Additionality in U.S. Agricultural Conservation Programs: A Preliminary Analysis of New Data

Roger Claassen*
Eric Duquette*

Economic Research Service
U.S. Department of Agriculture
355 E Street S.W.
Washington, DC 20024-3221

Date: June 4, 2012

Selected paper #167 for presentation at the AAEA annual meeting,
August 12-14, 2012, Seattle Washington.

Abstract:
Payment programs that incentivize conservation practices on farms produce additional environmental gains only if farmers receiving payments adopt practices that they would not have adopted without the payment. For some conservation practices, the "additionality" of payments may be low if programs do not differentiate between farmers who would only adopt with a payment and those farmers that may find adoption of the practice profitably even without a payment. We use a Propensity Score Matching method to estimate unobserved counterfactual adoption behavior in a nationwide survey of farmers and calculate the level of additionality for five separate conservation payments in the U.S. that target nutrient management, pest management, conservation tillage, soil conservation, and buffer practices. We find high levels of additionality across the five types of conservation payment types, suggesting that these programs are effective in producing environment gains that would not have occurred without payment incentives.

*The views expressed are those of the authors and should not be attributed to the Economic Research Service or the USDA.

1. Introduction

The U.S. Federal Government spent more than $5 billion in fiscal year 2010 to encourage resource conservation and environmental quality on U.S. farms—the highest level (inflation-adjusted) since 1960 (Claassen, 2011). Since 2002, the vast majority of growth has been in working land programs—voluntary payment programs that encourage conservation practice adoption on land in agricultural production and focus on a broad range of resource concerns. These programs are designed to assist producers in the adoption of environmentally sound practices such as conservation tillage, nutrient management, integrated pest management, field-edge filter strips, and other practices that are compatible with ongoing agricultural production (Claassen and Ribaudo, 2006). After the 2002 Farm Act, funding for these voluntary payment programs increased ten-fold from $200 million per year in 2002 to nearly $2 billion per year in 2010.[1] The focus of our research is to assess the effectiveness of these programs at either increasing the number of farmers who adopt conservation practices or increasing overall levels of environmental quality beyond what would have been without payments from the programs.[2]

To understand these programs in terms of meaningful environmental outcomes, the evaluator must understand a long chain of events, many of which are difficult to observe and measure (Smith and Weinberg, 2004). In terms of water quality, for example, voluntary payment programs can encourage farmers to adopt nutrient management, field-edge filter strips, riparian buffers, and other practices that can reduce nitrogen runoff from farms. Reducing runoff may reduce the amount of nitrogen that is transported to water bodies, reducing nitrate concentrations in downstream water, and reducing associated water quality problems including eutrophication

---

[1] Data are obtained from yearly budget summaries from the Office of Budget and Policy Analysis, U.S. Department of Agriculture, http://www.obpa.usda.gov/budsum/budget_summary.html.

[2] The payments we examine come largely from the Environmental Quality Incentives Programs (EQIP), Conservation Stewardship Program (CSP), Conservation Reserve Program (CRP), and other smaller programs.

and hypoxia (Goolsby et al., 1999; Ribaudo and Johansson, 2006). Improved water quality can lead to an increase in fish and wildlife populations, for example, which can lead to improved opportunities for recreational and commercial fishing.

Additionality is a measure of the effectiveness of voluntary payment programs at inducing the adoption of conservation practices that would not have been adopted in absence of the payments from the program. The adoption of a practice without receiving any cost-sharing or incentive payments has been documented with many practices suggesting that these payments are not the only factor that farmers consider in their adoption decision (Lambert et al., 2006). Payments from voluntary payment programs are considered "additional" only if the program payments induce the adoption of conservation practices that would not have been adopted in absence of the payment. A concern about the effectiveness of a voluntary payment program would occur if the payments were, for example, all "non-additional." High levels of additionality are possible if programs can somehow identify those farmers least likely to adopt a conservation practice without a payment or can design a payment mechanism in which farmers most in need of a payment to be able to adopt self-select into the programs. Without intimate knowledge about the counterfactual behavior of farmers who receive payments in the absence of payments and/or the structure of payment distribution process of these voluntary programs, it is difficult to assess directly additionality.

Our analysis measures the level of additionality for each of five types of agricultural conservation practices (nutrient management, integrated pest management, conservation tillage, soil conservation structures, and buffer practices) using Propensity Score Matching (PSM) estimation. We define additionality in this paper as the difference in the practice adoption rate of farmers who receive a payment and the counterfactual adoption rate for the same set of paid farmers. PSM allows us to estimate the counterfactual behavior of paid farmers, that is, what they would have done in the absence of payments. We use non-repeated cross-sections of U.S. farmers from the U.S. Department of Agriculture (USDA) as part of the Agricultural Resources Management Survey (ARMS) for the years 2009 and 2010 (USDA/ERS, 2010).[3] ARMS is a nationally representative sample of farms providing extensive data on land use, crop and livestock production, production expenses, government payments, producer demographic characteristics, and other aspects of agricultural production. The sample of over 2,900 includes information on farmers' practice adoption, payment sources, and survey expansion factors (i.e., weights), which we use to adjust the typical PSM estimator to obtain nationally representative levels of additionally.

We find levels of additionality above 90 percent for many those voluntary payment programs that fund adoption for practices that currently have low-levels of adoption. These practices include nutrient management, integrated pest management, soil conservation structures, and buffer practices. In contrast, we estimate for conservation tillage, which is a practice that has relatively high levels of adoption (approximately 30 percent) compared to the other conservation practices, has a level of additionality of 63 percent for surveyed corn fields. Based on these estimates, the payments made by voluntary payment programs appear to be effective at inducing conservation participation among farmers that would not otherwise have occurred. We consider these results preliminary, however, while we consider additional data on USDA conservation programs, including details on where and when specific conservation practices were funded and possible interaction with state-level regulations, particularly those involving nutrient management. These data will help ensure that matches are made only between farms that face similar requirements and similar opportunities for receiving payments.

[3] The survey is administered by the USDA National Agriculture Statistics Service.

2. Conservation Practice Adoption and Payments

The 2002 Farm Act represented a major change in U.S. agri-environmental policy, shifting from a long-standing focus on soil conservation and structural practices to a broader set of environmental objectives and greater focus on management practices. The sharp increase in funding in the beginning in 2003 had a strong effect on the type of conservation practices adopted through working land conservation programs. Overall national rates of adoption among the five different types of conservation practices are between 1 and 30 percent. Payments, however, are received by only 1 to 6 percent of those operators who adopt a practice. This suggests that many farmers are adopting conservation practices for reasons other than payments from working land programs.

There is a large literature on the possible motivating factors for conservation practice adoption other than payments from voluntary payment programs (e.g., Ervin and Ervin, 1982; Featherstone and Goodwin, 1993; Fuglie and Kascak, 2001; Soule et al., 2000; Traoré et al., 1998; Wu and Babcock, 1998). These studies show a range of factors affect adoption, including field characteristics (e.g., productivity, erodibility), climate (average temperatures and rainfall), farmer characteristics (e.g., age, education), and farm characteristics (e.g., farm size, primary products). For instance, conservation tillage can reduce the cost of labor, fuel, and machinery and, in many cases, can be applied without a loss in crop yields. Any state and local mandates would also affect adoptions decisions. For instance, some states have requirements for livestock producers to develop and apply nutrient management plans (e.g., Ribaudo et al., 2003). Payments associated with these types of adoption decisions should clearly be considered as non-additional—they prompt adoption of practices in the absence of payments.

Many of the factors that affect adoption might also jointly affect a farmers' decision to seek and receive a payment for a particular practice. A farmer's decision to obtain a payment for a particular conservation practice might depend on his or her knowledge and expectation about the probability of receiving a payment to implement the practice. These expectations could vary by individual traits (e.g., education level) and prior experience with governmental agencies that administer the payments. Farm-specific conditions in a given year and the net benefits of the various types of available practices might also affect the need to seek a payment. Likewise, the precise goals of voluntary payment programs might vary by state and locality if these programs target payments towards certain types of farming operations and land types based on regional conservation goals. Further, accountability might be important to the working land programs. Farmers might be selected to receive a payment based upon their perceived ability to follow through and correctly implement a practice, perceptions which may depend on a farmer's past farming practices and current conditions of the field and operation.

