# Agricultural Cost Sharing and Conservation Practices for Nutrient Reduction in the Chesapeake Bay Watershed

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**Abstract**
Most evaluations of the impact of cost sharing policies designed to reduce non-point source pollution on water quality fail to incorporate behavioral responses, which are important because of the voluntary nature of these programs. In this article, a two-stage simultaneous equation approach is applied to data from a farmer survey to correct for voluntary self-selection into cost sharing programs, and account for substitution effects among conservation practices. The estimates obtained from the econometric model are linked with the Chesapeake Bay Program watershed model to estimate the change in abatement levels and marginal abatement costs for nitrogen, phosphorus and sediment after considering non-additional adoption due to nonrandom enrollment, as well as potential indirect effects on other conservation practices. We find that policy scenarios which do not account for non-additional adoption significantly overestimate the abatement achieved by environmental incentive payments. Accounting for nonrandom enrollment increases the average marginal cost of abatement by between 37 and 85 percent across the state of Maryland. However, estimated indirect effects of cost sharing suggest the presence of "crowding in" of other practices, leading to greater abatement and lower costs, particularly for phosphorus and sediment.

**Keywords**: multiple simultaneous equation models, water quality, abatement, environmental regulation
**JEL codes**: C31, C34, C54, Q53, Q58

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Nonpoint source (NPS) pollution from agriculture is the single largest source of impairment in many impaired water bodies in the United States (US EPA 2009). Agricultural nonpoint sources have largely escaped regulation. Instead, policies aimed at reducing NPS pollution from agriculture have involved paying farmers to either convert cropland to conservation uses or to adopt runoff-reducing farming practices. Since 2002, the government has turned increasingly to the latter through cost sharing of practice implementation costs. In 2012, for example, the federal Environmental Quality Incentives Program (EQIP) spent $1.38 billion to subsidize such agricultural best management practices (BMPs).

Evaluating the actual achievement of cost sharing is complicated by several factors. First, enrollment in cost sharing is voluntary, so evaluations of additionality (BMP adoption and associated reductions in NPS runoff above and beyond what farmers would have done in the absence of cost sharing) need to account for selection bias due to nonrandom enrollment (Lichtenberg and Smith-Ramirez 2011; Mezzatesta, Newburn, and Woodward 2013). Second, 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 (Dorfman 1996; Wu and Babcock 1998; Khanna 2001; Cooper 2003; Lichtenberg 2004a; Fleming 2014). For example, Lichtenberg (2004a) and Fleming (2014) find empirical evidence for substitution and complementarity within groups of working-land BMPs.

For these reasons, evaluations of the impact of environmental policies on NPS pollution should consider behavioral response—including additionality and indirect effects—to the extent possible. Studies on reducing agricultural NPS pollution conducted to date do not. To cite some recent examples, Kling et al. (2014) evaluate the impact of cover crop incentive payments over a large area of the Mississippi basin. In this model, they use an evolutionary algorithm to optimize over a complex search space, showing the importance of using integrated assessment models to identify the costs and resulting benefits of policy scenarios. In an analysis of the Chesapeake Bay watershed, Wainger et al. (2013) identify the most cost effective land use changes to reduce NPS runoff from agriculture. While shedding light on the connection between agricultural land use and water quality, these studies are based on the implementation costs of conservation practices, not observed behavioral responses. In the absence of data that allow estimation of farmer behavioral response, these studies are forced to ignore nonrandom enrollment and indirect effects associated with environmental payments, and assume instead that both uptake and additionality are complete.

This study investigates the importance of incorporating farmer behavioral responses in studying environmental incentive payments in the context of a cover crop cost sharing program aimed at improving water quality in the Chesapeake Bay. We estimate the effect of a cover crop incentive payment on the acreage share in cover crops, conservation tillage, and contour/strip cropping using farmer survey data in Maryland. Following Fleming (2014), we 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 estimated treatment effects of cover crop cost sharing are then translated to water quality using geographic and land use data from the EPA Chesapeake Bay Program (CBP) watershed model. Surveyed farmers are matched with the water quality model at a detailed geographic scale, and the estimated farm-level treatment effects of cost sharing are used to derive farm-level abatement and costs. Inverse sampling weights allow expansion of the farm-level results to a wider geographic scale of river basin and state.

