Agricultural Cost Sharing and Water Quality in the Chesapeake Bay: Estimating Indirect Effects of Environmental Payments

Patrick Fleming

This article analyzes the effect of agricultural cost sharing for cover crops on the acres of three conservation practices. A survey of farmers from Maryland is used to estimate the direct effect of cover crop cost sharing on the acres of cover crops, and the indirect effect of cover crop cost sharing on the acres of two other practices: conservation tillage and contour/strip cropping. A two-stage simultaneous equation approach is used to correct for voluntary self-selection into cost-sharing programs, and to account for substitution effects among conservation practices. Using model parameters from the U.S. Environmental Protection Agency's Chesapeake Bay Program, the estimated effects of cost sharing are then translated to pollution reduction in order to quantify water quality benefits. The results indicate that the large cover crop cost sharing effort in Maryland had considerable effects on cover crop acreage, substantially reducing nitrogen and phosphorus runoff. Moreover, after accounting for the indirect effects on conservation tillage, the cost per pound of phosphorus abatement in the Chesapeake Bay decreased by between 60–67%.

Key words: Abatement, cost sharing, Environmental Quality Incentives Program, EQIP, environmental subsidies, multiple simultaneous equation models, nonpoint source pollution, water quality.

JEL codes: C31, C34, Q53, Q58.

According to the U.S. Environmental Protection Agency (EPA), nonpoint source (NPS) pollution from agriculture is the single largest source of impairment in U.S. rivers and streams (EPA 2009). The primary policy instrument used to address this problem is cost sharing—a payment offered to farmers intended to incentivize the adoption of best management practices (BMPs). In 2012, for example, the federal Environmental Quality Incentives Program (EQIP) spent $1.38 billion to subsidize such agricultural conservation practices.

However, providing accurate information on the tradeoff between these costs of conservation and changes in farmer adoption decisions is complicated by several factors. First, enrollment in cost sharing is voluntary, so evaluations of the policy effect need to account for selection bias (Mezzatesta, Newburn, and Woodward 2013; Lichtenberg and Smith-Ramirez 2011). Second, and most critically for this article, patterns of substitution and correlation among agricultural practices may cause incentive payments for a given practice to have indirect effects on the adoption of other practices, for both agronomic and economic reasons (Dorfman 1996; Wu and Babcock 1998; Khanna 2001; Cooper 2003; Lichtenberg 2004a).[1]

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[1] A related problem is that of slippage (Khanna, Isik, and Zilberman 2002; Lichtenberg 2004b; Lichtenberg and Smith-Ramirez 2011), in which incentive payments for practices used on cultivated land cause a farmer to replace environmentally benign land uses (such as pasture or woodland) with more intensive cultivation. In the case of slippage, there is a substitution between land uses, rather than a substitution between working-land conservation practices.

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There is limited evidence regarding substitution and complementarities between conservation practices. Lichtenberg (2004a), for example, finds empirical evidence for substitution and complementarity within a group of seven BMPs from cross-price effects of binary models with dual specifications. Cooper (2003) uses a simultaneous equation framework to account for correlation in the adoption of five BMPs in a survey of farmers' hypothetical willingness-to-accept incentive payments. Using a multinomial logit framework, Wu and Babcock (1998) estimate joint adoption decisions of conservation tillage, crop rotation, and soil nitrogen testing, treating each of the eight possible combinations of practices as a mutually-exclusive alternative. These authors find a positive correlation in the adoption of crop rotation and conservation tillage, along with a corresponding reduction in soil erosion. With a multinomial probit model, Dorfman (1996) analyzed correlation in the adoption of two agricultural conservation practices used by apple growers. Finally, Khanna (2001) uses a modified bivariate probit to model the sequential adoption of two related BMPs—soil testing and precision fertilizer application. Khanna finds this bivariate method preferable in comparison to estimating inter-related conservation decisions as either independent or collapsed into a single adoption equation.

However, among the empirical studies that have examined correlation in the adoption of multiple conservation practices, none are designed to identify the causal effect of cost-sharing programs. They either do not consider cost-sharing programs at all, or, in the case of Cooper (2003), are not intended to address the problems of self-selection and additionality of cost-sharing programs. These studies also do not consider the spatial extent or acreage of conservation practice adoption, which is needed to translate the estimated effects of cost sharing to nutrient reduction and water quality benefits.

This article investigates the effect of a large cover crop cost-sharing initiative in Maryland on the acreage of three erosion-control practices. Specifically, it estimates the direct effect of cover crop cost sharing on cover crop acreage, along with the indirect effect of this cost sharing on the acreage in conservation tillage and contour/strip cropping. Using data from a 2010 survey of Maryland farmers, I estimate both cost-sharing enrollment and BMP adoption in a two-stage system of simultaneous equations with simulated maximum likelihood techniques and quasi-random Halton sequences. The first-stage model is a trivariate probit to estimate the cost-sharing enrollment decision for each practice. The second-stage model estimates conservation practice acreage shares for farmers with and without cost-sharing for cover crops. In the second stage, a multivariate tobit is used and selection bias is accounted for with generalized residuals from the first stage.

The estimated treatment effect of cover crop cost sharing is calculated for both enrolled and unenrolled farms. These estimated effects are then translated to water quality benefits using model parameters from the EPA's Chesapeake Bay Program (CBP). I combine the econometric results with the CBP's modeled nitrogen and phosphorus loads, BMP costs, and pollution abatement efficiencies to calculate a cost per pound of abatement for both enrolled and unenrolled farms.

The results indicate that, among enrolled farmers, the acreage share of cover crops as well as conservation tillage increased substantially due to cost sharing. Cover crop acreage share increased from an estimated counterfactual of 0.023 without cost sharing to 0.292 with cost sharing (a treatment effect of 0.269). Similarly, there was an estimated increase in the acreage share in conservation tillage from 0.188 to 0.446 following enrollment in cover crop cost sharing. The increase in conservation tillage acreage reflects a beneficial indirect effect of the cover crop cost sharing program, due to agronomic and economic complementarities between the practices (Blum et al. 1997; USDA SARE 2012). This provides evidence for crowding in of additional farmer investment in conservation due to public spending on the environment (Albers, Ando, and Chen 2008). In contrast, the change in acreage share of contour/strip is very small. Overall, the indirect effects on other practices are estimated to decrease the cost of phosphorus abatement in the Bay by between 60–67% for the farmers enrolled in cover crop cost sharing in Maryland.

The estimated coefficients also indicate that extending cost sharing to farmers not currently enrolled in cover crop cost sharing would be expected to have a substantial direct effect, increasing cover crop acreage share from 0.024 without cost sharing to an estimated counterfactual of 0.278 after enrollment (a treatment effect of 0.254). The expected indirect effect on conservation tillage is also positive and large, but not measured precisely enough to establish that it is different from zero. Similar to the enrolled group, the effect on contour/strip is small.

This research makes several unique contributions to the literature. First, it provides a methodological improvement using a two-stage simultaneous equation approach that accounts for both self-selection due to nonrandom enrollment into cost-sharing programs and correlation among the adoption decisions for conservation practice use. In contrast, prior research using propensity score matching techniques has been able to account for self-selection bias; however, it is not suited for capturing the correlation among adoption decisions, thereby ignoring potential indirect effects (Mezzatesta, Newburn, and Woodward 2013; Claassen and Duquette 2013). The methodological approach used in this article is most similar to that of Lichtenberg and Smith-Ramirez (2011), who use an endogenous switching regression model to account for both self-selection into cost-sharing programs and estimate farm acreage in multiple conservation practices. Unlike the present article, Lichtenberg and Smith-Ramirez aggregate cost share enrollment for any of a group of eight cropland conservation practices into a single equation. The present analysis does not aggregate funding across practices, but uses a trivariate probit to estimate a cost share enrollment equation for each practice studied. I also base the switching regression on a single practice, as opposed to an aggregation of practices. Thus, the present methodology does not assume that cost share awards for different practices have equal effects on the acreage shares estimated in the second stage, but rather allows heterogeneous effects of cost share awards for different practices.

