k must be non-negative ($d_k \geq 0$) and cannot exceed z, the maximum deviation ($z - d_k \geq 0$), which also must be non-negative ($z \geq 0$). Again, the common weight for each principal component must be strictly positive ($\omega_i \geq \varepsilon$).

With these constraints, the programming model finds the deviation $d_k \ \forall k$, the common weight $\omega_i \ \forall i$, and the maximum deviation z over all farms to minimize the weighted sum of the average common-weight DEA score across farms ($\frac{1}{K}\sum_{k=1}^{K} d_k$) and the maximum deviation (z), where the parameter $0 \leq t \leq 1$ determines the weight for the two parts of the objective function. Given a solution to model (4), the common-weight DEA adoption intensity score for farm k is $\tilde{S}_k = \sum_{i=1}^{I} \omega_i \tilde{X}_{ik} = S_k - d_k$.

The first term of the objective function minimizes the average deviation of the common-weight DEA sustainability score from the conventional DEA score for all farms, and is the operative objective when t = 1. The second term of the objective minimizes the maximum deviation between the common-weight DEA sustainability score and the conventional DEA score for all farms, which is the operative objective when $t = 0$. This later case is equivalent to a minimax criterion that minimizes the maximum deviation, i.e., minimizes the interval over which the deviations are dispersed. Varying t between these two extremes allows examining the different sets of optimal solutions that result when compromising between minimizing the average of the deviations and minimizing the dispersion of the deviations. Other measures of dispersion could be used, but the minimax criterion used here is the most conservative.

As Despotis (2002) explains, when $t = 0$, the farm-specific deviations d_k are no longer choice variables, and the model becomes:

$$\begin{aligned}&\text{Minimize } h(d_k, \omega_i, z) = z \\ &\text{subject to } S_k - \sum_{i=1}^{I} \omega_i \tilde{X}_{ik} - z \le 0 \ \forall k, \ \ \omega_i \ge \varepsilon \ \forall i, \ \ z \ge 0.\end{aligned} \tag{5}$$

When $t = 1$, the maximum deviation z is no longer a choice variable and the model becomes:

$$\begin{aligned}&\text{Minimize } h(d_k, \omega_i) = \frac{1}{K}\sum_{k=1}^{K} d_k \\ &\text{subject to } S_k - \sum_{i=1}^{I} \omega_i \tilde{X}_{ik} = d_k \text{ and } d_k \ge 0 \ \forall k, \ \omega_i \ge \varepsilon \ \forall i.\end{aligned} \tag{6}$$

Finally, for $0 < t < 1$, t is varied in a consistent manner and model (4) is solved for each value of t. For example, the analysis here varies t from 0.01 to 0.99 with a step size of 0.01, so that over the range $0 \le t \le 1$, 101 solutions are found. Note that the solution (common weights $\omega_i \ \forall i$, deviations $d_k \ \forall k$, and implied scores $\tilde{S}_k \ \forall k$) is constant over ranges of the parameter t, so that not all of these solutions will be unique (see Despotis (2002, 2005) for empirical examples).

The average of each farmer's adoption intensity score over the range of t then serves as a measure to rank farmers. For notation, let $\tilde{S}_{k,t}$ denote farm k's common-weight DEA adoption intensity score $\tilde{S}_k$ for the value of the parameter t, so that the average is $\bar{S}_k = \frac{1}{Z}\sum_{t=0}^{1} \tilde{S}_{k,t}$, where Z is the total number of solutions (not necessarily unique) over the range of t. For example, the analysis here solves for 101 common-weight DEA solutions by varying t from 0 to 1 using a step size of 0.01, finding 16 unique solutions. Averaging $\tilde{S}_{k,t}$ across t puts more weight on solutions that are optimal over wider ranges of t.

Once computed, the DEA adoption intensity scores can be interpreted as cardinal measures of how close a farmer has gotten to the best practices frontier defined by the peer group that composes the full data set. For example, a score of 0.75 means that a farmer's BMP adoption intensity is 75% of the best observed among the peer group defined by the full data set.