3. Measuring Additionality

Our empirical measure of additionality represents what is commonly known in the program evaluation literature as the "average treatment-effect-on-the-treated" (ATT). The ATT is a common statistic used to evaluate the effect of a "treatment" provided by a government program on an outcome of interest. In this paper, we define ATT as the expected effect of a payment (treatment) on the rate of adoption of a particular conservation practice for those farmers who received a payment for the practice. More formally, we let treatment (*D*) equal to *1* when a farmer receives a payment for a particular conservation practice and *0* when no payment is received. The adoption outcome for farmer *i* when receiving a payment is denoted Y_{i1}. (Since the structure of the additionality measure is the same across conservation practices, we exclude subscripts indicating the type of conservation practice payment for clarity.) Farmers that receive payments for a particular conservation practice will always have adopted that conservation practice such that $Y_{i1} = 1$ for every farmer *i* when $D_i = 1$. The adoption outcome for farmer *i* under non-treatment is denoted Y_{i0} and can be either *0* or *1* because some farmers may choose to adopt a conservation practice without payment. Upon conditioning on farmers who receive payments, the additionality of a particular conservation payment program is given by:

$$E[Y_{i1} - Y_{i0} \mid D = 1]. \tag{1}$$

The challenge of in calculating this measure is that Y_{i0} represents an unobserved counterfactual behavior and must be estimated.

If payments to farmers were randomly assigned, additionality could simply be calculated as $E[Y_{i1} \mid D = 1] - E[Y_{i0} \mid D = 0]$ since the unobserved mean adoption outcome, $E[Y_{i0} \mid D = 1]$, would be equal to $E[Y_{i0} \mid D = 0]$. If the adoption of a practice and payment reception are endogenous, treatment may not be orthogonal to the outcome and we may have $E[Y_{i0} \mid D = 0] \neq E[Y_{i0} \mid D = 1]$, and the expectation in equation (1) would potentially capture factors that are correlated with assignment to payment and also affect the outcome. The potential for the incidence of payments and practice adoption to be jointly related suggests that this might be the case. If the relationship is positive, as we hypothesize, then in a model which improperly controls for factors which affect both adoption and payment, the size of the effectiveness of payments at inducing conservation practice adoption would be overstated and levels of additionality would be biased upwards.

One solution to the inference problem is to rely on the *conditional independence assumption* (CIA). If a set of covariates, Z, satisfies CIA the outcome and treatment assignment are independent. Under such a set of covariates, additionality is measurable as:

$$E[Y_{i1} - Y_{i0} \mid Z, D = 1] = E[Y_{i1} \mid Z, D = 1] - E[Y_{i0} \mid Z, D = 0]. \qquad (2)$$

The CIA is also known as "selection on observables" because, for the assumption to hold, Z must be observable to the researcher. [4] In our case, Z might include covariates such as characteristics about the field, farm, farmer, and controls for possible preferences of the agency and budget constraints. The independence or *unconfoundness* of practice adoption and payments received is not directly testable, although we discuss and provide some common sensitivity checks for assessing the robustness of the results to deviations from the assumption in our results section.

4. Propensity Score Matching Estimation

Valid estimates of the *ATT* under CIA are also achievable by alternatively conditioning on propensity scores, $P_i = pr(D_i = 1 \mid Z_i) \in (0,1)$ estimated from a binary model treatment (Rosenbaum and Rubin, 1983).[5] In our case, we want to know the mean adoption outcome under non-payment for those farmers who received payment and the Propensity Score Matching (PSM) method a matching estimator to estimate the unobserved counterfactual outcomes (e.g. Caliendo and Kopeinig, 2008; Heckman et al., 1998b; Heckman et al., 1997). In PSM, matches are based on the propensity of a given individual to receive a specific treatment, or, in our application, the probability that the producer receives a payment for practice adoption. Propensity scores can be

4 A necessary condition for this assumption to hold and be able to identify the mean impact of treatment on the treated is for $E[Y_{i0} \mid Z, D = 1] = E[Y_{i0} \mid Z, D = 0]$.

5 Propensity scores also have the advantage of being one-dimensional, whereas conditioning on the multidimensional Z and can make certain matching estimators (discussed further below) more difficulty when the number of covariates in Z is large.

estimated econometrically using a discrete choice model (e.g., logit or probit). The probability of receiving a payment for practice adoption is modeled as a function of the field, farm, and farmer characteristics believed to influence the receipt of a practice adoption payment. While these methods are relatively new to agricultural economics, a number of applications exist (e.g., Chabé-Ferret and Subervie, 2011; Chabé-Ferret and Subervie, 2010; Liu and Lynch, 2011; Lynch et al., 2007; Mezzatesta et al., 2011; Pufahl and Weiss, 2009).

In addition to the CIA, the validity of PSM as a policy evaluation method rests upon a second assumption often referred to as "overlap" or "common support." Farms available for matching must have some positive probability of receiving conservation payments and not receiving conservation payments. Satisfying this condition ensures that farms in the payment group will not be compared to non-payment farms that are inherently different. Farms with relevant field, farm, and farmer characteristics that lie outside a specified range of common support for payment and non-payment farms are not used for matching. One way this is implemented in PSM is by restricting the set of observations available for matching so that the largest propensity score of the treated observations is no larger than the largest propensity score of the control observations and that the smallest propensity score for the control observations is no smaller than the smallest propensity score of the treated observations. In terms of policy, for example, this assumption excludes non-payment farms from the comparison group if they are ineligible for conservation payments (in general or for a specific practice) or face regulations that do not apply to payment farms.

Matching methods must also account for policy factors that could affect the likelihood that a given farmer receives a payment for a given practice. Agri-environmental policy poses a major challenge for matching because it involves a complex mix of Federal, state, and local programs. Agri-environmental priorities are often set at the state or even local level. Many states have agri-environmental programs and regulations, particularly for confined animal feeding operations (CAFOs) (Ribaudo, et al., 2003). Even federal programs are often tailored to meet local resource conservation and environmental needs. In EQIP, for example, decisions about resource concerns to target and practices to support are made largely at the state level, but priorities and practices supported can vary among local jurisdictions within a state.

Enrollment in USDA conservation programs is also competitive (Cattaneo et al., 2005). Producers seeking payments must apply for a specific program, providing a proposal for the application of specific practices in specific fields. Farmers may differ in their propensity to seek funding, perhaps because of differences in general attitudes about government, differences in familiarity with USDA in general or conservation programs in particular, or differences in willingness to install or use conservation practices as prescribed by government conservation practice standards. Because farmer proposals for funding often exceed available funding, program managers select proposals according to likely environmental benefits and costs, creating another set of factors that must be controlled for in the matching process (e.g.,. soil erodibility, proximity to water, and other factors believed to affect the environmental impact of an action taken on a given farm or field).

Clearly, this patchwork of policies must be considered in the estimation of propensity scores and the selection of matching methods. Because there are multiple programs and regulations, not all of which are Federal, an alternate approach is to match the payment farms with non-payment farms within the same geographic area, such as a state or region, where policies are likely to be the same or very similar for all surveyed farms. For example, matching large livestock farms in different states would be inappropriate if one state requires nutrient management plans but the other does not. Comparing producers in a regulated state to producers in a non-regulated state may result in underestimating the additionality of payments made in the unregulated state and/or overestimate additionality in the regulated state. Finding good matches may, however, be difficult when sample sizes are limited without reaching across state boundaries.

An important step in matching is assessing the quality of proposed matching control observations (the unpaid farmers) to the treatment observations. One empirical test is *covariate balancing* which tests for the similarity of the covariates *Z* for the treated and control groups. This entails performing a *t-test* of equality of the means for each covariate. If equality of means is not rejected for any of the covariates then the proposed matching control observations are observationally equivalent (based on the selection of observable explanatory variables) to the treatment observations. Selection on observables is another name for the CIA.

5. Kernel Matching

Based on equation (2), the basic matching estimator for obtaining the *ATT* can be formulated as the following:

$$\hat{A}TT = \frac{1}{n_1} \sum_{i \in \{T_i = 1\}} \left\{ (Y_i \mid D_i = 1) - \sum_{j \in \{T_j = 0\}} \omega_{ij} (Y_j \mid D_j = 0) \right\}, \qquad (3)$$

where n_1 is the number of treated observations, i indexes the treated observations, j indexes the control observations, and ω_{ij} is the weight given to the control observation j when matched to the i^{th} treated observation. Under simple nearest-neighbor matching, a treated observation is matched, as measure by predicted propensity scores from a treatment model, to the *N* nearest control observations. Weights in this case are just $\omega_{ij} = 1/N$. The *ATT* is then simply the average difference in the outcome of the treated observations and their respective weighted counterfactual estimates.