We compare estimated cost-effectiveness under the standard assumption of perfect additionality used in the existing literature with a more realistic scenario in which a wide range of known behavioral responses to cost sharing are considered, including the problem of self-selection and non-additionality of cover crop payments, and indirect effects of cover crop incentive payments on other practices. We measure the relative magnitude of these behavioral factors in terms of their effect on overall pollution abatement and cost. Due to the simultaneous nature of the decisions involved when farmers make land use changes in response to environmental incentives, the system of simultaneous regression equations accounts for correlation in cost share enrollment and land use decisions for all practices under consideration.

We find that the standard scenario in which all incentive payments for cover crops lead to additional adoption is highly optimistic. While estimates of additional acreage due to the cover crop program are high, only 73% of nitrogen abatement can be attributed to the effect of enrollment among currently enrolled farms, and only 54% would be attributed to enrollment in the counterfactual scenario in which unenrolled farms participate. This increases the average marginal cost of abatement across the state by between 37 and 85 percent. Similar effects are seen when applying estimates of additionality to phosphorus and sediment. Second, the estimated indirect effects show evidence of "crowding in" of other conservation practices in response to the cover crop incentive payment. When translating these effects to their impacts on water quality, predicted abatement levels improve substantially among currently unenrolled farms due to indirect effects. Among enrolled farmers, the change in abatement and costs due to indirect effects at the state level is negligible. This suggests that the beneficial effects of crowding due to the incentive payment would be larger for farms that do not yet participate in the cost share program. The predicted benefits of indirect effects are particularly strong for phosphorus and sediment runoff, for which other conservation practices may play a more decisive role than cover crops.

Our analysis highlights several key findings and contributions to the literature. First, building upon the methodology of Fleming (2014) and other prior evaluations of cost sharing enrollment such as Lichtenberg and Smith-Ramirez (2011), we show that ignoring behavioral responses to conservation cost sharing leads to significant errors in estimating both the cost and effectiveness of these programs in the context of NPS pollution abatement. Second, this study has important policy implications. We analyze the behavioral response to incentives among both enrolled and unenrolled farmers, as well as farmers in different geographic river basins. This allows us to develop distributions of NPS pollution abatement costs that are relevant for the targeting of increased funding for the cover crop program, or utilizing agriculture as a supplier of credits for nutrient trading (Horowitz and Just 2013). Both approaches are being proposed as essential to meet the total maximum daily load (TMDL) for the Chesapeake Bay Watershed, which has garnered national attention as the largest TMDL to be implemented thus far in the United States. Finally, this study incorporates a wide range of behavior in comparison to previous literature on farmer response to cost sharing. By utilizing an econometric methodology capable of simultaneously accounting for self-selection and correlation among the acreage decisions for conservation practice use, this study is able to provide estimates of the net effect of environmental incentive payments on agricultural NPS pollution downstream.

**Background**

Agriculture can play a large role in improving water quality. In the Chesapeake Bay, for example, an estimated 45 percent of nitrogen, 44 percent of phosphorus, and 65 percent of sediment entering the Bay arise from agricultural sources.[1] In 2009, the EPA enacted a TMDL for the Chesapeake Bay watershed, the largest TMDL to date, which mandates reductions of nitrogen, phosphorus and sediment by 2025.

The State of Maryland, in partnership with the federal government, has used cost sharing for almost 30 years to reduce agricultural NPS nutrient emissions into the Chesapeake Bay. In recent years, the State has aggressively promoted cost sharing for cover crops in particular. The Maryland Agricultural and Water Quality Cost Sharing (MACS) program has more than quadrupled spending since 2005. In 2013, the MACS program spent $26.7 million, of which nearly 80 percent of this budget was allocated to cover crops. In 2014, a record 478,000 acres of cover crops were planted with the help of cost share funding, representing about 37% of harvested cropland in in the state. The MACS budget is large enough that eligible applicants are not normally denied funding.[2] Other cost share programs—such as the federal Environmental Quality Incentives Program (EQIP) and Chesapeake Bay Watershed Initiative (CBWI)—have also been available in the state in recent years, providing funding not only for cover crops, but also other erosion-control practices. Thus, the state of Maryland itself—due to its aggressive promotion of cost sharing and its variable production conditions which make it likely that farmers adopt multiple conservation practices—is favorable for the study of behavioral responses to cost sharing such as additionality and substitution (indirect) effects on other field practices.