Second, the methodological contribution has important policy implications. While direct effects of cost sharing have been studied in several contexts, it is not known to what extent indirect effects are positive, negative, or negligible, that is, whether the cost-share program induces crowding out of other practices, crowding in of those practices, or has no significant indirect effects. This article finds that the net indirect effect is positive for the cover crop cost-sharing program in Maryland, providing evidence that public dollars spent on the environment can crowd in further private investment (Albers, Ando and Chen 2008). Specifically, additional nitrogen abatement is between 20–35% higher after considering indirect effects of the cover crop incentive payment, with even greater indirect gains seen for phosphorus abatement. Given that the cover crop program must be renewed annually, this has important implications for cost effectiveness, and for policy goals of reducing NPS pollution.

Background

Agriculture will need to play a large role in improving water quality in waterways, estuaries, and coastal waters. In the Chesapeake Bay, for example, an estimated 45% of nitrogen, 44% of phosphorus, and 65% of sediment entering the bay arise from agricultural sources. In 2009, the EPA enacted a total maximum daily load (TMDL) for the Chesapeake Bay watershed, the largest TMDL to date, which mandates reductions of nitrogen, phosphorus, and sediment by 2025.

To reduce agricultural NPS nutrient emissions into the Chesapeake Bay, the state of Maryland has used cost-sharing incentive payments for over thirty years. The centerpiece of this effort has been the Maryland Agricultural and Water Quality Cost Sharing (MACS) program, which has quintupled spending since 2005. The program budget was $31.2 million in 2015, and approximately 80% of these funds are devoted to cover crops. One-third of harvested cropland in the state is treated with cover crops funded through MACS.[2] Base payments begin at $45 per acre for traditional cover crops, and eligible crop types include rye, barley, wheat, triticale, canola, forage radish, and certain legumes such as clover. Federal cost-share programs, such as EQIP, have also been available in Maryland, providing funding for conservation practices. Total EQIP funds spent in Maryland were about $9 million in 2013, but only a small portion of that funding was allocated to cover crops. In 2015, for

[2] Available at: http://mda.maryland.gov/resource_conservation/counties/MACSAR2015FINAL.pdf.

example, less than 1% of EQIP projects in Maryland involved planting cover crops.[3]

Like other cost share programs, enrollment in MACS is voluntary. Farmers apply through the soil conservation district between June and July prior to Fall planting. There are several field eligibility requirements, including that farmers must be in good standing with MACS and be in compliance with the Maryland Nutrient Management Program (NMP).[4] The MACS funding itself is allocated through the Chesapeake Bay Restoration Fund and the Chesapeake Bay 2010 Trust Fund. Nearly all cost-sharing in the state is linked to attempts to improve Chesapeake Bay water quality. Thus, the state of Maryland itself—due to its aggressive promotion of cost sharing and the differences in topography and farm type, which increase the likelihood that farmers in the state adopt multiple conservation practices—is favorable for the study of behavioral responses to cost sharing such as additionality and indirect effects on other field practices.

The practices studied in this article—cover crops, conservation tillage, and contour/strip cropping—were chosen because they are all used to reduce erosion on working cropland. Other common conservation practices—such as riparian buffers or grass-lined waterways—are either not implemented as field practices on working cropland, or are only present on a small portion of a field. Cover crops are grown over the winter when many fields are left bare and vulnerable to wind, rain, and snowmelt erosion. Cover crops also add organic matter to the soil, and may be harvested in the spring if climatic conditions allow. Conservation tillage is any method of soil cultivation that leaves the crop residue on fields before and after planting, thus leaving the soil structure intact and reducing erosion. Contour farming and strip cropping are two related methods of controlling soil loss from working cropland.[5]

Economic analysis has revealed patterns of correlation in the adoption of a variety of conservation practices (Dorfman 1996; Wu and Babcock 1998; Cooper 2003; Lichtenberg 2004a). Conservation tillage is considered in two of these empirical studies (Wu and Babcock 1998; Cooper 2003) but not in combination with either cover crops or contour/strip cropping. Lichtenberg (2004a) estimates the cross-price elasticities for seven different conservation practices, including contour/strip cropping and cover crops. This author does not find a statistically significant cross-price elasticity between these practices.

Agronomic studies provide hypotheses for the potential patterns of correlation that may be observed between cover crops, conservation tillage, and contour/strip cropping. For example, cover crops and conservation tillage have complementary effects in improving soil quality by adding increased organic matter to the soil (USDA SARE 2012), and suppressing the emergence of certain weeds (Blum et al. 1997). Reeves (1994) also demonstrates that cover crops are especially important in conservation tillage systems because of the increased need for crop rotation to maintain productivity. This evidence suggests complementarity between cover crops and conservation tillage. The potential interactions between cover crops and contour/strip cropping, as well as between conservation tillage and contour/strip cropping, are less well known. The Revised Universal Soil Loss Equation (RUSLE) shows diminishing returns in erosion reduction efficiency with the adoption of contour farming and strip cropping after the adoption of either conservation tillage or cover crops (RUSLE2 2014), which suggests patterns of substitution between contour/strip and other practices. However, both cover crops and conservation tillage provide certain benefits to farmers in addition to erosion reduction, which may

[3] Information on EQIP spending on cover crops in Maryland is available at: http://www.nrcs.usda.gov/wps/portal/nrcs/main/md/programs /financial/eqip/. Information on the Chesapeake Bay Watershed Initiative (CBWI) in Maryland is available at: https://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/programs/initiatives/?cid=STELPRDB1047323. The survey instrument used in this article did not distinguish between federal and state cost-share programs. However, MACS is the dominant source of cover-crop funding in Maryland.

[4] The NMP requires all farmers grossing $2,500 or more to follow a nutrient-management plan, specifying how much fertilizer, manure, or other nutrient sources may be safely applied to crops. The Maryland NMP does not require farmers to adopt specific BMPs. See http://mda.maryland.gov/resource_conservation/Pages/farmer_information.aspx for more details. Other eligibility requirements for MACS funding include a five-acre minimum, and seeds must be tested and labeled following Maryland Seed Law and Regulations.

[5] Contour farming is the planting of rows along the contours of a field, perpendicular to the prevailing slope. Strip farming involves the establishment of grass or alfalfa fields in alternating strips between fields of cash crops. Both practices slow runoff and capture sediment. Contour farming and strip cropping were identified separately in the farmer survey used in this article, but are frequently adopted jointly. For this reason, as well as limited adoption of these two practices, they were aggregated into a single practice in the econometric analysis.

Table 1. Conservation Practice Adoption, Cost Share Enrollment, and Percent of Operating Acres by Practice Type

Practice type	Number of farms			Average percent acres	
	No Adoption [1]	Adoption without cost share [2]	Adoption with cost share [3]	Adoption without cost share [4]	Adoption with cost share [5]
Cover crops	300	49	92	24.0%	32.1%
Conservation tillage	226	189	26	55.7%	54.9%
Contour/Strip	367	65	9	28.6%	22.4%

outweigh the diminishing returns shown by the RUSLE.

In short, for both economic and agronomic reasons it is likely that the subsidies devoted to cover crops will have indirect effects on other practices. However, in the context of cost sharing it is not known if these indirect effects will be positive, negative, or negligible. Thus, it is necessary to test for potential indirect effects empirically, in order to grasp the overall consequence of cost sharing on farmer behavior and, more importantly, water quality.

Data

Data comes from a survey of Maryland farmers drawn from the Maryland Agricultural Statistics Service (MASS) master list of farmers. The survey questionnaire was mailed to 1,000 farm operations with telephone follow-up administered by MASS in 2010. Stratified random sampling ensured a sufficient number of responses from large operations, and sampling weights were provided by MASS for deriving accurate population estimates. The weighted sample was designed to be representative of Maryland agriculture at the state level. Farmers were asked whether they implemented any of the conservation practices studied, the acreage upon which each practice was used, and whether or not cost sharing was received for each practice. Of the 523 responses received, 457 provided complete surveys usable for this analysis. Additionally, farms were excluded if they did not report any crops on their land (including pasture and hay), which resulted in a usable dataset of 441 farms.