We use a kernel-based matching estimator which has the advantage of using all the control observations to construct the counterfactual, resulting in greater statistical efficiency than other types of matching estimators such as nearest-neighbor estimators (Heckman et al., 1998a; Heckman, et al., 1998b; Heckman, et al., 1997). Control observations under kernel-based matching are weighted by the kernel weights, $\omega_{ij} = \frac{G\left((\hat{P}_j - \hat{P}_i)/\kappa\right)}{\sum_{k\in\{T_k=0\}} G\left((\hat{P}_k - \hat{P}_i)/\kappa\right)}$, where $G(\cdot)$ is a kernel density function (e.g., Gaussian, uniform, triangular, and Epanechnikov) and κ is the bandwidth parameter for smoothing.[6] With kernel-weighting, the weight that the practice adoption outcome has on the estimated counterfactual behavior for the treatment observation declines with distance between the propensity score of the treated observation and the control observation. Therefore, the estimated counterfactual behavior places a greater emphasis on control observations that are most similar in terms of probability of receiving a payment.[7]

We adjust equation (3) by the observation survey weights, ω_i^s, to obtain nationally representative estimates of additionality:

$$\widehat{ATT} = \sum_{i\in\{T_i=1\}} \bar{\varpi}_i^s \left\{ (Y_i \mid D_i = 1) - \sum_{j\in\{T_j=0\}} \tilde{\omega}_{ij} (Y_j \mid D_j = 0) \right\}, \tag{4}$$

[6] Our current models set $\kappa = .02$.
[7] A disadvantage of kernel-based estimators is that they might overweight control observations that might more appropriately be considered as inappropriate for matching to treatment observations.

where $\bar{\varpi}_i^s = \frac{\omega_i^s}{\sum_{l \in \{T_l=1\}} \omega_l^s}$, $\tilde{\omega}_{ij} = \frac{\bar{\varpi}_j^s \omega_{ij}}{\sum_{k \in \{T_k=0\}} \bar{\varpi}_k^s \omega_{ik}}$, and $\bar{\varpi}_j^s = \frac{\omega_j^s}{\sum_{k \in \{T_k=0\}} \omega_k^s}$. Our methodology for including survey weights is similar to a method by Zanutto (2006) who finds that ignoring the survey weights from a complex survey can lead a substantial bias in the estimated effects of a PSM estimator.[8] As Zanutto notes, survey-weights are unnecessary for the treatment model because the estimated propensity scores are used only for measuring the similarity of observations in the sample and not to infer behavior about the underlying population.

Estimates of the counterfactual outcomes for kernel-based matching estimators can alternatively be generated from a weighted regression of the outcomes of the control observations on an intercept with the weights specified as the kernel weights from the treatment model (A. Smith and E. Todd, 2005). Since our adoption outcome variable of interest is whether a farmer chooses to adopt a particular conservation practice, we obtain estimates of the additionality for each of our five types of conservation payments with a weighted *probit* regression for the respective adoption outcome for the payment, where the model includes only a constant in the latent propensity index and weights given the estimated kernel weights.

All farmers who receive payments for a particular practice adopt that practice. Thus, we calculate a mean estimate of additionality for each of the paid farmers as 1 minus the estimated counterfactual outcome from the kernel weighted probit model for adoption outcome matching unpaid farmers. We average the estimates over each of the paid farmers to obtain an overall mean estimate of additionality and, for comparison, report the same calculation when taking into account the survey-weights.

[8] Zanutto (2006) uses a stratified propensity score matching method and, therefore, the method for including survey weights represents cannot be directly applied to the kernel-based matching of our analysis.

6. Data

To make high quality matches, the data describing farms must be rich enough to account for all factors affecting conservation practice adoption, the willingness to seek payments from a conservation program, and the likelihood that farms would be selected by the program agency to receive payments. In this respect, the ARMS survey is a very rich source of data, providing information on operation size, commodities produced, production expenses, overall government payments, land tenure (for the farm, overall), operator age and education, off-farm work, and many other characteristics of the farm, the farmer, and his or her household.

We use data from two separate field-level survey implementations of ARMS for a subsample of surveyed farms drawn from selected states.[9] The survey covers corn operations in 2010 and wheat operations in 2009, with each year of the survey consisting of a unique cross-section of sampled farmers.[10] In the corn survey, there are 2,284 field-level usable observations in ARMS for fertilizer and pesticide applications, conservation practices, irrigation, soil erodibility, and the presence of wetlands. The size of our sample decreases to 1,628 observations when merge with to the farm-level ARMS survey. Each field-level observation includes a survey-weight for generating population estimates that are representative of U.S. farmers. The survey weights account for the complex survey design and for farmer non-response.

In addition to combing the field- and farm-level surveys in ARMS, we geocode observations to link historical climate data (e.g., long term averages for precipitation and temperature) from nearby weather stations and soil productivity measures from the USDA

[9] Selected states in the 2009 wheat survey include California, Colorado, Idaho, Illinois, Kansas, Michigan, Minnesota, Missouri, Montana, Nebraska, North Dakota, Ohio, Oklahoma, Oregon, South Dakota, Texas, and Washington; For the 2010 corn survey, states include Colorado, Georgia, Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, New York, North Carolina, North Dakota, Ohio, Pennsylvania, South Dakota, Texas, and Wisconsin.

[10] The ARMS field survey has been administered yearly since 1996, with the exception of 2008 when no survey was performed. Question of payments for conservation practice were first included in 2009.

Natural Resources Conservation Service (NRCS). Not all fields have geographic coordinates and we lose some additional observations in the geocoding process. Our final estimation sample consists of 1,499 observations for 2010 corn fields. Our final sample size for the 2009 wheat survey is 1,439 observations after a similar merging of field and farm ARMS surveys and geocoding process.

Our analysis examines the field-level adoption for the five different conservation practices of nutrient management, pest management, conservation tillage, soil conservation structures, and buffer practices.[11] In addition to being asked whether the practice was in use on the surveyed field, respondents in the 2009 and 2010 surveys were asked when the practice was installed or first used and whether cost-sharing or an adoption incentive payment was received. Table 1 summarizes the variables we consider in our analysis by treatment status of conservation payments received (*Unpaid* vs. *Paid*) the surveyed corn fields of 2010.[12] The variable *Adopted Practice* shows the fraction of surveyed corn fields that adopted a practice by treatment status within a given practice group. For the untreated corn fields in 2010, practice adoption ranged from 1.6 percent for integrated pest management conservation practices to more than 30 percent for conservation tillage practices. Soil conservation structures had been installed by the current producer on 12 percent of surveyed fields while buffer practices and nutrient or manure management had been adopted on roughly 5 percent of surveyed fields. For wheat fields

[11] Each of the practice groups are defined by subsets of practices. Buffer practices include field-edge filter strips, field borders, and riparian buffers. Soil conservation structures include terraces, grassed waterways, grade stabilization structures, and water and sediment basins. Conservation tillage includes no-till, mulch till, and ridge-till. Nutrient and manure management includes comprehensive nutrient management and manure management. We only observe integrated pest management as a single indicator variable even though it summarizes several different type of pest management practices.

[12] The appendix includes a similar table for the 2009 wheat survey.

surveyed in 2009, adoption rates ranged from 3 percent for nutrient management practices to 14 percent for soil conservation structures.[13]

We focus on the role of incentives in conservation practice adoption by considering only those adoption decisions made by the current producer (the survey respondent). Many of the soil conservation structures on survey fields have been in place before the beginning of the current producer's tenure due to seventy-five years of promotion and cost-sharing by the USDA for these types of structures.[14] Thus, we exclude structural and vegetative practices (e.g., terraces, filter strips) that were installed before the beginning of the current farmer's tenure. We also assume that management practices are re-adopted annually. When the reported date of initial adoption precedes the current producer's tenure, the date of initial adoption is assumed to be the first year of the current producer's tenure and it is assumed that the current producer did not receive a payment for initial adoption.

Panel A in Figure 1 shows the percent of fields that were adopted with the assistance of conservation payments generally accounted for 50 percent or less of total adoption on fields in the 2010 corn survey, although the percentage receiving payments varied widely across practices. Very few corn producers who adopted conservation tillage said they received a payment for doing so. For buffer practices, soil conservation structures, and nutrient and manure management, 30-40 percent of producers said they received payments. In the 2009 wheat survey, the percentage of producers receiving conservation payments was generally higher (see Panel B in Figure 1). For buffer practices and manure/nutrient management, more than 50 percent of producers reported receiving adoption-related payments. More than 40 percent of wheat producers reported receiving payments related to soil conservation structures.

[13] The wheat questionnaire did not include questions about conservation tillage payments.
[14]For roughly 40 percent of respondents (in both the wheat and corn surveys) who reported one or more structural or vegetative practices, the practices were installed before the beginning of the current farmer's tenure.