The practices studied in this article—cover crops, conservation/no-till, and contour/strip cropping—were chosen because they are comparable in two important respects. First, all three conservation practices are used as field practices on working cropland to reduce erosion. Cover crops are grown over the winter when many fields are left bare and vulnerable to wind, rain, and snowmelt erosion. 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.[3] Other common conservation practices—such as riparian buffers—are not implemented as field practices on working cropland, but rather around the edges of waterways. Second, all these practices can be implemented throughout a field, and thus have comparable acreages on a farm. Certain other erosion control practices on working fields—such as grass-lined waterways—are only present on a small portion of a field.

As a way to track progress toward meeting the TMDL, the CBP has developed a watershed model that links land use and farmer practices to the amount of nitrogen, phosphorus and sediment reaching the Bay. The CBP watershed model is also the tool used to measure compliance with TMDL requirements by all jurisdictions. The most recent CBP watershed model (Phase 5.3) divides the 64,000-square-mile Chesapeake Bay watershed into more than 2,000 river segments delineating political and physical boundaries, simulates the origination and transport of pollution using 20-years of historical data, and continually tracks important water quality indicators at 296 monitoring stations.[4]

The CBP watershed model is calibrated based on historical measurements, and necessarily makes certain simplifications of a complex process in developing the model's parameters. The watershed-level pollution process can be thought of as a "water quality production function" (Rabotyagov, Valcu and Kling, 2013) or a "fate and transport" function (Shortle and Horan, 2013), linking multiple pollution sources to their destination downstream. While the historical measurements utilized in the CBP watershed model are grounded in real-world processes, the parameters in the model itself do not explicitly account for nonlinearities in NPS pollution generation, such as interactions between neighboring pollution sources

(Rabotyagov, Valcu and Kling, 2013).[5] In this article, we use information on edge-of-stream agricultural pollution loads for nitrogen, phosphorus, and sediment, the ratios of pollution reaching the Bay from the edge-of-stream in each segment ("delivery factors"), and the percentage pollution reduction efficiencies for each conservation practice. The manner in which this data is utilized to link farmer behavioral response to water quality will be described in more detail below. In short, the robust data available for linking farmer practices to water quality in the Chesapeake Bay watershed makes this a favorable region to assess the implications of environmental payment programs such as cost sharing.

## Data

We use data 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 population estimates. Of the 523 responses received, 424 farmers provided complete surveys usable for this analysis. The survey asked farmers whether they implemented each of the three conservation practices studied, acreage in each practice, and whether cost sharing was received for each practice (see Lichtenberg, Parker and Lane (2012) for a more complete description).[6]

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—93 respondents adopted cover crops with cost sharing compared to 46 respondents who adopted without cost sharing. In contrast, conservation tillage and contour/strip are primarily self-funded when adopted. Specifically, 26 respondents adopted conservation tillage with cost sharing, compared to 185 respondents who adopted without cost share funding. Similarly, 9 respondents adopted contour/strip with cost sharing compared to 64 respondents who adopted without cost sharing. 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, 32.2% of a farm's operating acreage is in cover crops among farmers who adopted with cost sharing compared to 23.6% 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 (55.9%) compared to farms that adopted with cost sharing (54.9%).

Table 2 summarizes the variables from the survey data collected on farm characteristics (e.g., topography, operating acreage, animal units, distance to surface water bodies), and farmer characteristics (e.g., education, income share from farming). Topography variables include the percentage of operated acres moderately sloped (two to eight percent grade) and steeply sloped (greater than eight percent). Among other factors, the survey also asks farmers about the number of animals on the farm, and the distance from the farm in miles to the nearest surface water body—including lakes, streams, wetlands and bay.