Table 1 summarizes BMP adoption, acreage share, and cost share enrollment for each of the three practice types. Columns (1) to (3) show the (unweighted) number of respondents in the sample who reported adoption with cost sharing, adopted without cost sharing (i.e., self-funded adopters), and did not adopt the practice. For cover crops, more respondents adopt with the financial assistance of cost sharing than without funding—ninety-two respondents adopted cover crops with cost sharing compared to forty-nine respondents who adopted without cost sharing. In contrast, conservation tillage and contour/strip are primarily self-funded when adopted. Columns (4) and (5) show the acreage share in each practice type that is adopted. Acreage share is defined as the acreage in the conservation practice divided by the total operating acreage of the farm, where operating acreage is the sum of land owned and land rented, minus any land rented to others. Among the respondents who adopted cover crops, those who adopted with the incentive payment from cost sharing allocate a higher acreage share to the practice. Specifically, almost one-third of a farm's operating acreage is in cover crops among farmers who adopted with cost sharing compared to less than one-quarter among farmers who adopted without cost sharing. However, this is not the case for conservation tillage, where the average acreage share is approximately equal on farms that adopted without cost sharing compared to farms that adopted with cost sharing.

Table 2 summarizes the variables from the survey data collected on farm characteristics (e.g., topography, operating acreage, land tenure, cattle, distance to nearest surface water body), and farmer characteristics (e.g., education, income share from farming, experience farming). Topography variables include the proportion of operating acres by slope class: flat

Table 2. Descriptive Statistics for Maryland Farmers, 2010

Variable	Mean	Std. Dev.	Min	Max
Distance to the nearest water body (miles)	0.44	1.3	0	11
Proportion income from farming	0.56	0.4	0.01	1
Proportion acres in slope class Flat (< 2% grade)	0.50	0.4	0	1
Moderate (2-8% grade)	0.42	0.4	0	1
Steep (>8% grade)	0.08	0.2	0	1
Proportion acres rented	0.26	0.3	0	1
Operating acres (thousands)	0.48	0.9	0.002	9.78
Dairy or Beef Cattle (thousands)	0.07	0.2	0	2.688
Highest level of education attained Did not graduate high school	0.15	0.4	0	1
High school grad or greater	0.85	0.4	0	1
Years experience farming	41.38	18.0	0	80
Erosion reduction benefit (tons reduced / $) Cover crops	0.032	0.016	0.009	0.118
Conservation tillage	0.081	0.043	0.021	0.256
Contour/Strip	0.036	0.026	0.006	0.152

N = 441 for all variables

slope (less than 2% grade), moderate slope (2–8%), and steep slope (greater than 8%). Among other factors, the survey also asks farmers about the number of animals on the farm and the distance in miles from the farm to the nearest surface water body—including lakes, streams, wetlands, and bays. The survey did not include field-level information such as the number or size of individual fields on a farm.

In addition to the explanatory variables from the survey, I also construct variables for the per-unit cost of erosion reduction that serve as a proxy for the private on-farm erosion reduction benefits for each conservation practice.[6] Specifically, using data from the Chesapeake Bay Program's watershed model and per-acre BMP costs, I calculate the tons of erosion reduction per unit cost. These benefits are calculated as the tons of soil loss reduced per acre due to practice adoption, divided by the cost per acre of practice adoption. Costs per acre for cover crops are assumed to equal $31.40, the per acre cost of seed and planting for rye estimated by Wieland et al. (2009).[7] Rye is one of the most common cover crops used in Maryland. Conservation tillage implementation costs are from 2009 Maryland grain marketing budgets, based on the per-acre cost of planting corn with minimum-till methods plus the per-acre herbicide costs necessary to plant without tilling.[8] For contour/strip farming, per-acre EQIP reimbursement rates were considered a proxy for implementation costs. Finally, erosion reduction per acre is calculated from the CBP data as the edge-of-field agricultural sediment load in a river segment, multiplied by the BMP reduction efficiency in that river segment. Since the purpose of calculating these costs is to include the private benefits of erosion reduction as an explanatory variable in the econometric model, edge-of-field sediment loads are used rather than edge-of-stream loads. Erosion reduction per dollar varies cross-sectionally across the state of Maryland, and is matched with farmers in the survey by overlaying the polygons for river segments from the CBP watershed model with the ZIP Codes of the surveyed farms. Since these are essentially inverse input costs, it is expected that the acreage share in the conservation practice would be higher as the private benefits per unit of cost are higher.

Specification and Estimation of the Econometric Model

This section describes the specification and estimation of the econometric model. I use a

[6] Note that erosion reduction is not the only private benefit of cover crop and conservation tillage adoption. Other benefits of cover crops, for example, include adding organic matter to the soil and the potential to harvest in the spring. Harvested cover crops receive a lower cost share payment by MACS.

[7] Other cover crop cost estimates are available in Wieland et al. (2009) for different crop types and planting methods. Rye planted by drilling is considered the most cost effective. Note that seed costs have increased since 2009, which makes the current MACS cover crop incentive payment of $45/acre more appropriate. For example, 2015 seed costs for cereal rye are $32.14 to $42.86/acre, in addition to the planting costs of at least $11/acre. Slightly higher seed costs are observed for both wheat and barley. Available at: http://www.kingsagriseeds.com/.

[8] Available at: https://extension.umd.edu/grainmarketing/crop-budgets.

two-stage approach to estimate the effects of cover crop cost sharing on conservation practice use. I concentrate on cover crop cost sharing since cover crops have been the most aggressively promoted practice in Maryland and in the Chesapeake Bay Program in recent years. In the first stage, I estimate enrollment in cost sharing for three conservation practices. In the second stage, I estimate the share of farm acreage in each of the three practices as a function of cost-sharing enrollment using a control function approach in which generalized residuals from the first stage are included in the second stage to correct for self-selection into cost-sharing programs (Wooldridge 2014). The second-stage model is estimated using a multivariate tobit with endogenous switching of several core explanatory variables, with switching based on enrollment in cover crop cost sharing in order to focus on the most policy-relevant practice.[9] This switching regression model allows for the calculation of treatment effects based on the estimated acreage shares with and without enrollment in cover crop cost sharing. Finally, enrollment in cost sharing for the other two practices—conservation tillage and contour/strip—are included as covariates in each second-stage equation in order to separately identify the indirect effects of cover crop cost sharing from the effect of cost sharing for these other practices. By disaggregating the enrollment decisions for individual practices, the econometric model allows for separate effects of cost sharing for cover crops, conservation tillage, and contour/strip, an advantage of this model relative to Lichtenberg and Smith-Ramirez (2011).

In the model, each farmer j is assumed to be a profit-maximizing agent who chooses from a set of $m = \{1, 2, 3\}$ erosion-control practices on her farm. A farmer may adopt all the practices, no practices, or any combination thereof. The farmer simultaneously decides whether or not to apply for cost sharing for any of these practices, and cost-sharing enrollment for practice type m does not exclude the possibility of enrolling in cost-sharing programs for other practices. However, the decisions are not made independently. There may be correlation in the adoption of conservation practices, cost-share enrollment, and importantly between cost-share enrollment and practice adoption, given the problem of self-selection into cost-share programs.

[9] Switching was also limited to cover crops in order to allow for a sufficient number of farmers in each regime for the purpose of econometric identification.

Cost Sharing

First consider the cost-sharing decision. Cost-share enrollment depends on factors Z_{jm} influencing the application decision of farmer j for practice m, and the funding agency's subsequent award decision. These factors include the expected farm-level and broader environmental benefits of the practice, transaction costs of application, practice costs, and other farm-level factors such as land quality. A functional representation of a linear-in-parameters cost-share decision model is

$$(1)\quad C_{jm} = 1 \;\; if \;\; Z_{jm}\gamma_m + u_{jm} \geq 0, \;\; m = \{1, 2, 3\}$$

$$C_{jm} = 0 \;\; if \;\; Z_{jm}\gamma_m + u_{jm} < 0, \;\; m = \{1, 2, 3\}$$

where γ_m is a vector of parameters to be estimated for cost share enrollment for each of the three practice types, and u_{jm} is an error term. It is expected that the same set of factors will influence cost-share enrollment for all practices.

Note that farmers who receive cost sharing for one conservation practice may be more or less likely to enroll in cost sharing for other practices. Unobserved farm and farmer characteristics may contribute to correlation in the error terms for each of the practices studied. Accordingly, the variance-covariance matrix of error terms for each of the $m = \{1, 2, 3\}$ practices will be unrestricted, such that

$$(2)\; \Omega_C = Var\begin{pmatrix} u_1 \\ u_2 \\ u_3 \end{pmatrix} = \begin{pmatrix} \sigma_1^2 & \sigma_{21} & \sigma_{31} \\ \sigma_{12} & \sigma_2^2 & \sigma_{32} \\ \sigma_{13} & \sigma_{23} & \sigma_3^2 \end{pmatrix}.$$

Here, Ω_C is the 3x3 variance-covariance matrix of error terms of the cost-share equations for cover crops, conservation tillage, and contour/strip. The error terms are assumed to be jointly normal, thus the system of equations represented in equations (1) and (2) is estimated as a trivariate probit.