For those farmers in the survey who have been farming for decades, some practice adoption decisions were made decades ago. It is not clear that decisions made 20 or more years in the past are comparable to more recent decisions about conservation practice adoption and conservation program participation. Increasing farm size and specialization, technical change, and the evolution of conservation policy suggest that focus on more recent conservation practice adoption decisions may more be appropriate when measuring the level of additionality for currently existing conservation payment programs. One way we attempt to control for this possibility is by including information on tenure in our empirical models.

Other than the *Adopted Practice*, Table 1 also highlights (with shaded cells) the mean values of the baseline explanatory variables of our treatment models that are significantly different across treatment status based on a simple t-test of means.[15] For the 2010 surveyed corn fields, farmers that received a payment for a nutrient management practice were, on average, younger (*Age of operator*) and more likely to own the field (*Owns Field*). Among the same set of paid farmers, the fields were more likely to be located in a cooler climate (*15 yr. avg. max. temperature (°C)*), deemed highly erodible by NRCS (*Highly Erodible*), and larger in size (*Field Size*). These same set of characteristics show up as significantly different across treatment status for some of the other four types of conservation practices. For some of these other practices, however, soil productivity (*NCCPI*), nearby wetland proximity (*Wetland*), and whether the operator had a college degree (*College degree*) are also more likely to be associated with mean values which are significantly different across treatment status. Soil conservation structures (e.g., terraces) are the only practice type for which the mean precipitation levels (*15 yr. avg. precipitation (mm)*) are different for paid and unpaid farmers, with paid farmers more likely to be

[15] The reported means and standard deviations of the variables are prior to the application of kernel weights from the estimated treatment model and are not adjusted by the ARMS survey weights to represent population estimates.

located in areas with greater precipitation. Likewise, conservation tillage is the only practice type for which the occupation of the farmer (*Primarily a farmer*) is significantly different across treatment status.

7. Propensity Score Estimates

We report in Table 2 the estimated coefficients from the treatment models for each of the practice types for the 2010 surveyed corn fields. Each model includes, in addition to the baseline variables of Table 1, quadratic terms for field size and operation size and interactions of operation size with whether the field was highly erodible, irrigated, or contained a wetland, the age of the farmer, and whether the farmer had a college degree. For instance, the likelihood that a farmer receives a payment for soil conservation structures decreases with precipitation and age but increases with higher average temperatures and when a farmer owns the field. In general, the ability of the variables to predict the likelihood that a farmer receives a payment (i.e., $P_i = pr(D_i = 1 | Z_i)$) for a particular conservation practice type varies by type of practice. These models do not include controls for policy differences that might differ by state and/or regions (e.g., through coordinated state policies that target environmental goals in the Chesapeake Bay watershed). Thus, some variables, such as the differences in climate and operation size, might be potentially less predictive when also including controls for these more geographically defined variables.[16]

[16] An alternative approach in the PSM literature for controlling for differences that might exist across stratum such as states is to run separate treatment models for each state, restrict matches to be within states, and then average estimated additionality levels across states. We attempted this with our data but found that the small number of treated observations in our sample led to several instances of perfect multicollinearity between our payment indicator variable and some of our binary explanatory variables when using state level treatment models. This was also the case for some practices when we considered the spatially more aggregate Farm Resource Regions (USDA/ERS 2010).

Figure 2 shows the distribution of propensity scores by treatment status for each of the conservation practices. With the estimated propensity scores, we calculate the kernel weights to apply to the control observations for each treated observation. Our covariate balancing tests suggest that the means of the kernel-weighted observed explanatory variables are well-matched. For all of the variables with significant differences between means of the unweighted control and treated observations reported in Table 1, not a single variable for any of the five practices types has a significant difference (i.e., $p>.1$) in the means of the weighted observations.

8. Estimates of Additionality

The first column of results in Table 3 presents the mean estimates of additionality for each of the type of conservation practices when we use the Gaussian kernel-based matching estimator with a bandwidth of .02. (Bootstrapped standard errors are in parentheses.) We separately obtain these estimates for the corn and wheat surveys, although the additionality estimate for conservation tillage is unavailable in 2009 because surveyed farmers in that year were not asked about possible conservation tillage payments received. In general, these estimates represent relatively high levels of additionality. For nutrient management, pest management, and buffer practices, additionality estimates are above 90%. Soil conservation structures have a slightly lower level of additionality of 82.6 percent and conservation tillage has the lowest of the five types of practices of 63.1 percent.

The lower estimates of additionality for soil conservation structures and conservation tillage could reflect two possibilities. First, it may be that conservation payment programs with lower levels of additionality have more difficult in identifying who is in need of a payment. Soil conservation structures and conservation tillage practices have the highest levels of reported adoption among the five practice types (see Figure 1), which could be because these practices have higher expected net returns even without a payment. If agencies do not consider expected net returns as a criterion for payment eligibility or are not able to sufficiently quantify the expected net returns of a practice for a farmer, payments may end up going to farmers who have less of a financial need for the payment to be able to adopt a practice. Second, our models for estimating the propensity scores would need to capture the same factors that agencies use to determine payment eligibility. Although we are not able to include controls in our treatment models which could directly account for agency eligibility criteria, many of the variables we do include such as operation size would be expected to indirectly capture such program targets.

The second column of results reports the estimates of additionality when we use the observation specific survey weights from ARMS. The survey-weighted estimates represent the level of additionality that would be expected by the application of conservation programs across the entire U.S. population of farmers. For nutrient management practices, the adjustment to the mean estimate of additionality is lowered somewhat. For the remaining practices, the survey-weighted results do not different substantially from the unweighted results.

The last two columns of Table 3 report the levels of additionality we estimate by using the surveyed wheat fields in 2009. The results also indicate high levels of additionality for the conservation payment programs.

9. Discussion and Conclusion

U.S. agri-environmental policy relies heavily on voluntary incentive payments to encourage farmers to use more environmentally sound practices and improve environmental performance of their farms. The complexity of these policies presents a major barrier to research on their effectiveness. Simple regional differences in adoption of and payments for nutrient management do not necessarily imply that differences are due entirely to inter-state policy differences. This has never been formally performed at a national scale in the US, mainly due in large part to the lack of high quality data on practice adoption and associated payments. Our findings formally test for the additionality of these programs using the 2009 wheat and 2010 corn ARMS surveys, which are among the first national surveys to include data on conservation practice adoption and related payments for U.S. farms.

While the ARMS data provide a rich source of information about farms and farmers, a relatively small number of surveyed farms report adopting one of more of the practices listed in our four practice groups (with the exception of conservation tillage), a smaller number reported adopting practices in recent years (2003 or later), and fewer still report receiving payments associated with this adoption. The sample size is a potential limitation in terms of teasing out differences in producers who receive conservation payments and those who do not. Because the overall sample sizes are modest, the number of farms in the sample that actually received a payment for conservation practice adoption may or may not be adequate to separate payment from non-payment farms, potentially limiting our ability to construct quality matches. Furthermore, the limited number of treated observations we have at a state level restricts our ability to more directly control for state-level policies through stratum-based PSM methods. If there are differences in state policies that would be expected to be produced substantial differences in additionality, then our estimates of additionality may not fully account for these effects.

However, our findings of high levels of additionality are consistent with Mezzatesta et al. (2011), whom find high levels of additionality (above 80 percent) for acreage in the state of Ohio devoted to hayfield establishment, filter strips, and cover crops but a much smaller amount of additionality for conservation tillage acreage (less than 25 percent). The authors main findings suggest that the differences in the level of additionality between the practice types is largely due to differences in the participation of farmers (which has been the focus of our study) and that additionality appears to be larger for those conservation practices which have larger fractions of farmers who adopt without payment.

In most policy contexts, payments are defined to be additional only if the adoption of practices on payment farms leads to better environmental outcomes. For example, this could include lower fertilizer application rates, more post-plant application of nitrogen fertilizer, or less fall application of nitrogen fertilizer for nutrient management plans. Perhaps the best opportunity to study the role payments have in practice adoption and associated outcomes is in the case of payment for nutrient and manure management. For these practices, the majority of adoption has occurred in recent years (2003 or later) and a majority of farmers who report nutrient or manure management plans also report receiving a payment associated with adoption, although the proportion of farms reporting payments varies widely across regions. The ARMS survey ties nutrient management plans for fields to specific outcomes and will allow us to examine in future analyses such items as fertilizer application rates, timing, and method, manure and legume crediting, and soil and plant tissue testing.

References:

U.S. Department of Agriculture, Economic Research Service, *Agriculture Resource Management Survey (ARMS), Farm Financial and Crop Production Practices for Corn*, Washington DC, 2010.

A. Smith, J. and P. E. Todd. 2005. "Does Matching Overcome Lalonde's Critique of Nonexperimental Estimators?" *Journal of Econometrics*, 125(1–2), 305-53.