Estimation Results

We applied this PCA-DEA approach to 376 observations of the 16 variables from the soybean farmer survey summarized in Table 1. Before implementing DEA, we first conducted polychoric/polyserial PCA on the data set to reduce correlations among the variables and to convert categorical variables to be continuous. Using the eigenvalue-one criterion of Kaiser (1960), which retains components with eigenvalues greater than 1.0, we retained six components which accounted for 61.8% of the total variance. Next, these principal components were transformed using equation (2) so all values were positive. Finally, both conventional and common-weight DEA were applied to the transformed principal components.

Conventional DEA ranked 75 farms as on the best practices frontier for their adoption of weed resistance management BMPs (i.e., $S_k = 1.0$), showing the ability of common-weight DEA to increase the discriminating power of DEA. Common-weight DEA identified 16 unique solutions when solving models (4)–(6) for $t = 0.0$ to 1.0 with a step size of 0.01, then these common-weight DEA scores for each farm were averaged across the range of values of t to compute a global score for each farm.

Figure 2 presents histograms of both the conventional DEA adoption intensity scores and the average common-weight DEA adoption intensity scores for the 376 soybean growers. Conventional DEA ranked 75 growers with an adoption intensity of 1.0, while common-weight DEA ranked only one grower as such, demonstrating the increased discriminating power of the common-weight DEA approach. Across all growers, the average common-weight DEA score was 0.897, the standard deviation was 0.0558 and the minimum score was 0.639. In terms of quartiles, 25% of the farmers had adoption intensity scores exceeding 0.936, half had scores exceeding 0.900 and 75% had scores exceeding 0.865. These results imply that most growers have adopted most of the weed resistance management BMPs examined here, but that there is still room for many farmers to improve—25% of the growers had adoption intensify scores less than 0.865. The negative skew of the scores is apparent in Figure 2.

Using the observed conventional and common-weight DEA adoption intensity scores, estimation of beta probability densities via maximum likelihood is fairly straightforward. The beta density was chosen because it is a flexible density function with lower and upper limits. Following the theoretical limits on the adoption intensity scores, the lower and upper limits for estimating the beta densities were set to 0 and 1 rather than estimated. The resulting beta density function is $f(S) = \frac{\Gamma(\alpha+\omega)S^{\alpha-1}(1-S)^{\omega-1}}{\Gamma(\alpha)\Gamma(\omega)}$, where S is the DEA adoption intensity score, α and ω are parameters to estimate and $\Gamma(\cdot)$ is the gamma function. Maximum likelihood estimates of α and ω for both the conventional and common-weight DEA scores were significant ($p < 0.001$). For the conventional DEA scores, estimates were $\alpha = 7.101$ and $\omega = 0.3055$, while estimates for the common-weight DEA scores were $\alpha = 20.25$ and $\omega = 2.326$. The respective mean and standard deviation implied by these parameters are 0.959 and 0.0686 for the conventional scores and 0.897 and 0.0626 for the common-weight scores. For the common-weight scores, the implied mean is essentially the same as for the population average, but the estimated standard deviation is larger than its population counterpart. Figure 3 plots the resulting beta densities, showing how the common-weight DEA scores are lower than the conventional scores and the negative skew for both sets of scores.

Determinants of BMP Adoption Intensity

Following Simar and Wilson (2007), we use truncated regression and bootstrapping techniques to identify the effect of various factors on grower adoption intensity scores. The regression model is

$$\bar{S}_k = \beta_0 + \sum_{n=1}^{N} \beta_n Z_{nk} + \nu_k , \qquad (7)$$

where $\bar{S}_k$ is the average common-weight DEA score for farmer k, Z_{nk} is the n^{th} independent variable for farmer k, the β_n for $n = 0, \ldots, N$ are coefficients to estimate and ν_k is the error term for farm k.