This three-equation probit model is solved by simulated maximum likelihood (ML) estimation. The variance-covariance matrix of the cross-equation error terms (Ω_C) has values of one on the leading diagonal. The off-diagonal elements are estimated through Cholesky factorization, where $\hat{\rho}_{lk} = \hat{\sigma}_{lk}/\hat{\sigma}_l\hat{\sigma}_k$ is estimated as the correlation between cost share enrollment for practices l and k. The Geweke-Hajivassiliou-Keane (GHK) simulator (Greene 2003) is used to evaluate the 3-dimensional normal integrals in the likelihood function associated with equations (1) and (2). As described in Greene, the GHK simulator requires estimating a likelihood contribution for each observation within each random draw, R, of the simulation. The observation's estimated contribution is then the average of the values derived across all random draws (Train 2009). With these simulated contributions in hand, estimation can proceed by standard ML techniques. The algorithm's stopping rule is defined by convergence of the likelihood function (1e-7), the vector of parameter estimates (1e-6), and the scaled gradient vector (1e-4). Monte Carlo experiments show that the GHK estimates are consistent when $R \geq \sqrt{N}$ (Cappellari and Jenkins 2003). Here, the value of R is set equal to 50, which is well above the square root of the sample size.

Conservation Practice Acreage Share

Next, consider the farmer's conservation practice adoption decisions. Self-selection is a well-known problem that complicates estimation of the treatment effect of cost sharing on adoption decisions (Claassen and Duquette 2013; Mezzatesta, Newburn, and Woodward 2013). Unobservable characteristics that make one farmer more likely than another to enroll in a program must be accounted for in order to evaluate the program's effect on an outcome variable of interest. As documented by Wooldridge (2014), a standard method that corrects for the problem of self-selection in program evaluation is through the use of the generalized residual. These are obtained after estimating the enrollment decision for each practice type. Following this approach, the generalized residual for conservation practice m is estimated as

$$(3) \quad \hat{\lambda}_{jm} = \frac{f(Z_{jm}\hat{\gamma}_m)}{F(Z_{jm}\hat{\gamma}_m)} \ \ if \ \ C_{jm} = 1$$

$$\hat{\lambda}_{jm} = \frac{-f(Z_{jm}\hat{\gamma}_m)}{1 - F(Z_{jm}\hat{\gamma}_m)} \ \ if \ \ C_{jm} = 0$$

where $\hat{\lambda}_{jm}$ is estimated with a different function based on whether a farmer is enrolled or not in a cost-sharing program for practice m. Here, $f(\cdot)$ and $F(\cdot)$ represent the normal probability and cumulative density functions, respectively, and $\hat{\gamma}_m$ is the vector of estimated parameters for cost-sharing enrollment for practice m, as described above. Note that $\frac{f(Z_{jm}\hat{\gamma}_m)}{F(Z_{jm}\hat{\gamma}_m)}$ are the inverse Mills ratios associated with the first-stage selection equations for each practice. These residuals, when inserted as regressors in the acreage share equations, allow for consistent (though not efficient) estimation of the effect of cost share. As Heckman (1979) showed, the estimated coefficient associated with this regressor is the covariance of error terms between the selection (i.e., cost share) and outcome (i.e., acreage share) equations, based on the assumption that these errors are distributed jointly normal.

Acreage share equations are estimated simultaneously for the three practice types in a multivariate tobit framework with acreage shares censored from below at zero.[10] Let s_{jm} represent the share of operating acreage devoted to practice type m by farmer j, where the index $m = \{1, 2, 3\}$ indicates the practice types of cover crops, conservation tillage, and contour/strip, respectively. Further, let superscript $i = \{w, o\}$ indicate endogenous switching of certain parameters, where i=w if $C_{j1} = 1$ (i.e., enrolled in cover crop cost sharing) and i=o if $C_{j1} = 0$ (i.e., not enrolled in cover crop cost sharing). Accordingly, the observed acreage share s_{jm} is defined in a trivariate model based upon a latent variable s^{*i}_{jm} with the following empirical specification:

$$(4) \quad s^{*i}_{jm} = X_{jm}\beta^i_m + \sum\nolimits_{m=1}^{3} \hat{\lambda}_{jm}\delta^i_m + \varphi_m C_{j2} + \tau_m C_{j3} + \varepsilon_{jm}$$

where $s_{jm} = s^{*i}_{jm}$ if $s^{*i}_{jm} \geq 0$, $s_{jm} = 0$ otherwise.

In equation (4), X_{jm} are variables that influence the acreage share decision. The set of

[10] Censoring from above at one is very rare in the data and thus not considered here.

observables Z_{jm} from equation (1) contains many of the same variables included in X_{jm}, such as farmer education, share income from farming, and farm characteristics such as slope and farm size. However, for purposes of identification, the matrix Z_{jm} must contain some variables not included in X_{jm}. Following Lichtenberg and Smith-Ramirez (2011), I use distance to the nearest water body as an exclusion restriction such that it is included in Z_{jm} but not X_{jm}. Distance to the nearest body of water is a proxy for potential risk of water quality impairment, which matters to the government funding agency but not necessarily to the farmer. Thus, the acreage equations are identified by this exclusion restriction as well as by the nonlinearity of the cost-share equations. I also test distance to the Chesapeake Bay (calculated from the centroid of the farmer's ZIP Code) as an alternative exclusion restriction, and the results are qualitatively the same as those shown below.[11]

Note that $\hat{\lambda}_{jm}$ in equation (4) are the estimated generalized residuals, to allow for the potential correlation between all three cost-share decisions and conservation practice acreage. Certain parameter estimates in equation (4) may switch based upon observed enrollment in the cover crop cost sharing program, C_{j1}. The parameter estimates that switch include those associated with the generalized residuals from the three enrollment equations, the erosion benefit variable, and the constant term. Thus, $\theta^i_m = \{\beta, \delta\},\ i = \{w, o\}$ are parameters that may be estimated separately for each of the two regimes (with or without enrollment). An advantage of this framework in comparison to other methods is its generality to estimate heterogeneous effects since the possibility that $\hat{\theta}^w_m \neq \hat{\theta}^o_m$ should not be precluded in advance for regressors related to the private benefits of BMP adoption, as well as for generalized residuals from the first-stage enrollment equations. However, in many cases no statistically significant difference is observed between parameter estimates across cost-share regimes (i.e., $\hat{\theta}^w_m = \hat{\theta}^o_m$), in which case the switching regression unnecessarily adds to the number of parameters to be estimated. For this reason, along with data limitations that prevented model convergence as the number of parameters to be identified increased, I restricted parameters to be equal across regimes when there is no prior theoretical reason to expect a difference between cost-share regimes.[12]

The switching regression framework has previously been utilized in the cost-share literature to separately identify the effect of explanatory variables on enrolled and unenrolled farmers (Lichtenberg and Smith-Ramirez 2011). Unlike Lichtenberg and Smith-Ramirez (2011), this article uses cost-share enrollment for one specific practice—cover crops—to determine regime switching, while separately considering the effect of cost-share awards for other practices by including them as endogenous right-hand variables. That is, the variables C_{j2} and C_{j3} in equation (4) indicate enrollment in cost sharing for conservation tillage and contour/strip, respectively. Thus, the estimated coefficients φ_m and τ_m represent the effect of enrollment in conservation tillage and contour/strip cost sharing on the acreage share of practice m.

Errors of the system of equations (4) are assumed to be distributed jointly normal, and unobserved characteristics may contribute to correlation in the adoption of all three practices. Thus, the variance-covariance matrix of errors across acreage share equations, Ω_s, is of the following form:

$$(5)\ \Omega_s = Var\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{pmatrix} = \begin{pmatrix} \sigma^2_{\varepsilon 1} & \sigma_{\varepsilon 2\varepsilon 1} & \sigma_{\varepsilon 3\varepsilon 1} \\ \sigma_{\varepsilon 1\varepsilon 2} & \sigma^2_{\varepsilon 2} & \sigma_{\varepsilon 3\varepsilon 2} \\ \sigma_{\varepsilon 1\varepsilon 3} & \sigma_{\varepsilon 2\varepsilon 3} & \sigma^2_{\varepsilon 3} \end{pmatrix}.$$

The off-diagonal elements represent the covariance between acreage share decisions for each of the practice types.