Caliendo, M. and S. Kopeinig. 2008. "Some Practical Guidance for the Implementation of Propensity Score Matching." *Journal of Economic Surveys*, 22(1), 31-72.

Cattaneo, A., R. Claassen, R. Johansson and M. Weinberg. 2005. "Flexible Conservation Measures on Working Land: What Challenges Lie Ahead?" Economic Research Report, ERR-5, Economic Research Service, U.S. Department of Agriculture.

Chabé-Ferret, S. and J. Subervie. 2011. "Estimating the Causal Effects of French Agro-Evironmental Schemes on Farmers' Practices." (Working paper presented at the OECD Workshop on the Evaluation of Agri-Environmental Policies, Braunschweig, Germany, June 20-22).

Chabé-Ferret, S. and J. Subervie. 2010. "Evaluating Agro-Environmental Schemes by Did Matching: Theoretical Justification, Robustness Tests, and Application to a French Program." (Working paper presented at the Fourth World Congress of Environmental and Resource Economists, Montreal, Canada, June 28-July 2).

Claassen, R. 2011. "USDA Conservation Spending on Working Agricultural Lands Bucks Long-Term Trend." *Amber Waves*, 9(3), 60.

Claassen, R. and M. Ribaudo. 2006. "Conservation Policy Overview." *Agricultural Resource and Environmental Indicators*, Economic Information Bulletin, EIB-16, Economic Research Service, U.S. Department of Agriculture, 168-74.

Ervin, C. A. and D. E. Ervin. 1982. "Factors Affecting the Use of Soil Conservation Practices: Hypotheses, Evidence, and Policy Implications." *Land Economics*, 58(3), 277-92.

Featherstone, A. M. and B. K. Goodwin. 1993. "Factors Influencing a Farmer's Decision to Invest in Long-Term Conservation Improvements." *Land Economics*, 69(1), 67-81.

Fuglie, K. and C. Kascak. 2001. "Adoption and Diffusion of Natural-Resource-Conserving Agricultural Technology." *Review of Agricultural Economics*, 23(3), 386-403.

Goolsby, D., W. Battaglin, G. Lawrence, R. Artz, B. Aulenbach, B. Hooper, R. Keeney and G. Stensland. 1999. "Flux and Sources of Nutrients in the Mississippi-Atchafalaya River Basin: Topic 3 Report." U.S. Department of Commerce, National Oceanic and Atmospheric Administration.

Heckman, J., H. Ichimura, J. Smith and P. Todd. 1998a. "Characterizing Selection Bias Using Experimental Data." *Econometrica*, 66(5), 1017-98.

Heckman, J. J., H. Ichimura and P. Todd. 1998b. "Matching as an Econometric Evaluation Estimator." *Review of Economic Studies*, 65(2), 261-94.

Heckman, J. J., H. Ichimura and P. E. Todd. 1997. "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme." *Review of Economic Studies*, 64(4), 605-54.

Lambert, D., P. Sullivan, R. Claassen and L. Foreman. 2006. "Conservation Compatible Practices and Programs: Who Participates?" Economic Research Report, ERR-14, Economic Research Service, U.S. Department of Agriculture.

Liu, X. and L. Lynch. 2011. "Do Agricultural Land Preservation Programs Reduce Farmland Loss? Evidence from a Propensity Score Matching Estimator." *Land Economics*, 87(2), 183-201.

Lynch, L., W. Gray and J. Geoghegan. 2007. "Are Farmland Preservation Program Easement Restrictions Capitalized into Farmland Prices? What Can a Propensity Score Matching Analysis Tell Us?" *Applied Economic Perspectives and Policy*, 29(3), 502-09.

Mezzatesta, M., D. Newburn and R. Woodward. 2011. "Additionality and the Adoption of Farm Conservation Practices." Unpublished Manuscript, August.

Pufahl, A. and C. R. Weiss. 2009. "Evaluating the Effects of Farm Programmes: Results from Propensity Score Matching." *European Review of Agricultural Economics*, 36(1), 79-101.

Ribaudo, M., N. Gollehon, M. Aillery, J. Kaplan, R. Johansson, J. Agapoff, L. Christensen, V. Breneman and M. Peters. 2003. "Manure Management for Water Quality: Costs to Animal Feeding Operations of Applying Manure to Land." Agricultural Economic Report, AER-824, Economic Research Service, U.S. Department of Agriculture.

Ribaudo, M. and R. Johansson. 2006. "Water Quality—Impacts of Agriculture." *Agricultural Resource and Environmental Indicators*, Economic Information Bulletin, EIB-16, Economic Research Service, U.S. Department of Agriculture.

Rosenbaum, P. R. and D. B. Rubin. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrika*, 70(1), 41-55.

Smith, K. and M. Weinberg. 2004. "Measuring the Success of Conservation Programs." *Amber Waves*, 2(4), 14-21.

Soule, M. J., A. Tegene and K. D. Wiebe. 2000. "Land Tenure and the Adoption of Conservation Practices." *American Journal of Agricultural Economics*, 82(4), 993-1005.

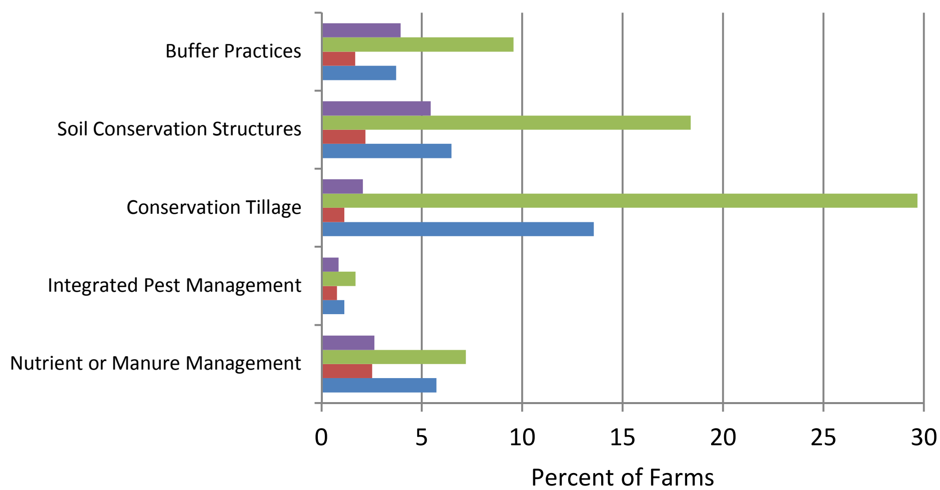
Traoré, N., R. Landry and N. Amara. 1998. "On-Farm Adoption of Conservation Practices: The Role of Farm and Farmer Characteristics, Perceptions, and Health Hazards." *Land Economics*, 114-27.

Wu, J. and B. A. Babcock. 1998. "The Choice of Tillage, Rotation, and Soil Testing Practices: Economic and Environmental Implications." *American Journal of Agricultural Economics*, 80(3), 494-511.

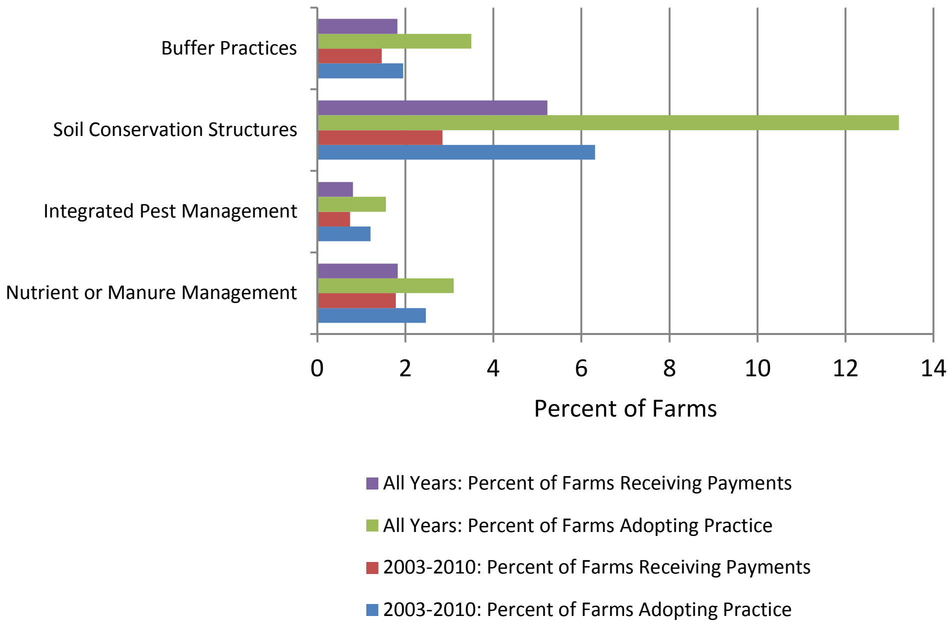
Zanutto, E. L. 2006. "A Comparison of Propensity Score and Linear Regression Analysis of Complex Survey Data." *Journal of Data Science*, 4(1), 67-91.