As mentioned above, we use spatial information from the CBP watershed model to translate the analysis of farmer behavior to water quality impacts for nitrogen, phosphorus and sediment loads. Finally—using the CBP data and per-acre BMP costs—we derive a cost per pound of erosion reduction for each practice in order to calculate the on-farm erosion reduction benefits of conservation practice adoption. This cost is calculated as the cost per acre of implementation divided by the pounds of erosion reduced per acre on a working field. Costs per acre for cover crops are taken from Wieland et al. (2009), in particular a cost of $31.40 per acre for rye drilled based on seed and planting costs in 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, per-acre EQIP reimbursement rates were considered a proxy for implementation costs. Finally, erosion-reduction per acre is calculated 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 erosion reduction 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. The costs per pound of erosion reduced vary cross-sectionally across the state of Maryland, and are then matched with farmers in the survey by overlaying the CBP river segments with the zip codes of the surveyed farms. Like any input cost with downward sloping demand, it is expected that the acreage share in the conservation practice would be lower when the cost per pound erosion reduced is higher.

## Empirical Model

This section describes the estimation of the effect of cost sharing on farmer behavior. The econometric model is similar to that found in Fleming (2014), in which a two-stage simultaneous equation regression model is estimated. In the first stage, cost sharing enrollment is simultaneously estimated for three conservation practices using a multivariate probit model. In the second stage, we estimate the share of farm operating acreage in the three conservation practices using a multivariate tobit framework. Generalized residuals from the first stage are included in the second stage to correct for self-selection into cost sharing programs. In the second stage, the explanatory variables are allowed to have different effects based on whether or not a farmer receives cost sharing for cover crops. This allows for estimation of separate treatment effects for individual farmers in the sample, both those enrolled in cover crop cost sharing programs and those who are unenrolled.

### *Estimation of the effect of cost sharing on farm conservation behavior*

In the model, each farmer $j$ is assumed to be a profit-maximizing agent who chooses from a set of conservation practices on her farm, where p= $\{cc, cs, ct\}$ refers to enrollment in a cost sharing program for cover crops, contour/strip, and conservation tillage, respectively. The farmer simultaneously decides whether or not to apply for cost sharing for any of these practices. Note that receipt of cost sharing for a given BMP does not exclude the possibility of receiving cost sharing for other practices.

These adoption and enrollment decisions are not made independently. There may be correlation in the adoption of conservation practices, enrollment in cost sharing programs, and importantly between cost share enrollment and conservation practice adoption, given the problem of self-selection into cost share programs.

*First-stage – Cost sharing enrollment*

Consider first the cost sharing decision. Cost share receipt depends on factors entering the farmer's enrollment decision and the funding agency's award decision, including the expected conservation benefits of the BMP (proxied by a farm's distance to surface water bodies), transaction costs of application (proxied by the share of income from farming), BMP erosion reduction costs, and other farm-level factors such as topography and farm size. Assuming these variables enter the model linearly, a functional representation of the cost share decision is:

(1)
$$C_j^p = 1 \quad if \quad Z_j^p \gamma^p + u_j^p \geq 0, \qquad p = \{cc, cs, ct\}$$
$$C_j^p = 0 \quad if \quad Z_j^p \gamma^p + u_j^p < 0, \qquad p = \{cc, cs, ct\}$$

where $Z_j^p$ are the factors influencing the cost share decision of farmer $j$ for program enrollment $p$ (it is expected that the same set of factors will influence cost share enrollment for all practices); $\gamma^p$ is a vector of parameters to be estimated for cost share enrollment for each of the three practice types; and $u_j^p$ is an error term.

Note that farmers who receive cost sharing for one conservation practice may be more likely to receive cost sharing for other practices. Unobserved farm and farmer characteristics may contribute to positive correlation in the error terms for each of the practices. Accordingly, the variance-covariance matrix of error terms for each of the 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, $\Omega_C$ is the 3x3 variance-covariance matrix of error terms of the cost-share equations for cover crops, contour/strip, and conservation tillage. The error terms are assumed to be jointly normal, thus the system of equations represented in (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 ($\Omega_C$) has values of one on the leading diagonal. The off-diagonal elements are estimated through Cholesky factorization, where $\hat{\rho}_{p,q} = \hat{\sigma}_{p,q}/\hat{\sigma}_p\hat{\sigma}_q$ is estimated as the correlation between enrollment in cost share programs for $p$ and $q$. The Geweke-Hajivassiliou-Keane (GHK) simulator (Greene 2003, p. 931-933) is used to evaluate the 3-dimensional normal integrals in the likelihood function associated with equations (1) and (2). The simulated ML estimation technique is described in more detail in Fleming (2014).