To justify the assumption of joint normality implied by this selection model, I tested for joint normality using a procedure developed by Pagan and Vella (1989). Predictions from

[11] Results of this robustness check are shown in the online supplementary appendix.

[12] The indicators of cost-share enrollment for contour/strip and conservation tillage may be expected to have different effects across the cost-share regimes. However, effects of the indicators of cost-share enrollment were not able to be identified separately due to insufficient variation within regimes. For example, among the unenrolled group, all farmers have zero cover crop acreage if they have also received cost share for conservation tillage.

each of the first-stage multivariate probit equations are weighted by the generalized residuals in both their linear, squared, and cubed forms. These weighted predictions are then included as covariates in each of the second-stage acreage share equations as a type of Regression Error Specification Test (RESET). If the coefficient estimates on these variables are jointly different from zero, it suggests model misspecification due to violation of joint normality. The chi-squared value for joint statistical significance was χ^2_{27} =33.32, with a corresponding p-value of 0.1866, indicating that the model is not mis-specified due to a violation of normality. Details of this test are shown in the online supplementary appendix to this article.

The multivariate tobit model is solved using simulated ML techniques. In order to reduce the computational burden of simulated ML estimation, quasi-random Halton sequences are employed to generate the multivariate normal random draws.[13] Results of this model are shown in table 4 below, with treatment effects shown in table 5.

Estimation Results

The primary interest of the econometric analysis is to identify the effect of cost share enrollment for cover crops on both acreage share in cover crops and the other erosion-control practices. Before turning to that, however, I briefly present the coefficient estimates of the independent variables for the multivariate probit and tobit models shown in tables 3 and 4, respectively.

Cost Sharing Estimation Using Multivariate Probit

Results for the trivariate probit in table 3 show coefficient estimates for the explanatory variables that affect cost-share enrollment. Distance to the nearest water body in miles serves as a proxy for public environmental benefits from the perspective of the regulatory agency, and is an exclusion restriction that identifies cost-sharing enrollment. As expected, it is negative for cover crops and conservation tillage, indicating a lower likelihood of receiving cost share for farms located farther from a water body. This result is consistent with lower expected water quality benefits from farms located further away from surface water bodies. The coefficient estimate on distance to a water body is small in magnitude and not significantly different from zero for contour/strip.

The proportion of family income from farming may be considered a proxy for the transaction costs of cost-share application, as well as the opportunity cost of time. As expected, the higher the share of income from farming, the more likely incentive payments are received in the case of cost sharing for cover crops and conservation tillage. For contour/strip cropping, the relationship is negative but not significantly different from zero.

Topography also influences cost-sharing enrollment, insofar as it affects both the expected conservation benefits as well as a farmer's need to adopt erosion-control practices. Having a greater share of moderately-sloped land tends to increase the likelihood of cost-share enrollment for all three practices, with statistically significant differences in enrollment rates for both cover crops and contour/strip practices. The share of steeply-sloped land does not have a statistically significant influence on cost share enrollment for any of these three practices.

The coefficient estimate of the erosion reduction per dollar spent on cover crops is negative and significant, indicating that farmers are less likely to enroll in cover crop cost sharing when erosion reduction is more affordable. In other words, farmers tend to enroll in the cover crop cost sharing program when the private erosion-reduction benefits of the practice are lower. In contrast, the effect of erosion reduction per dollar spent on both conservation tillage and contour/strip are not statistically significant.

Several other variables appear in the trivariate probit, including farm size, share of acres rented, farmer education, experience, and a dummy variable indicating whether a

[13] Halton sequences improve coverage of the domain of integration (Cappellari and Jenkins 2003), and each sequence is defined by a unique prime number, P. In this case, $P = \{2, 3, 5\}$ were used, respectively, for the equations involving cover crops, conservation tillage, and contour/strip. An initial number of sequence elements B are burned within each iteration to reduce correlation of the Halton sequences in each of the three dimensions. Following the advice of Train (2009), B was set equal to five in order to correspond with the largest prime number used in generating the Halton sequences. Fewer random draws R are required with Halton sequences due to its improved coverage of the domain of integration. Convergence was attained with $R = 20$.

Table 3. Estimated Coefficients on Probability of Cost Share Receipt, Multivariate Probit

	Cost Share Enrollment		
	Cover crops	Cons. tillage	Contour/strip
Erosion benefit (tons reduced / $)			
Cover crops	−0.6748*	–	–
	(0.351)		
Cons. tillage	–	−0.3489	–
		(0.288)	
Contour/strip	–	–	0.5931
			(0.383)
Distance to the nearest water body (miles)	−0.1186*	−0.2248*	0.0051
	(0.067)	(0.132)	(0.088)
Proportion income from farming	0.383	0.5060*	−0.5525
	(0.272)	(0.289)	(0.385)
50+ acres in corn, soybeans and/or small grains (1=yes)	1.1301***	0.2591	0.4992
	(0.291)	(0.319)	(0.421)
Proportion acres in slope class			
Moderate (2 - 8% grade)	0.6104***	0.2059	0.8519**
	(0.204)	(0.252)	(0.399)
Steep (> 8% grade)	0.3164	−1.1293	−0.7261
	(0.588)	(0.939)	(0.768)
Proportion acres rented	0.0428	0.3926	−0.1306
	(0.263)	(0.328)	(0.316)
Log operating acres	0.2335**	−0.078	0.1684
	(0.103)	(0.089)	(0.176)
Completed high school (1=yes)	0.7456***	0.8860**	0.1489
	(0.260)	(0.396)	(0.398)
Years experience farming	0.0005	0.0076	0.006
	(0.005)	(0.006)	(0.009)
Missing farm income	−4.1992***	−3.3338***	−3.2090***
	(0.424)	(0.265)	(0.323)
Observations	441	441	441

Note: Asterisks ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Robust standard errors in parentheses.

farm has fifty or more acres in annual crops such as corn, soybeans, and small grains. These variables have the expected influence on cost-sharing enrollment, or no statistically significant effect at all. Additionally, seventeen respondents had missing values for proportion income from farming. These missing values were set equal to zero, and a dummy variable for "missing farm income" was included to account for any bias from including these observations.[14] The "missing farm income" variable has negative and statistically significant effects for all three practices, indicating that farmers who did not report their proportion of income from farming were, on average, less likely to be enrolled in cost-sharing programs.

Conservation Practice Acreage Share Estimation Using Multivariate Tobit

In the results presented in table 4, the dependent variable is the share of operating acres on a farm allocated to each of the conservation practices. The system of equations is estimated as a multivariate tobit using many of the same independent variables contained in the cost-sharing equations, along with cost-share enrollment itself. Cost-sharing enrollment for cover crops determines endogenous regime-switching for several of

[14] I initially included imputed values for proportion of income from farming for these seventeen observations, where the missing value was replaced with the average proportion income from farming among all others in that farm's revenue class (e.g., 0 to 2,499, 2,500 to 4,999, 5,000 to 9,999, etc.). However, the "missing farm income" dummy variables were still negative and statistically significant when imputing values, indicating bias in the attempted imputation technique.