Figure 1. – Conservation Practice Adoption and Payments by Practice and Adoption Year

Panel A - 2010 Corn Survey

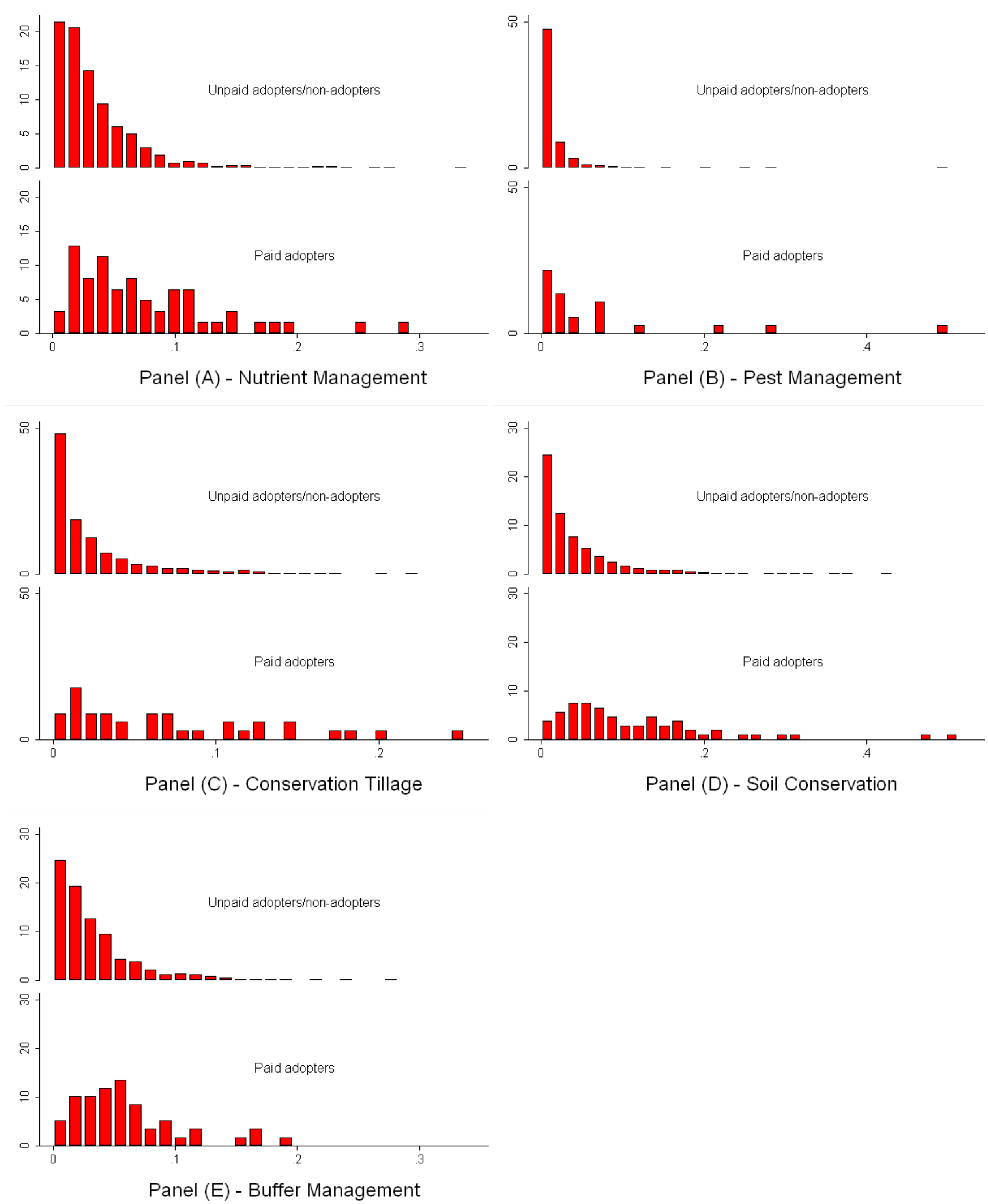


Panel B - 2009 Wheat Survey[2]



(Source: 2009 and 2010 Agricultural Resources Management Survey.)
[1] Buffer practices include field-edge filter strips, field borders, and riparian buffers. Soil conservation structures include terraces, grassed waterways, grade stabilization structures, and water and sediment basins. Conservation tillage includes no-till, mulch till, and ridge-till. Nutrient and manure management includes comprehensive nutrient management and manure management. Integrated pest management is a single indicator variable even though it summarizes several different type of pest management practices.
[2]Farmers in the wheat survey where not asked about conservation tillage payments

Figure 2. – Propensity Scores by Conservation Practice Type and Treatment Status, Corn 2010



Notes: Frequency of control observations (unpaid adopters or unpaid non-adopters) and treatment observations (adopters with payment) observations by propensity score bins for each of the five types of conservation practices.

Table 1. –Summary of Variables, 2010 Corn: Means, Standard Deviations, and Tests of Differences in Means by Treatment Status and Practice Type [a]

	All Practices	Nutrient Management		Pest Management		Conservation Tillage		Soil Conservation		Buffer Practices	
	Either	Paid	Unpaid	Paid	Unpaid	Paid	Unpaid	Paid	Unpaid	Paid	Unpaid
Adopted Practice (=1)	.465[b]	1	.057	1	.016	1	.301	1	.122	1	.050
	(.499)	(0)	(0.23)	(0)	(0.13)	(0)	(.46)	(0)	(.33)	(0)	(.22)
Field											
NCCPI	0.532	0.533	0.493	0.533	0.495	0.534	0.459	0.527	0.629	0.531	0.647
	(0.21)	(0.21)	(0.21)	(0.21)	(0.19)	(0.21)	(0.22)	(0.21)	(0.18)	(0.21)	(0.15)
15-yr avg. precip. (mm)	8.815	8.802	9.162	8.818	8.589	8.819	8.634	8.781	9.532	8.855	8.992
	(2.21)	(2.22)	(2.08)	(2.20)	(3.12)	(2.20)	(2.66)	(2.23)	(1.71)	(2.20)	(1.73)
15-yr avg. max. (°C)	0.241	0.241	0.233	0.241	0.24	0.241	0.242	0.24	0.25	0.241	0.237
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Highly erodible (=1)	0.104	0.1	0.226	0.102	0.261	0.103	0.139	0.096	0.269	0.102	0.104
	(0.31)	(0.30)	(0.42)	(0.30)	(0.45)	(0.30)	(0.35)	(0.30)	(0.45)	(0.30)	(0.31)
Field is irrigated (=1)	0.093	0.094	0.057	0.091	0.174	0.091	0.167	0.094	0.06	0.091	0.104
	(0.29)	(0.29)	(0.23)	(0.29)	(0.39)	(0.29)	(0.38)	(0.29)	(0.24)	(0.29)	(0.31)
Wetland (=1)	0.031	0.03	0.057	0.03	0.13	0.03	0.083	0.032	0.015	0[c]	0[c]
	(0.17)	(0.17)	(0.23)	(0.17)	(0.34)	(0.17)	(0.28)	(0.18)	(0.12)	(0)	(0)
Farm and Farmer											
Oper. size (1,000 ac.)	1.142	1.145	1.068	1.141	1.192	1.128	1.719	1.133	1.331	1.125	1.132
	(1.95)	(1.97)	(1.17)	(1.96)	(0.98)	(1.96)	(1.48)	(1.94)	(2.14)	(1.95)	(1.97)
Field size (100 ac.)	0.519	0.525	0.367	0.52	0.488	0.521	0.434	0.512	0.676	0.513	0.594
	(0.61)	(0.62)	(0.39)	(0.61)	(0.86)	(0.61)	(0.39)	(0.60)	(0.75)	(0.61)	(0.67)
Owns field (=1)	0.578	0.571	0.774	0.575	0.783	0.578	0.611	0.573	0.701	0.573	0.75
	(0.49)	(0.50)	(0.42)	(0.49)	(0.42)	(0.49)	(0.49)	(0.50)	(0.46)	(0.50)	(0.44)
Primarily a farmer (=1)	0.87	0.87	0.868	0.869	0.913	0.867	0.972	0.871	0.851	0.87	0.792
	(0.34)	(0.34)	(0.34)	(0.34)	(0.29)	(0.34)	(0.17)	(0.34)	(0.36)	(0.34)	(0.41)
Age of operator	55.029	55.151	51.698	55.058	53.174	54.957	57.972	54.81	59.716	54.9	57.063
	(12.41)	(12.50)	(8.94)	(12.41)	(12.00)	(12.40)	(12.27)	(12.39)	(11.94)	(12.46)	(10.01)
College degree (=1)	0.205	0.202	0.283	0.202	0.391	0.202	0.333	0.196	0.388	0.203	0.333
	(0.40)	(0.40)	(0.46)	(0.40)	(0.50)	(0.40)	(0.48)	(0.40)	(0.49)	(0.40)	(0.48)
Number of observations	1,499	53	1,466	23	1,476	36	1,463	67	1,432	48	1,404

Notes: [a] Standard deviations in parentheses. Sample sizes vary by treatment model estimation. The table highlights those variables which have a p-value of .1 or smaller for a difference in means t-test across treatment status (*paid* and adopted vs. *unpaid* and either adopted or did not adopt). [b] For the All Practices column, *Adopted Practice* takes a value of 1 if any one of the conservation practices were adopted. [c] Variable perfectly predicts non-payment for practice and is not include in treatment model estimation.