Next, consider the farmer's BMP adoption decisions. Self-selection is a well-known problem that complicates estimation of the treatment effect of cost sharing on adoption decisions (Lichtenberg and Smith-Ramirez 2011; 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 recently by Wooldridge (2014), a standard method that corrects for the problem of self-selection in program evaluation is the control function approach which uses generalized residuals as regressors in the acreage share equations to control for potential correlation in the error terms, thereby allowing consistent though not efficient estimation of the effect of cost sharing. The estimated coefficient associated with these regressors will be 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. Let $s_j^n$ represent the acreage share for farmer $j$ in practice type $n$, where the index $n = \{cc, cs, ct\}$ indicates the practice types of cover crops, contour/strip, and conservation tillage respectively. Further, let superscript $i = \{w, o\}$ respectively indicate with or without enrollment in the cover crop cost sharing program. The dependent variable $s_j^n$ represents the share of operating acreage devoted to practice type $n$. Since it is not possible to allocate less than zero acres to a land use, this variable is considered to be censored from below at zero.[9]

Accordingly, the observed acreage share, $s_j^n$, can be defined as a multivariate tobit model based upon a latent variable ${s^*}_{j,i}^{n}$ with the following empirical specification:

(3) $${s^*}_{j,i}^{n} = X_j^n \beta_i^n + \sum_{p=1}^{3} \hat{\lambda}_{j,i}^{p}\, \delta_i^n + \varphi_i^n C_j^{cs} + \tau_i^n C_j^{ct} + \varepsilon_{j,i}^{n}\ ;$$

$$\text{where } s_j^n = {s^*}_{j,i}^{n} \text{ if } {s^*}_{j,i}^{n} \geq 0,$$

$$s_j^n = 0 \text{ otherwise,}$$

$$\text{and where } i = w \ if\ C_j^{cc} = 1; \text{ and } i = o\ if\ C_j^{cc} = 0.$$

In equation (3), $X_j^n$ are variables that influence the acreage share decision. The set of variables $Z_j^p$ from equation (1) contains many of the same variables included in $X_j^n$, such as farmer education and farm characteristics such as slope and farm size. However, for purposes of identification, the matrix $Z_j^p$ contains some variables not included in $X_j^n$. Following Lichtenberg and Smith-Ramirez (2011), we assume that distance to the nearest water body—a proxy for runoff risk—matters to the government but not to the farmer and is thus included in $Z_j^p$ but not

$X_j^n$, so that acreage equations are identified by this exclusion restriction as well as by the nonlinearity of the cost share equations. Note that $\hat{\lambda}_{j,i}^p$ are the estimated generalized residuals from each of the three cost share enrollment equations in (1), to allow for the potential correlation between all three cost share decisions and conservation practice acreage. The variables $C_j^{cs}$ and $C_j^{ct}$ represent enrollment in cost share programs for contour/strip and conservation tillage, respectively.

The parameter estimates in equation (3) may switch based upon observed enrollment in a cover crop cost sharing program, $C_j^{cc}$. Cost sharing for cover crops is used to indicate switching because the primary interest of this study is to evaluate the large cover crop cost sharing effort in Maryland. Then $\theta_i^n = \{\beta, \delta, \varphi, \tau\}, i = \{w, o\}$ are parameters estimated separately for each of the two regimes, which will be used to estimate the treatment effect of cover crop cost sharing (discussed in more detail shortly).

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). An advantage of this framework in comparison to other methods is its generality to estimate heterogeneous effects. Parameter estimates are allowed to vary based on a farmer's cost share status ($\hat{\theta}_w^n \neq \hat{\theta}_o^n$), a possibility that should not be precluded in advance, especially for regressors related to the cost of BMP adoption. Unlike Lichtenberg and Smith-Ramirez (2011), this study uses cost share receipt 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 right hand variables.