Table 4. Estimated Coefficients on Conservation Practice Acreage Share, Multivariate Tobit with Endogenous Switching based on Cover Crop Enrollment

	Acreage share in conservation practice - *Switching based on cover crop cost share*					
	Cover crop		Cons. tillage		Contour/strip	
	Cost Share=1	Cost Share=0	Cost Share=1	Cost Share=0	Cost Share=1	Cost Share=0
Erosion benefit (tons reduced / $)						
Cover crops	−0.2203	0.1989*	–		–	
	(0.201)	(0.120)				
Conservation tillage	–		−0.1331	0.0167	–	
			(0.174)	(0.102)		
Contour/strip	–		–		0.2848	0.2561*
					(0.462)	(0.155)
Generalized residual (covar. w/ 1st stage)						
Cover crop enrollment	−0.0404	−0.0229	−0.1248	−0.2579	0.128	−0.1042
	(0.136)	(0.195)	(0.208)	(0.251)	(0.285)	(0.299)
Cons. tillage enrollment	0.258	0.0515	0.3761	0.489	0.3525	0.1734
	(0.253)	(0.268)	(0.340)	(0.322)	(0.498)	(0.480)
Contour/strip enrollment	−0.1044	−0.2456	0.8373*	0.9570*	0.8980**	1.1066***
	(0.338)	(0.418)	(0.509)	(0.534)	(0.382)	(0.420)
No-till enrollment (1=yes)	−0.1302		−0.2677		−0.5288	
	(0.484)		(0.652)		(0.947)	
Contour/strip enrollment (1=yes)	0.0067		−1.901		−1.5289	
	(0.711)		(1.160)		(0.944)	
Proportion income from farming	0.1699**		0.0453		−0.0999	
	(0.086)		(0.120)		(0.136)	
50+ acres in corn, soybeans and/or small grains (1=yes)	0.1144		0.5631***		0.2279*	
	(0.095)		(0.124)		(0.138)	
Proportion acres in slope class						
Moderate (2-8% grade)	0.0087		0.2414**		0.0272	
	(0.079)		(0.095)		(0.114)	
Steep (> 8% grade)	−0.4098**		−0.0699		0.164	
	(0.183)		(0.202)		(0.195)	
Proportion acres rented	−0.1058		0.2659***		0.0688	
	(0.080)		(0.087)		(0.133)	
Log operating acres	−0.009		−0.0339		0.0525	
	(0.030)		(0.037)		(0.042)	

Continued

Table 4. Continued

	Acreage share in conservation practice - *Switching based on cover crop cost share*					
	Cover crop		Cons. tillage		Contour/strip	
	Cost Share=1	Cost Share=0	Cost Share=1	Cost Share=0	Cost Share=1	Cost Share=0
Completed high school (1=yes)		−0.107		0.0761		−0.0068
		(0.099)		(0.112)		(0.124)
Years experience farming		−0.002		−0.0001		0.0026
		(0.001)		(0.002)		(0.003)
Log cattle		−0.0049		−0.027		0.0108
		(0.021)		(0.032)		(0.034)
No cattle (1 = no cattle)		−0.0321		−0.0974		−0.2666
		(0.098)		(0.140)		(0.170)
Missing farm income		0.1493		−0.1408		0.0733
		(0.195)		(0.189)		(0.217)
Observations	92	349	92	349	92	349

Note: Asterisks ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Robust standard errors in parentheses.

the explanatory variables, and cost-share enrollment for conservation tillage and contour/strip cropping are included as endogenous right-hand side variables. Generalized residuals, as specified in equation (3), are included to correct for farmer self-selection into cost-share programs. While the coefficient estimates of the generalized residuals shown in table 4 are not individually significant in every case, a Wald test for joint significance of these variables shows they are jointly significant at the 10% level, with $\chi^2_{(18)} = 26.8$ (p =0.0824). Given the strong theoretical reasons to account for selection bias in cost-share enrollment coupled with this joint significance, the Heckman selection model is justified to control for unobservables influencing both enrollment and acreage-share decisions.

The coefficient estimates for the erosion reduction benefits per unit of cost indicate heterogeneous responses by the enrolled and unenrolled groups. For unenrolled farmers, higher erosion reduction benefits lead to increased acreage shares in cover crops. This is equivalent to downward-sloping demand among the unenrolled farmers for cover crops. In contrast, the acreage shares for enrolled farmers do not exhibit the same sensitivity. The qualitative results for conservation tillage are the same, though they are not statistically significant. The lack of statistical significance of these results may reflect the fact that conservation tillage has other important private benefits from the perspective of the farmer, aside from erosion reduction, including reduced labor cost at planting time.

The coefficient estimates of the indicators for conservation tillage and contour/strip cost-sharing programs show, in general, a negative relationship with the acreage shares of each practice, though these results are not statistically significant. Note that the inclusion of the generalized residuals for each practice's cost-share enrollment equation makes these endogenous explanatory variables consistent. These results suggest the targeting of the conservation tillage and contour/strip cost-share programs was not successful, insofar as farmers who received incentive payments for these practices did not significantly increase their acreage shares in these practices. Moreover, cross-practice effects were also not statistically significant, indicating no evidence for crowding in/out of other conservation practices due to cost-share

Table 5. Estimated Treatment Effect of Cover Crop Cost Share Enrollment on Conservation Acres, Enrolled (ATT) and Unenrolled (ATU) Farmers

	(1) Farmers with annual and/or perennial crops		(2) Farmers with corn, soybeans, and other annual crops	
Sample size:	N = 441		N = 327	
	Enrolled	Unenrolled	Enrolled	Unenrolled
Cover crops (cc)				
Without	0.023	0.024	0.049	0.041
With	0.292	0.278	0.296	0.308
Change	0.269***	0.254**	0.247***	0.267
Cons. tillage (ct)				
Without	0.188	0.152	0.231	0.225
With	0.446	0.279	0.465	0.318
Change	0.258**	0.127	0.234*	0.093
Contour/strip (cs)				
Without	0.051	0.028	0.100	0.045
With	0.091	0.027	0.090	0.023
Change	0.040	−0.001	−0.010	−0.023

Note: Asterisks ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

enrollment in conservation tillage or contour/strip programs.

Finally, several other controls related to farm and farmer characteristics appear on the right-hand side of the multivariate tobit. For the reasons discussed above, these variables were constrained to be equal across regimes. These controls have the expected effect on acreage shares, or no statistically significant effect at all.[15]

Treatment Effects of Cost Sharing for Cover Crops

Table 5 provides estimates for the direct effect of cost sharing for cover crops on the acreage share in cover crops. It also provides estimates for the indirect effect of cost sharing for cover crops on the acreage shares of both conservation tillage and contour/strip, thus accounting for the effect of cover crop cost sharing on the overall mix of erosion-control practices on a farm. An advantage of estimating acreage shares in a system of equations is that it allows one to calculate both the average treatment effect on the treated subjects (ATT) enrolled in cost sharing, and the average treatment effect on the untreated (ATU) for unenrolled subjects (Heckman and Vytlatil 2007). The ATT is of course relevant for program evaluation. However, the ATU is also policy-relevant because it represents the expected effect of extending the cost-share program to farmers not yet receiving incentive payments, which will likely be needed to meet stricter water quality goals under the TMDL requirements.

Treatment effects are calculated for each farmer j and practice m based on conditional expectations of acreage shares in a practice. The estimates are conditional on observed covariates X, Z, and C, as well as unobserved factors reflected in $\hat{\delta}_m$ (i.e., the estimated covariance between enrollment and acreages, calculated as the coefficient estimate associated with the generalized residuals $\hat{\lambda}_{jm}$). Four conditional expectations are calculated for each practice m: (a) acreage share for enrolled farmers given enrollment; (b) acreage share for enrolled farmers if there was no enrollment; (c) acreage share for unenrolled farmers if there was enrollment; (d) acreage share for unenrolled farmers given no enrollment. Note that cases (b) and (c) represent the counterfactual expected outcomes. Let J^w and J^o be the set of enrolled and unenrolled farmers, respectively, and as before, let C_{j1} indicate cost sharing for cover crops, and C_{j2}

[15] Not all factors that influence conservation practice acreage shares or cost-share enrollment were able to be included. Omitted variable bias from such unobserved factors may influence the coefficient estimates and marginal effects of individual regressors. However, the use of generalized residuals ensures consistent treatment effect estimates in the presence of unobservables affecting both selection and outcome equations. See Heckman and Vytlacil (2007), and also Di Falco, Veronesi, and Yesuf (2011), for recent examples of using generalized residuals to control for omitted variables in selection and outcome equations.