Table 2 summarizes the data used for the independent variables to estimate equation (7). *Education* is the highest level of education completed in years by the farmer: high school (12 years), some college (14 years), vocational/technical training (14 years), college graduate (16 years), or advanced degree (18 years). *Experience* is years of farming experience for the operator, *CropAcreage* is the total acres of cropped land operated, and *%Own* is the percentage of operated land owned by the farmer. Other variables included the percentage of herbicide applications made by a custom applicator (*%CustomApp*) and average crop yield expected byt eh farmer (*AverageYield*). The coefficient of variation of county average soybean yield for the previous 10 years (*YieldCV*) and the percentage difference between a farmer's reported expected soybean yield and the county average soybean yield (*YieldDifference*) measure geographic variation in yield risk and land quality. A Herfindahl index of crop diversity (*CropDiversity*) and an indicator variable denoting whether or not the farm raises commercial livestock (*Livestock*) are included to measure farm enterprise diversity (Hurley et al. 2009a). The Herfindahl index ranges from 0.25 if the farmer splits crop acreage equally among corn, cotton, soybean, and other crops and 1.0 if the farmer plants all crop acreage to soybeans. The analysis included each farmer's reported cost per acre for controlling weeds including time, effort, chemicals and equipment (*ControlCost*) and the additional value per acre each farmer reported obtaining for planting RR soybeans instead of conventional soybeans (*ValueRR*). At the end of the telephone survey, respondents were asked an open-ended question about their most important concerns regarding weed management. Responses were coded with an indicator variable to denote whether or not the farmer mentioned herbicide resistant weeds: *ResistanceConcerns* = 1 if the grower mentioned resistance, 0 otherwise. Table 2 reports statistical descriptions of the covariates used in model (7).

On average, growers had about the equivalent of a two-year vocational/technical degree and almost 30 years of farming experience. Respondents operated on average almost 1,250 acres, owning on average a little more than 40% of these acres, used custom herbicide application on about a third of their acres, and reported expected soybean yield of almost 50 bu/ac. The average county yield coefficient of variation was almost 14% and respondents on average, expected soybean yields more than 20% higher yields than the county average yield. The crop diversity index implies that on average, respondents split their acreage roughly with half in soybeans and half in another crop, and about a third had commercial livestock production on the farm. The average cost for controlling weeds was more than $33 per acre and the average reported value for RR soybeans was essentially $22.50 per acre.

The survey also contained 13 questions asking growers about the importance of various herbicide characteristics and concerns when selecting herbicides (Hurley et al. 2009a). 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 soybeans, with responses were coded as 0, 1, 2, 3, and 4, respectively. Table 2 also summarizes grower responses to these 13 questions as well. On average, respondents ranked all of these herbicide characteristics and concerns relatively highly. Concerns about herbicide consistency, yield loss, crop safety and health were among the most highly ranked, while the time to apply herbicides and the effects of herbicides on wildlife were among the lowest ranked concerns.

Because responses were highly correlated and categorical, we used polychoric PCA on these 13 variables to reduce data dimensions and to create variables for use in estimating model (7). We retained five principal components which accounted for 71.7% of total variance. The first principal component can be interpreted as each farmer’s concern about human health and environmental effects, with questions 9 through 13 receiving most of the weight. The second principal component mainly weights questions 2 and 3 and so we interpret it as each farmer’s concerns about herbicide effectiveness. The third principal component mostly weights questions 4 and 7, which we interpret as the farmer’s concern about time for weed management. The fourth principal component is about the cost of the herbicide application, with a weight of 0.69 for the question 1. The fifth principal component is mainly about crop safety, with most weight is given to question 5.

Because the dependent variable for model (7), the adoption intensity score for each farmer, is bounded between zero and one, 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 for DEA scores. Table 3 reports estimation results for model (7), including 95% confidence intervals for each regressor.