Errors of the system of equations (3) are assumed to be distributed jointly normal, but are never observed simultaneously across regimes $i = \{w, o\}$. Thus, the variance-covariance matrix of errors across acreage share equations, $\Omega_s$, is of a block diagonal form:

$$(4) \qquad \Omega_s = Var\begin{pmatrix} \varepsilon_1^1 \\ \varepsilon_2^1 \\ \varepsilon_3^1 \\ \varepsilon_1^0 \\ \varepsilon_2^0 \\ \varepsilon_3^0 \end{pmatrix} =$$

$$\begin{pmatrix} \sigma_{\varepsilon 11}^2 & \sigma_{\varepsilon 21 \varepsilon 11} & \sigma_{\varepsilon 31 \varepsilon 11} & . & . & . \\ \sigma_{\varepsilon 11 \varepsilon 21} & \sigma_{\varepsilon 21}^2 & \sigma_{\varepsilon 31 \varepsilon 21} & . & . & . \\ \sigma_{\varepsilon 11 \varepsilon 31} & \sigma_{\varepsilon 21 \varepsilon 31} & \sigma_{\varepsilon 31}^2 & . & . & . \\ . & . & . & \sigma_{\varepsilon 10}^2 & \sigma_{\varepsilon 20 \varepsilon 10} & \sigma_{\varepsilon 30 \varepsilon 10} \\ . & . & . & \sigma_{\varepsilon 10 \varepsilon 20} & \sigma_{\varepsilon 20}^2 & \sigma_{\varepsilon 30 \varepsilon 20} \\ . & . & . & \sigma_{\varepsilon 10 \varepsilon 30} & \sigma_{\varepsilon 21 \varepsilon 31} & \sigma_{\varepsilon 30}^2 \end{pmatrix}$$

The off-diagonal elements on the leading block diagonals represent the covariance between conservation acreage decisions for each of the practice types.

The six equation 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. 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, contour/strip, and conservation tillage. The simulated ML estimation technique with Halton sequences is described in more detail in Fleming (2014).

Treatment effects for both enrolled and unenrolled farmers are then calculated based on estimated acreage shares from parameter estimates $\hat{\theta}_w^n \neq \hat{\theta}_o^n$ (Heckman and Vytlacil, 2007).

$$(5) \qquad \widehat{TET}_j^n = \{\hat{s}_{w,j}^n - \hat{s}_{o,j}^n\} \text{ for enrolled farmer } j,$$

$$\widehat{TEU}_j^n = \{\hat{s}_{w,j}^n - \hat{s}_{o,j}^n\} \text{ for unenrolled farmer } j.$$

For enrolled farmers, $\hat{s}_{o,j}^n$ is a counterfactual based upon parameter estimates from unenrolled farmers, $\hat{\theta}_i^n$, representing the acreage share that would have been observed had these farmers not been enrolled in cover crop cost sharing programs. For unenrolled farmers, the counterfactual is $\hat{s}_{w,j}^n$, representing the expected acreage share if these farmers had been enrolled.

**Estimation results**

This section contains the estimated treatment effects of cover crop cost sharing enrollment, based upon the two-stage econometric model of cost share enrollment and adoption of conservation practices. Parameter estimates from the multivariate probit model for enrollment and multivariate tobit model on acreage share in the practice types are reported in the Appendix in Tables A1 and A2, respectively.

Table 3 shows the average treatment effects for enrolled and unenrolled farmers. Averages are weighted by the inverse sampling weights provided by MASS for the stratified random sampling used in the survey. The average treatment effects on the treated (ATT) are reported in column [1] of Table 3, which reflect the effectiveness of the program as it exists currently. The ATT for the share of operating acreage devoted to cover crops is 0.216 and significant at the 1% level. Hence, the MACS cover crop cost sharing program had a large effect on enrolled farmers, who have a 0.26 share in cover crops with enrollment compared to only a 0.05 share counterfactually estimated for their acreage in cover crops without enrollment. There was also a positive indirect effect on conservation tillage acreage that is significant at the 1%

level, showing an increase of 0.076 in the share of operating acreage devoted to conservation tillage due to enrollment in the cover crop program. Meanwhile, the indirect effects on contour/strip acreage ss estimated to be 0.008 and not statistically significant for enrolled farmers.