Table 2. – Estimated Coefficients for Treatment Models for Surveyed Corn Fields in 2010

	Nutrient Management	Pest Management	Conservation Tillage	Soil Conservation	Buffer Practices
NCCPI	-0.39	-0.071	-0.44	1.01***	1.59***
	(-1.15)	(-0.14)	(-1.05)	(2.83)	(3.70)
15-yr avg. precip. (mm)	0.074*	-0.0041	0.039	0.072*	0.0051
	(1.95)	(-0.08)	(0.95)	(1.93)	(0.11)
15-yr avg. max. temp. (°C)	-7.97**	-1.56	-3.61	4.79*	-5.75
	(-2.34)	(-0.37)	(-1.01)	(1.75)	(-1.52)
Highly erodible (*HE*) (=1)	0.14	-0.11	-0.074	0.71***	-0.19
	(0.57)	(-0.29)	(-0.20)	(3.31)	(-0.63)
Field is irrigated (*FI*) (=1)	-0.23	0.56	0.10	-0.95**	0.10
	(-0.44)	(1.05)	(0.23)	(-2.12)	(0.28)
Wetland (*WL*) (=1)	0.68	0.69	0.54	0.30	-
	(1.41)	(1.22)	(1.06)	(0.53)	
Oper. size (*OS*) (1,000 ac.)	0.18	0.85	1.54***	0.078	-0.083
	(0.55)	(1.36)	(3.52)	(0.35)	(-0.28)
Operation size^2	-0.047	-0.17*	-0.10***	-0.0062	-0.0053
	(-1.52)	(-1.91)	(-2.70)	(-1.08)	(-1.49)
Field size (100 ac.)	-0.29	-0.97**	-0.53	0.46**	0.18
	(-0.63)	(-2.50)	(-0.90)	(2.02)	(0.64)
Field size^2	-0.018	0.19***	-0.049	-0.076	-0.043
	(-0.07)	(2.64)	(-0.14)	(-1.30)	(-0.46)
Owns field (=1)	0.48***	0.39*	0.15	0.25*	0.34**
	(3.16)	(1.87)	(0.90)	(1.79)	(2.20)
Primarily a farmer (=1)	0.0092	0.097	0.56	-0.085	-0.23
	(0.04)	(0.31)	(1.30)	(-0.45)	(-1.19)
Age of operator (*AGE*)	-0.016**	-0.0038	0.028***	0.017**	0.0067
	(-2.15)	(-0.35)	(2.64)	(2.56)	(0.92)
College degree (*CD*) (=1)	0.35	0.44	0.84***	0.45***	0.56***
	(1.62)	(1.36)	(3.09)	(2.64)	(2.65)
HE X *OS*	0.22	0.45*	0.11	-0.080	0.12
	(1.49)	(1.80)	(0.59)	(-0.49)	(0.55)
FI X *OS*	0.13	-0.12	0.16	0.18*	0.13
	(0.63)	(-0.37)	(0.93)	(1.68)	(1.04)
WL X *OS*	-0.29	-0.010	-0.093	-0.36	-
	(-0.92)	(-0.03)	(-0.41)	(-0.67)	
AGE X *OS*	0.0027	-0.0035	-0.013**	-0.000046	0.0028
	(0.49)	(-0.36)	(-2.36)	(-0.01)	(0.55)
CD X *OS*	-0.038	-0.015	-0.32**	-0.027	-0.24
	(-0.29)	(-0.07)	(-2.14)	(-0.36)	(-1.52)
Constant	-0.071	-2.11**	-4.04***	-5.62***	-2.08**
	(-0.09)	(-1.96)	(-3.95)	(-7.30)	(-2.44)
Observations	1,499	1,499	1,499	1,499	1,452

Notes: * p<.1, ** p<.05, *** p<.01; Each column reports the results from treatment model estimation the respective conservation practice type.

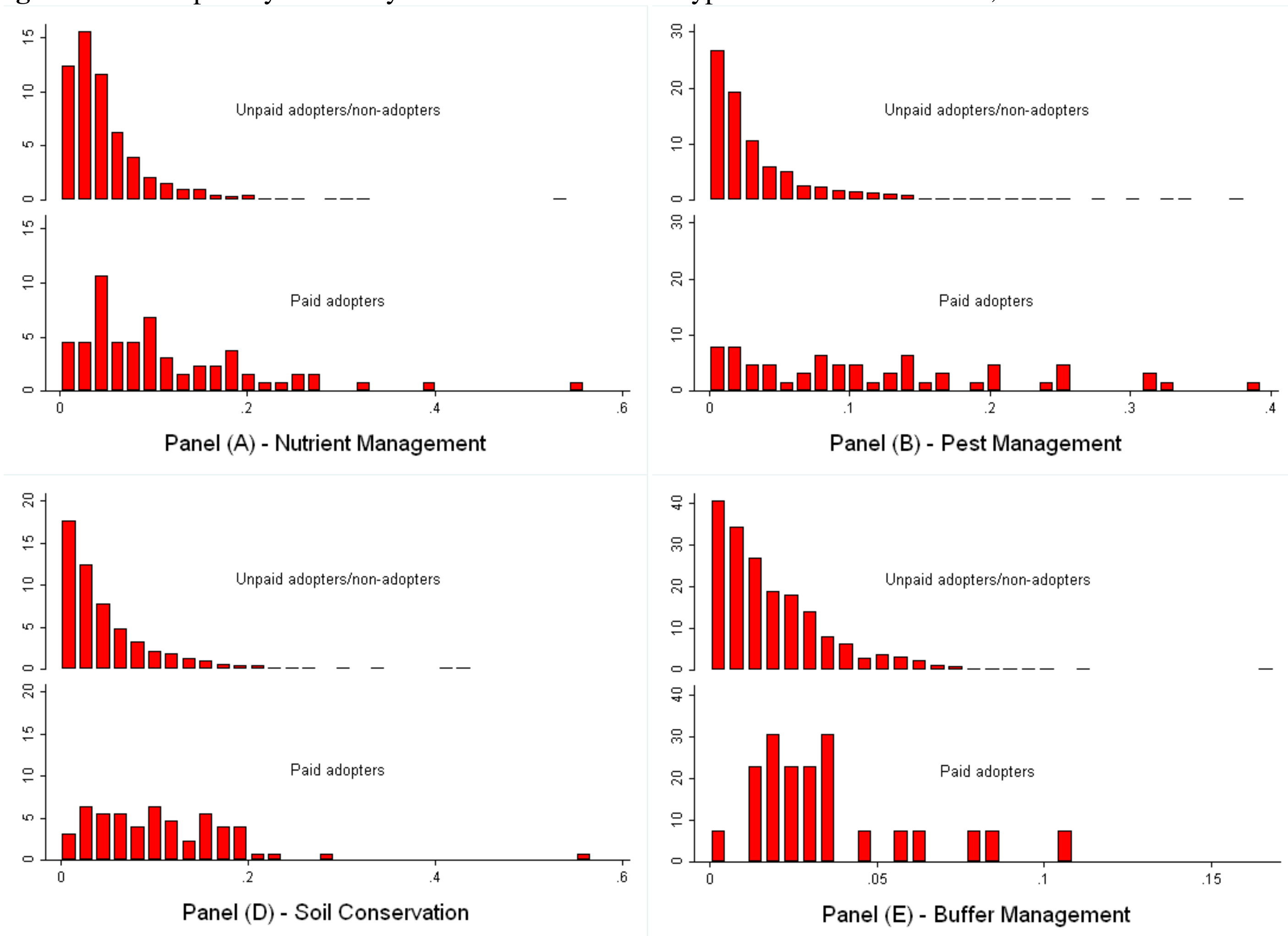
Table 3. – Estimated Additionality ($\widehat{ATT}$) by Conservation Practice Type