Few of the regression coefficients in Table 3 are significant, only *ValueRR* and *ResistanceConcern*, plus the 4th and 5th principal components measuring concerns about herbicide cost and crop safety, respectively. The implication of the negative coefficient for *ValueRR* is that growers who more highly value the RR trait in soybeans have lower adoption intensity scores for weed resistance management BMPs, suggesting that over reliance on the RR system is detrimental to the adoption of weed resistance management BMPs. However, though statistically significant at the 5% level, the marginal effect for *ValueRR* is small. Based on the coefficient in Table 3, a $10/ac increase in a farmer's reported value of the RR trait for soybeans implies a decrease of 0.006 in the farmer's adoption intensity score. Given that the average reported value for the RR trait is $22.49 per acre and the average adoption intensity score is 0.897, this decrease represents less than a 1% change in the score after more than a 44% increase in the value of the RR trait.

The positive coefficient for *ResistanceConcern* implies that growers reporting concern about herbicide resistant weeds have higher adoption intensify scores for weed resistance management BMPs, suggesting that these growers understand the connection between these BMPs and the evolution of herbicide resistance in weeds. *ResistanceConcern* is an indicator variable, so a change from 0 to 1 implies that a grower switches from not being concerned about herbicide resistant weeds to being concerned about them. Based on the coefficient in Table 3, this change would on average increase the BMP adoption intensity score by 0.018, or 2% from the average score of 0.897. The fourth and fifth principal components for the factors farmers consider when in applying herbicides are both positive and significant, suggesting that farmers who give more importance to cost or crop safety in herbicide application tend to have higher adoption intensities for weed resistance management BMPs.

Frisvold et al. (2009) analyzed these same data using count data models to examine the total number of weed resistance management BMPs adopted by growers. Their analysis found that growers with more education and yields higher than the county average tended to adopt more weed resistance management BMPs, while growers in counties with greater yield variability and in crop reporting districts with greater prevalence of herbicide resistant weeds tended to adopt fewer weed resistance management BMPs.

Our analysis used a different metric for BMP adoption (the DEA score rather than the total number of BMPs adopted) and a wider set of practices (the additional variables in the bottom portion of Table 1). We did not find a statistically significant effect for any of the same factors on our measurement of weed resistance management BMP adoption intensity, but rather a different set of factors as discussed above. In addition to the variables included by Frisvold et al. (2009), our analysis also included principal components and other variables measuring farmer attitudes, concerns, and values and these factors had statistically significant effects on the DEA score measuring BMP adoption intensity. Our results suggest that the pertinent factors driving farmer adoption of weed resistance management BMPs have more to do with farmer attitudes, concerns, and values, than farmer characteristics, and as such, imply different avenues for programs and policies to increase farmer adoption of weed resistance management BMPs.

Conclusion and Discussion

Probably the most significant challenge identified thus far for the widespread adoption of transgenic crops has been the growing problem with herbicide resistant weeds. To slow the spread of the problem, weed scientists and others have developed a large set of interrelated best management practices (BMPs) for weed resistance management (Norsworthy et al. 2012). Increasing farmer adoption of these practices is a goal most agree would help maintain the benefits of herbicide tolerant crops and herbicides in general. Here we presented an alternative method for measuring the intensity of farmer adoption of practices in this large set of interrelated practices and then used regression analysis to identify factors determining this adoption intensity.

A common characteristic of survey data measuring farmer adoption of the numerous weed resistance management BMPs is that the data are highly correlated and typically categorical. For example, practices such as use of supplemental tillage to control weeds and the crop tillage system are correlated, as is scouting of weeds after herbicide application and controlling weed escapes. Furthermore, survey based measures of adoption tend to offer respondents categorical rankings or indicators to choose from to measure their degree of adoption of these practices. For example, asking for subjective assessments of how often a specific practice is used or whether or not it is used, not what percentage of acres or how many hours were devoted to a specific practice.