and C_{j3} indicate cost sharing for conservation tillage and contour/strip. The four conditional expectations are then calculated as follows:

$$(6a) \quad E\left(\hat{s}^{w}_{jm} \; C_{j1}=1, X, Z\right) = X'_j \hat{\beta}^{w}_{m} + \hat{\varphi}_m C_{j2} + \hat{\tau}_m C_{j3} + \sum_{m=1}^{3} \hat{\lambda}_{jm} \hat{\delta}^{w}_{m} \text{ for } j \epsilon J^{w}$$

$$(6b) \quad E\left(\hat{s}^{o}_{jm} \; C_{j1}=1, X, Z\right) = X'_j \hat{\beta}^{o}_{m} + \hat{\varphi}_m C_{j2} + \hat{\tau}_m C_{j3} + \sum_{m=1}^{3} \hat{\lambda}_{jm} \hat{\delta}^{o}_{m} \text{ for } j \epsilon J^{w}$$

$$(6c) \quad E\left(\hat{s}^{w}_{jm} \; C_{j1}=0, X, Z\right) = X'_j \hat{\beta}^{w}_{m} + \hat{\varphi}_m C_{j2} + \hat{\tau}_m C_{j3} + \sum_{m=1}^{3} \hat{\lambda}_{jm} \hat{\delta}^{w}_{m} \text{ for } j \epsilon J^{o}$$

$$(6d) \quad E\left(\hat{s}^{o}_{jm} \; C_{j1}=0, X, Z\right) = X'_j \hat{\beta}^{o}_{m} + \hat{\varphi}_m C_{j2} + \hat{\tau}_m C_{j3} + \sum_{m=1}^{3} \hat{\lambda}_{jm} \hat{\delta}^{o}_{m} \text{ for } j \epsilon J^{o}.$$

Following the standard approach of Heckman and Vytlacil (2007), the treatment effect on a treated farmer—$\widehat{TET}_{jm}$— is then calculated as a difference in estimated outcomes, in this case (6a) minus (6b), for each practice m. Similarly, the treatment effect on an untreated farmer—$\widehat{TEU}_{jm}$— is estimated as (6c) minus (6d). Average treatment effects for each practice are weighted-averages of the estimates for each farmer, weighted by the sampling weights, ω, from the farmer survey, such that

$$(7) \quad \widehat{ATT}_m = \sum_{j=1}^{J^w} \omega_j \left(\widehat{TET}_{jm}\right), \quad \text{where } \sum_{j=1}^{J^w} \omega_j = 1$$

$$\widehat{ATU}_m = \sum_{j=1}^{J^o} \omega_j \left(\widehat{TEU}_{jm}\right), \quad \text{where } \sum_{j=1}^{J^o} \omega_j = 1.$$

Table 5 shows an increase in cover crop acreage share from an estimated 0.023 without cost sharing to 0.292 with cost sharing (an ATT of 0.269 for enrolled farmers). This indicates that enrolled farmers, on average, added cover crops to a little over one-quarter of their operating acres with the incentive payment compared to the counterfactual without cost sharing. This ATT is of a similar magnitude to that found in previous surveys of farmers in Ohio (0.237) (Mezzatesta, Newburn, and Woodward 2013) and somewhat higher than that previously found by Lichtenberg and Smith-Ramirez for cover crops in Maryland (0.081), though different methodologies were used in these studies.

Among enrolled farmers, enrollment in cost sharing for cover crops had positive indirect effects. Cover crop cost sharing enrollment increases farmers' acreage share in conservation tillage from an estimated counterfactual 0.188 without cost sharing to 0.446 with cost sharing. This positive indirect effect is likely due to the economic and agronomic complementarity between the two practices discussed earlier. Cover crops and conservation tillage have complementary effects in improving soil quality by stimulating soil biological activity (USDA SARE 2012) and suppressing the emergence of certain weeds (Blum et al. 1997). Enrollment in cost sharing for cover crops does not have discernible indirect effects on contour/strip, both statistically and in terms of magnitude.

Intuitively, cost sharing for cover crops has two beneficial effects among the enrolled group: cost sharing both incentivizes the adoption of cover crops, and it crowds in private investment in other conservation practices, particularly conservation tillage. The mechanisms by which crowding in occurs for conservation practices depend on both the agronomic and economic complementarities among specific practices.

Turning to the unenrolled farmers, the qualitative pattern of direct and indirect effects is the same as that observed among the enrolled, although the effect on conservation tillage is smaller and measured with less precision. The increase in cover crop acreage share among this group—from 0.024 without cost sharing to a counterfactual of 0.278 with cost sharing (an ATU of 0.263)—indicates that unenrolled farmers would add cover crops to their acreage in similar proportional shares to the enrolled group if they were included in the cover crop program. This suggests the potential for a substantial increase in cover-crop adoption by further targeting the cost-share program to those who are currently unenrolled.

Table 6. Estimated Effect of Cover Crop Cost Share on Non-Point Source Agricultural Pollution in the Chesapeake Bay, With and Without Indirect Effects

	Abatement per farm due to cost sharing			
	Enrolled		Unenrolled	
	Direct [1]	Overall [2]	Direct [3]	Overall [4]
Nitrogen (pounds)				
Eastern Shore	1,912	2,295	1,129	1,233
Potomac	1,190	1,493	301	326
Patux./Susque./Western	886	1,196	156	169
Phosphorus (pounds)				
Eastern Shore	38	99	23	41
Potomac	23	61	7	11
Patux./Susque./Western	15	50	3	5

Note: Columns [1] and [3] indicate load reduction due to the direct effect of cover crop cost share on cover crops. Columns [2] and [4] indicate the direct effect plus the indirect effect on other BMPs. Average agricultural runoff loads, BMP load reduction efficiencies, and ratios of load delivered to the Chesapeake Bay differ by major river basin.

As with enrolled farmers, enrollment of farmers who do not currently participate in the cover crop program would be expected to have virtually no effect on contour/strip. Thus, the indirect effects of extending incentive payments beyond the currently enrolled group face fewer potential gains, and greater uncertainty.

As a robustness check, I estimate the regression results and treatment effects for a subset of the sample in which only farms with annual crops (i.e., corn, soybeans, small grains, vegetables, or tobacco) are included. In practice, this excludes farms with only hay and pasture, and increases the homogeneity of farm types within the estimation procedure. These results are shown in column (2) of table 5. The estimated effects are qualitatively the same, but measured less precisely. In particular, the ATU for cover crop acreage share is no longer significantly different from zero with this reduced sample, adding further caution to any potential policies that would seek to aggressively expand cost sharing beyond the group of currently enrolled farms.

Water Quality and Policy Implications

The question then remains: what does this mean for agricultural NPS pollution in the Chesapeake Bay? It is crucial to integrate economic and biophysical models in order to better understand the effect of policy on environmental quality (Wu et al. 2004; Claassen, Langpap, and Wu 2017). Table 6 shows the estimated effect of cover crop cost sharing on nitrogen (N) and phosphorus (P) levels in the bay. These estimates are based on the econometric results presented above, along with model parameters from the EPA's Chesapeake Bay Program watershed model. Treatment effects are matched with the watershed model parameters by overlaying the polygons for river segments from the watershed model with the ZIP Codes of the surveyed farms.

Let $\bar{z}_{ps}$ be the load per acre from cropland within each river segment, s, in Maryland for pollutant $p = \{N, P\}$. Further, practice efficiencies, η_{mps}, are the proportional reduction of pollutant p due to the adoption of practice m, where $0 \leq \eta_{mps} < 1$. Practice efficiencies are constant across the study region, with the exception that η_{1ps} for cover crops varies spatially between the geographic regions of coastal plain and non-coastal plain when $p = nitrogen$. Finally, delivery factors, δ_{ps}, are the proportional reduction of pollutant p as it travels from the edge-of-stream in geographic region s downstream to the bay.

The direct effect of cost sharing is the abatement due only to the increased adoption of cover crops, not accounting for indirect effects. Let $\Delta q_{jp}^{w,D}$ represent the change in abatement of pollutant p on farm j, with the superscript D indicating the direct effect. Letting A_j refer to the operating acres on a farm, the direct change in abatement in the bay due to cover crop enrollment is calculated as follows:

$$(8)\quad \Delta q_{jp}^{w,D} = A_j \cdot (\widehat{TET}_{j1} \cdot \bar{z}_{ps} \cdot \eta_{1ps}) \cdot \delta_{ps}, \text{ for enrolled farmer } j,$$

$$\Delta q_{jp}^{o,D} = A_j \cdot (\widehat{TEU}_{j1} \cdot \bar{z}_{ps} \cdot \eta_{1ps}) \cdot \delta_{ps}, \text{ for unenrolled farmer } j.$$

In contrast, the overall effect of cover crop cost sharing enrollment represents both abatement due to increased adoption of cover crops, as well as abatement due to indirect effects on other field practices. Letting the superscript $D+I$ indicate the sum of the direct and indirect effects, or the "overall" effect,

$$(9)\quad \Delta q_{jp}^{w,D+I} = \sum\nolimits_{m=1}^{3} (\widehat{TET}_m \cdot \bar{z}_{ps} \cdot \eta_{mps}) \cdot \delta_{ps}, \text{ for enrolled farmer } j,$$

$$\Delta q_{jp}^{o,D+I} = \sum\nolimits_{m=1}^{3} (\widehat{TEU}_m \cdot \bar{z}_{ps} \cdot \eta_{mps}) \cdot \delta_{ps}, \text{ for unenrolled farmer } j.$$

Average abatement per farm is then calculated as the weighted average of Δq_{jp}^{w} and Δq_{jp}^{o} across all enrolled and unenrolled farms, respectively, weighted by the sampling weights from the farmer survey. These weighted averages are shown in table 6, with results broken down by major river basins in Maryland.[16] Columns (1) and (3) of table 6 are based on the direct effect, while columns (2) and (4) are based on the overall effect.