	2010 Corn Fields		2009 Wheat Fields	
	Without survey weights	Survey-weighted	Without survey weights	Survey-weighted
Nutrient Management	0.927	0.879	0.969	0.977
	(0.013)	(0.033)	(.010)	(.009)
Pest Management	0.975	0.970	0.944	0.939
	(0.017)	(0.013)	(.020)	(.035)
Conservation Tillage	0.631	0.618	-	-
	(0.032)	(0.029)		
Soil Conservation	0.826	0.839	0.910	0.912
	(0.020)	(0.027)	(.013)	(.016)
Buffer practices	0.945	0.957	0.987	0.982
	(0.001)	(0.009)	(.003)	(.008)

Note: The table reports mean estimates of the *ATT* from a Gaussian kernel-based propensity score matching estimator with a bandwidth of .02. Standard errors (in parentheses) are bootstrapped with a 1,000 independent draws. Survey-weighted results are representative of the U.S. population of farmers and are obtained by calculating the weighted average difference in outcomes between treatment and matched control observations with observation-specific survey weights. The 2009 wheat survey did not include questions about payments received for conservation tillage.

Appendix:

Figure 2A. – Propensity Scores by Conservation Practice Type and Treatment Status, Wheat 2009



Notes: Frequency of control observations (unpaid adopters or unpaid non-adopters) and treatment observations (adopters with payment) observations by propensity score bins for each of the five types of conservation practices.

Table A1. –Summary of Variables, 2009 Wheat: Means, Standard Deviations, and Tests of Differences in Means by Treatment Status and Practice Type [a]

	All Practices	Nutrient Management		Pest Management		Soil Conservation		Buffer Practices	
	Either	Paid	Unpaid	Paid	Unpaid	Paid	Unpaid	Paid	Unpaid
Adopted Practice (=1)	.204[b]	1	.019	1	.021	1	.077	1	.013
	(.403)	(0)	(0.14)	(0)	(0.14)	(0)	(.27)	(0)	(.11)
Field									
NCCPI	0.333	0.327	0.334	0.341	0.333	0.416	0.34	0.41	0.347
	(0.19)	(0.17)	(0.19)	(0.19)	(0.19)	(0.18)	(0.19)	(0.18)	(0.19)
15-yr avg. precip. (mm)	5.803	5.082	5.843	5.226	5.784	6.636	5.983	6.302	6.065
	(2.59)	(2.45)	(2.60)	(2.43)	(2.63)	(2.70)	(2.57)	(2.54)	(2.62)
15-yr avg. max. (°C)	0.236	0.23	0.237	0.229	0.237	0.251	0.235	0.23	0.238
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
Highly erodible (=1)	0.191	0.44	0.177	0.549	0.173	0.377	0.186	0.333	0.185
	(0.39)	(0.50)	(0.38)	(0.50)	(0.38)	(0.49)	(0.39)	(0.48)	(0.39)
Field is irrigated (=1)	0.088	0.067	0.089	0.059	0.096	0 [c]	0 [c]	0 [c]	0 [c]
	(0.28)	(0.25)	(0.28)	(0.24)	(0.30)	(0)	(0)	(0)	(0)
Wetland (=1)	0.057	0.013	0.059	0 [c]	0 [c]	0.014	0.064	0 [c]	0 [c]
	(0.23)	(0.12)	(0.24)	(0)	(0)	(0.12)	(0.25)	(0)	(0)
Farm and Farmer									
Oper. size (1,000 ac.)	3.521	4.843	3.449	4.501	3.651	3.329	3.531	2.891	3.554
	(4.13)	(5.58)	(4.02)	(5.78)	(4.19)	(2.61)	(4.14)	(2.23)	(4.19)
Field size (100 ac.)	1.28	1.691	1.257	1.742	1.276	1.618	1.293	1.526	1.294
	(1.47)	(1.71)	(1.46)	(1.74)	(1.45)	(2.45)	(1.46)	(1.62)	(1.50)
Owns field (=1)	0.468	0.36	0.474	0.353	0.463	0.478	0.457	0.375	0.459
	(0.50)	(0.48)	(0.50)	(0.48)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Primarily a farmer (=1)	0.933	0.987	0.93	1 [c]	1 [c]	0.928	0.93	0.958	0.928
	(0.25)	(0.12)	(0.26)	(0)	(0)	(0.26)	(0.26)	(0.20)	(0.26)
Age of operator	55.806	51.827	56.025	51.451	56.066	60.623	55.699	56	56.042
	(11.85)	(10.55)	(11.88)	(11.36)	(11.79)	(11.72)	(11.88)	(13.43)	(11.91)
College degree (=1)	0.306	0.4	0.301	0.529	0.289	0.29	0.302	0.208	0.308
	(0.46)	(0.49)	(0.46)	(0.50)	(0.45)	(0.46)	(0.46)	(0.42)	(0.46)
Number of observations	1,439	75	1,364	51	1,213	69	1,244	24	1,208

Notes: [a] Standard deviations in parentheses. Sample sizes vary by treatment model estimation. The table highlights those variables which have a p-value of .1 or smaller for a difference in means t-test across treatment status (*paid* and adopted vs. *unpaid* and either adopted or did not adopt). [b] For the All Practices column, *Adopted Practice* takes a value of 1 if any one of the conservation practices were adopted. [c] Variable perfectly predicts non-payment for conservation practice and is not include in treatment model estimation.

Table A2. – Estimated Coefficients for Treatment Models for Surveyed Wheat Fields in 2009

	Nutrient Management	Pest Management	Soil Conservation	Buffer Practices
NCCPI	1.26**	1.13*	1.68***	1.62**
	(2.39)	(1.83)	(3.05)	(2.04)
15-yr avg. precip. (mm)	-0.055	-0.021	-0.024	0.0022
	(-1.30)	(-0.42)	(-0.58)	(0.04)
15-yr avg. max. temp. (°C)	-4.29	-6.46**	5.70**	-8.55*
	(-1.64)	(-2.03)	(2.40)	(-1.94)
Highly erodible (*HE*) (=1)	0.49**	0.78***	0.58**	0.48
	(2.57)	(3.78)	(2.50)	(1.37)
Field is irrigated (*FI*) (=1)	-0.061	0.31	-	-
	(-0.20)	(0.66)		
Wetland (*WL*) (=1)	-0.94	-	0.12	-
	(-1.19)		(0.16)	
Oper. size (*OS*) (1,000 ac.)	0.048	0.065	0.29*	0.19
	(0.58)	(0.77)	(1.85)	(0.80)
Operation size^2	-0.00084	0.00070	-0.016**	-0.013
	(-0.72)	(0.59)	(-2.46)	(-0.99)
Field size (100 ac.)	0.11	0.16	-0.040	0.20
	(1.22)	(1.34)	(-0.46)	(1.38)
Field size^2	-0.0098	-0.014	0.0098	-0.014
	(-1.00)	(-0.96)	(1.38)	(-0.84)
Owns field (=1)	-0.077	-0.11	0.029	-0.095
	(-0.62)	(-0.74)	(0.22)	(-0.51)
Primarily a farmer (=1)	0.49	-	-0.14	0.060
	(1.32)		(-0.56)	(0.14)
Age of operator (*AGE*)	-0.011	-0.0091	0.021**	0.0073
	(-1.45)	(-1.04)	(2.39)	(0.61)
College degree (*CD*) (=1)	0.046	0.52***	0.0053	-0.54
	(0.25)	(2.62)	(0.02)	(-1.36)
HE X *OS*	0.027	0.011	-0.0012	-0.024
	(0.87)	(0.31)	(-0.02)	(-0.27)
FI X *OS*	0.0026	-0.16	-	-
	(0.05)	(-0.78)		
WL X *OS*	0.026	-	-0.22	-
	(0.16)		(-0.83)	
AGE X *OS*	-0.00053	-0.0012	-0.0012	-0.0017
	(-0.37)	(-0.78)	(-0.54)	(-0.49)
CD X *OS*	0.014	-0.034	-0.022	0.088
	(0.45)	(-0.95)	(-0.39)	(0.93)
Constant	-0.91	-0.57	-5.13***	-1.47
	(-1.21)	(-0.74)	(-6.62)	(-1.25)
Observations	1,439	1,264	1,313	1,232

Notes: * p<.1, ** p<.05, *** p<.01; Each column reports the results from treatment model estimation the respective conservation practice type.