Here we described use of data envelope analysis (DEA) to develop a measure of farmer adoption intensity for this set of interrelated BMPs. DEA has been widely used to develop composite indicators of this sort in many contexts (Singh et al. 2009; Van Passel and Meul 2012; OECD 2008; Hatefi and Torabi 2010). The correlation among variables measuring farm-level adoption of each of these BMPS and the categorical nature of these adoption measures create problems for DEA. As a result, following Dong et al. (2012), we use polychoric principal component analysis (Kolenikov and Angeles 2009; Rigdon and Ferguson 1991) before applying the common-weight DEA method of Despotis (2002, 2005).

We applied the method to survey data from 376 soybean growers from ten states in the central and southern U.S. The empirical results show that the adoption intensity scores are fairly high, with an average score of 0.897, and a negative skew due to of a small number of growers with low scores. The implication is that most growers adopt most of the practices, but that there is room for improvement in the overall average and that there are some growers with relatively low adoption of weed resistance management BMPs.

Next, we regressed the common-weight DEA adoption intensity scores on various factors to identify significant covariates. Following Simar and Wilson (2007), we used a two-limit truncated regression and bootstrapping technique to estimate bias-corrected coefficients consistent with the DEA data generation process. We found a significant negative effect on BMP adoption intensity scores for growers who more highly valued the RR trait in soybeans and positive effects for growers who were concerned about herbicide resistant weeds and cost and crop safety when making herbicide decisions. Our findings were not consistent with the findings of Frisvold et al. (2009), who analyzed the same data using count data models of the total number of weed BMPs adopted. Their analysis identified significant farm and farmer characteristics that affected BMP adoption. Our analysis included these variables, as well as variables measuring farmer attitudes, concerns and values regarding weed control, and the significant covariates we identified were from among these factors, rather than the farmer characteristics.

More research and analysis of these data are needed to clarify the differences in these findings, but at this point our results suggest that farmer attitudes, concerns and values are also important determinates of adoption of practices for managing weed resistance. As such, it may be useful to examine sociological and psychological theories and empirical findings, as well as more traditional economic work, to develop more efficient policies and programs to address the growing problem of herbicide resistant weeds.

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Table 1. Statistical description of the weed resistance management BMP adoption data used in the analysis.

	Frequency of Adoption (% of Respondents)				
Practice	Never	Rarely	Sometimes	Often	Always
Scout fields before a herbicide application	1.1	1.6	10.4	31.9	55.1
Scout fields after a herbicide application	1.3	2.7	14.6	32.7	48.7
Start with a clean field, using a burndown herbicide application or tillage	9.8	5.6	13.0	14.9	56.7
Control weeds early when they are relatively small	0.3	1.3	10.4	37.0	51.1
Control weed escapes and prevent weeds from setting seeds	2.4	3.7	13.6	31.9	48.4
Clean equipment before moving between fields to minimize weed seed spread	34.6	26.3	18.6	10.1	10.4
Use new commercial seed that is as free from weed seed as possible	1.1	0.3	1.6	5.6	91.5
Use multiple herbicides with different modes of action during the season	18.6	20.0	33.2	14.6	13.6
Use tillage to supplement weed control provided by herbicide applications	37.2	22.9	24.5	7.7	7.7
Use the recommended application rate from the herbicide label	0.5	0.3	3.7	21.0	74.5
Variable	Mean	Standard Deviation		Minimum	Maximum
%RR	94.3	20.2		0.0	100.0
%RRPostNonRR	50.9	43.6		0.0	100.0
%NoTill	47.3	45.4		0.0	100.0
%MinTill	26.4	40.3		0.0	100.0
%Burndown	34.7	43.7		0.0	100.0
%Residual	21.8	38.1		0.0	100.0