Table 6 shows substantial reductions in runoff reaching the bay due to the direct effect of cover crop cost share. Average per-farm abatement is 1,912 lbs. and 38 lbs. for nitrogen and phosphorus, respectively, among enrolled farmers on the Eastern Shore. This direct effect is augmented by crowding in of other BMPs. Nitrogen abatement increases between 20–34% after considering indirect effects, while phosphorus abatement increases between 160–221 percent. Mechanically, the indirect effect on phosphorus runoff is larger due to the fact that conservation tillage is much more effective at reducing phosphorus runoff than nitrogen. In general, beneficial indirect effects are proportionally the largest in the combined Patuxent/Susquehanna/Western Shore river basins.

The right-hand side of table 6 displays abatement estimates for average unenrolled farms in each river basin. Substantial reductions in runoff would be expected by extending cost sharing to this group of farmers, as shown in column (3), although average abatement per farm is lower in this group than for the unenrolled group, since unenrolled farms are typically smaller than enrolled farms. The estimated indirect effects among unenrolled farms are also not as large. For example, average nitrogen abatement increases only 8–10% after accounting for crowding in of other practices.

Finally, what does this mean for the cost effectiveness of cover crop cost sharing? It remains to be seen how the estimated indirect effects influence the cost effectiveness of the cover crop cost sharing program. Table 7 shows estimates for the marginal abatement cost for nitrogen and phosphorus, assuming a base cost share payment of $45 per acre for cover crops planted in rye.[17] After considering the indirect effects of cost-share payments, nitrogen reduction becomes less expensive among already-enrolled farmers: payments decrease by 17% on the Eastern Shore, 17% in the Potomac, and 25% in the combined Patuxent/Susquehanna/Western Shore. The marginal abatement cost of phosphorus decreases with even greater magnitudes due to the effectiveness of conservation tillage at reducing phosphorus runoff. Phosphorus per-unit abatement costs decline between 60–67% in Maryland's major river basins after accounting for indirect effects.[18]

Among unenrolled farmers, column 3 of table 6 shows that the expected marginal abatement costs from expanding the cover crop program are similar to those achieved by those who are already enrolled, at least on the Eastern Shore and the Potomac River basins. However, the beneficial indirect effect

[16] While the survey was designed to be representative only at the broader level of the state of Maryland, an external validity check with the 2012 Census of Agriculture suggests that the sample corresponds with population characteristics at the level of the major river basins shown in table 6. See the online supplementary appendix for details.

[17] This base payment for cover crops planted in rye is a typical payment offered by MACS.

[18] These cost effectiveness estimates incorporate the Chesapeake Bay Program's delivery factors, δ_{ps}. However, the delivery factors do not currently account for residence time of nitrates in groundwater (personal communication with Guido Yactayo, Watershed Data Modeling Specialist from the *Chesapeake Bay Program*, 6/12/14), which imply that there is a delay between changes in management practices and full realization of improvements in water quality (U.S. Geological Survey 2003).

Table 7. Cost Effectiveness of Cover Crop Cost Share to Reduce Non-Point Source Agricultural Pollution in the Chesapeake Bay, With and Without Indirect Effects

	Marginal abatement cost ($ / pound)			
	Enrolled		Unenrolled	
	Direct [1]	Overall [2]	Direct [3]	Overall [4]
Nitrogen (pounds)				
Eastern Shore	$6.99	$5.80	$6.81	$6.17
Potomac	$8.22	$6.81	$10.71	$9.87
Patux./Susque./Western	$11.77	$8.87	$17.21	$15.27
Phosphorus (pounds)				
Eastern Shore	$379.53	$145.92	$366.83	$204.60
Potomac	$369.83	$147.49	$345.69	$207.46
Patux./Susque./Western	$583.24	$192.84	$683.66	$384.59

Note: Cost share award of $45 per acre for cover crop planted in rye. Averages weighted by farm sampling weights.

on conservation tillage causes the enrolled farmers' marginal abatement costs to be lower than those potentially obtained in the currently unenrolled group—for whom the indirect effects were smaller in magnitude.

In sum, the econometric estimates of the overall effects of the cover crop program translate to substantial improvements in water quality. The large cover crop cost sharing effort in Maryland had considerable beneficial effects with regard to the farmers already enrolled in the program, both through direct effects on cover crop acreage and indirect effects on conservation tillage. Moreover, cost-share enrollment could be expected to have further benefits by targeting farmers in the currently unenrolled group due to the additional acreage planted in cover crops. However, when comparing cost-effectiveness across the two groups, accounting for indirect effects indicates that N and P abatement is less costly among the enrolled group compared to those who are not yet enrolled.

Conclusion

This article has estimated the effect of cost sharing for cover crops on the acreage of three erosion-control practices—cover crops, conservation tillage, and contour/strip cropping—using a survey of Maryland farmers. The primary contribution of this article is that it analyzes both the direct and indirect effects of cost sharing for cover crops, a heavily-subsidized practice in the study region. It was unknown at the outset whether the indirect effects on conservation tillage and contour/strip would be positive, negative, or negligible. I find that the cover crop cost sharing initiative not only had considerable effects on cover crop acreage, but also on other practices.

Among the group of farmers currently enrolled in the cover crop program, the magnitude of the indirect effects is positive and substantial, consistent with crowding in of conservation efforts generally, and conservation tillage in particular. The crowding in of conservation tillage occurs in all of Maryland's major river basins. By connecting the econometric estimates to parameters from the EPA's Chesapeake Bay Program watershed model, I find that accounting for indirect effects decreases the cost per pound of nitrogen abatement by between 17–25%, and phosphorus abatement by between 60–67%. The potential direct effects of cost sharing on the currently unenrolled farmers are similar in magnitude to the estimates for the already enrolled group. However, the indirect effect on conservation tillage is smaller and measured with much less precision. Thus, the potential gains from extending cost sharing beyond those currently enrolled can be estimated with less confidence.

The indirect effects of the incentive payments considered in this article are environmentally beneficial, though they may not always be. The agronomic benefits of specific combinations of practices will differ in other regions (Blum et al. 1997), just as the private on-farm costs and benefits of cover crops themselves vary across different geographic regions of the United States (USDA SARE 2012). Further research is needed to improve our understanding of the role played by economic incentives in the adoption of multiple conservation practices in other agronomic and policy contexts. This includes further research on the possibility of indirect effects related to agricultural practices not considered in this article, but known to have important cross-practice correlations from prior empirical research (Dorfman 1996; Wu and Babcock 1998; Cooper 2003; Lichtenberg 2004a). Moreover, while this article focuses on the econometric identification of indirect effects—and briefly illustrates the potential magnitude of these effects in terms of water quality—more research should be done to integrate economic behavioral models with spatially-explicit biophysical models. Given the heterogeneity of farmer response to incentive payments, this would be needed in order to analyze potential variation in water-quality impacts and further policy implications.

A general implication of this article is that indirect effects can matter a great deal in programs like conservation cost sharing, and therefore accurate anticipation of their results requires the consideration of potential crowding in or crowding out of other practices. Depending on patterns of substitution or complementarity between practices, marginal abatement costs per unit of nitrogen and phosphorus are substantially higher or lower in comparison to those estimates that only account for direct effects. It is necessary for any program that seeks to encourage the adoption of conservation practices—be it cost sharing or water-quality trading—to consider whether substitution (crowding out) or complementarity (crowding in) of other practices may lead to indirect, unintended consequences for water quality.

Supplementary Material

Supplementary material are available at *American Journal of Agricultural Economics* online.

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