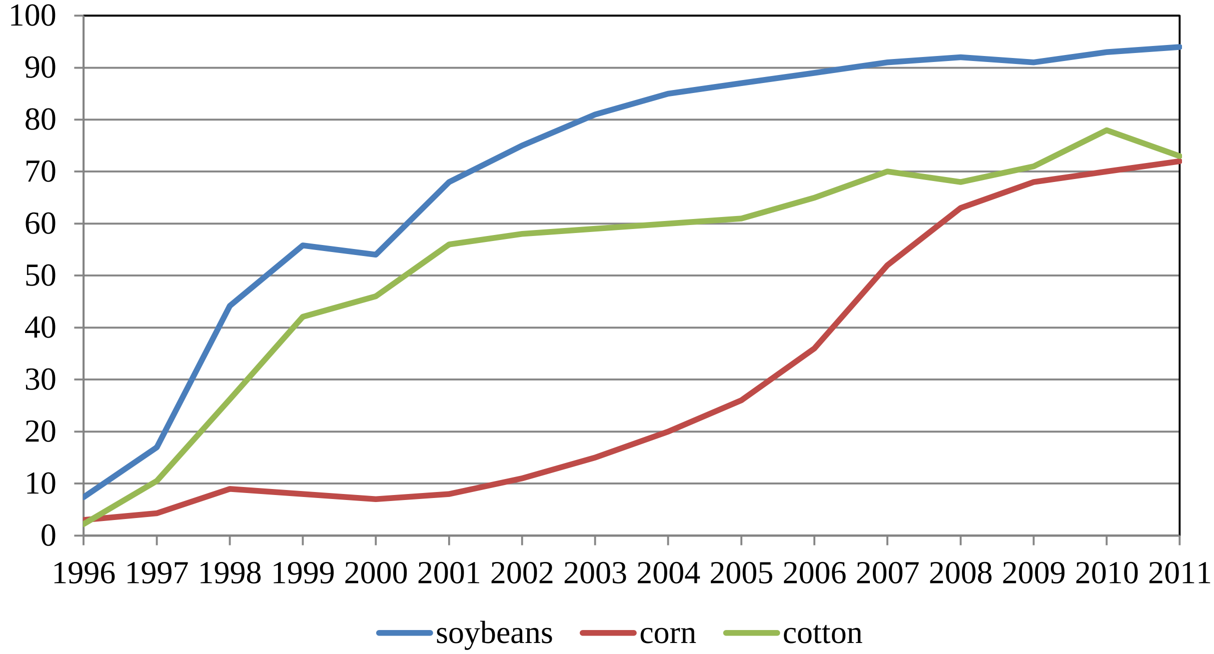
Table 2. Statistical description of variables used for two-limit truncated regression analysis of adoption intensity scores.

Variable	Mean	Standard Deviation	Minimum	Maximum
Education	13.89	1.80	12.00	18.00
Experience	29.19	10.79	3.00	70.00
CropAcreage	1,245	824	300	6,500
%Own	41.4	31.9	0	100
%CustomApp	35.1	45.5	0	100
AverageYield	49.5	17.1	25.0	336.0
YieldCV	0.139	0.043	0.055	0.325
YieldDifference	21.1	49.4	-128	855
CropDiversity	0.494	0.104	0.333	1.000
Livestock	0.322	0.468	0	1
ControlCost	33.28	26.48	5.00	225.00
ValueRR	22.49	19.44	0.00	200.00
ResistanceConcern	0.535	0.499	0	1
Factors related to herbicide choices				
1. The cost of the herbicide application	3.56	0.62	0	4
2. Reducing yield loss due to weed competition	3.95	0.21	3	4
3. The consistency of the herbicide's effectiveness at controlling weeds	3.97	0.18	3	4
4. Reducing the number of herbicide applications	3.56	0.63	0	4
5. Crop safety	3.93	0.26	3	4
6. Have a clean field	3.80	0.42	2	4
7. The time it takes to apply the herbicide	3.28	0.79	0	4
8. The flexibility of application timing	3.65	0.48	2	4
9. You, your family's and your employees' health	3.93	0.34	0	4
10. The public's health	3.79	0.53	0	4
11. The effect of the herbicide on wildlife	3.33	0.88	0	4
12. The effect of the herbicide on water quality	3.73	0.63	0	4
13. Erosion control	3.52	0.89	0	4

Table 3. Bootstrapped two-limit truncated regression results for determinants of BMP adoption intensity scores

		--- 95% confidence interval ---	
	Coefficient	Lower Bound	Upper Bound
Education	-0.00373	-0.00796	0.00050
Experience	-0.00002	-0.00075	0.00071
CropAcreage	0.00000	-0.00001	0.00001
%Own	-0.02070	-0.04405	0.00266
%CustomApp	0.00555	-0.00923	0.02033
AverageYield	0.00070	-0.00049	0.00190
YieldCV	-0.01522	-0.20823	0.17778
YieldDifference	-0.01823	-0.06661	0.03015
CropDiversity	-0.01115	-0.08864	0.06635
Livestock	0.00510	-0.00983	0.02003
ControlCost	-0.00006	-0.00032	0.00020
ValueRR	-0.00060	-0.00109	-0.00011
ResistanceConcern	0.01794	0.00378	0.03211
1st Principal Component	-0.00368	-0.01461	0.00725
2nd Principal Component	-0.00808	-0.02600	0.00984
3rd Principal Component	0.00270	-0.00930	0.01469
4th Principal Component	0.01908	0.00357	0.03458
5th Principal Component	0.02193	0.00649	0.03738
Constant	0.98006	0.77927	1.18084

Figure 1. Adoption rate of herbicide tolerant crops in the U.S. (1996-2011).



Source: USDA-NASS (2012).

Figure 2. Histogram of weed resistance management BMPs adoption intensity scores using conventional and common-weight DEA.

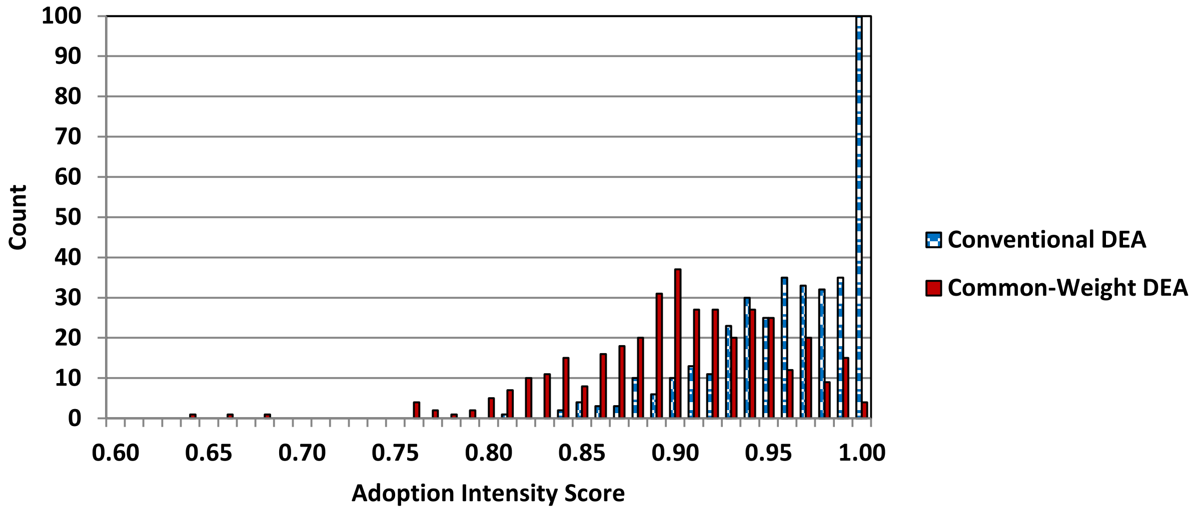


Figure 3. Plot illustrating the esitmated beta probabilty density fucntions for the conventional and common-weight DEA scores.