The average treatment effects on the untreated (ATU) in column [2] of Table 3 are also relevant. The ATU results provide an expectation for how the group of currently unenrolled farmers would respond if the program were expanded to include them. Column [2] shows the estimated ATU is 0.202 for acreage share in cover crops for unenrolled farmers, which is similar in magnitude to the ATT of 0.216 for enrolled farmers. This suggests that similar gains in adoption of cover crops are potentially available by expanding the MACS program to unenrolled farmers. For unenrolled farmers, the estimated indirect effects on conservation tillage and contour/strip are 0.126 and 0.149, respectively. Surprisingly, this suggests that the positive indirect effects for unenrolled farmers are larger in magnitude than the corresponding indirect effects for enrolled farmers. In other words, these estimates suggest that potential "crowding in" effects of cost sharing are likely greater for farmers not reached by the current program than for farmers who have been enrolled already. That said, the average farm size is much smaller in the group of unenrolled farms, so despite the similar estimated change in acreage shares of cover crops, there would be a smaller absolute number of additional acres adopted.

**Policy simulation methodology**

The primary difference with Fleming (2014) is that individual farm-level treatment effects are inserted into the CBP watershed model to develop farm-level abatement and costs. Unlike previous agricultural-water quality models, these estimated effects account for a wide range of farmer behavioral responses to environmental incentive payments. We compare abatement costs from the current standard approach which assumes all BMP adoption induced by incentive payments additional, with a more realistic scenario that accounts for self-selection and indirect effects. We then use inverse sampling weights to translate the econometric result from the farmer survey to the water quality impacts at the population level for the entire state of Maryland.

We begin with data on pollution loads, BMP efficiencies, and delivery factors from the CBP watershed model. Loads, $L_{kz}^{l}$ , are the pollution loadings by land use $l = \{crop, hay, pasture\}$, pollutant $k = \{nitrogen, phosphorus, sediment\}$, and geographic region $z$. Loads are expressed in pounds per acre at edge-of-stream for nitrogen and phosphorus, and tons per acre at edge-of-stream for sediment. Practice efficiencies, $\eta_{kz}^{n}$, are the proportional reduction of pollutant $k$ due to adoption of a given practice, where $0 \leq \eta_{kz}^{n} < 1$. As above, let $n = \{cc, cs, ct\}$ indicate the practices of cover crops, contour/strip, and conservation tillage, respectively. Practice efficiency parameters, $\eta_{kz}^{n}$, for a given practice type $n$ and pollutant $k$ are constant in the study region, with the exception that $\eta_{kz}^{cc}$ for cover crops varies spatially between the geographic regions of coastal plain and non-coastal plain when $k = nitrogen$. Finally, delivery factors, $\delta_{kz}$ , are the proportional reduction of pollutant $k$ as it travels from the edge-of-stream in geographic region $z$ downstream to the Chesapeake Bay.

Let $\widehat{TET}_j^n$ be the estimated effect of cover crop cost sharing on the acres of practice $n$ for enrolled farmer $j$. That is, if $A_j$ are total operating acres on farm $j$, $\widehat{TET}_j^n = A_j \cdot \{\hat{s}_{j,w}^{n} - \hat{s}_{j,o}^{n}\}$.[10] Similarly, $\widehat{TEU}_j^n$ is the estimated effect on acres of practice n for unenrolled farmer $j$. The finest level of spatial detail available in the farmer survey is zip code, whereas the data from the CBP described above is provided at the spatial level of river segment. To match the CBP watershed model parameters with the farmer survey, we calculate weighted-average loads by nutrient management plan (NMP) and land use, and weighted-average delivery factors, both at the zip code level.[11] This allows loads, reduction efficiencies and delivery factors to be expressed at the level of surveyed farm $j$.

With the farmer-level econometric results matched to the CBP data, we calculate the reduction in pounds of pollution to the Chesapeake Bay due to cover crop cost sharing. The direct effect of cost sharing (direct = due only to increased adoption of cover crops, not accounting for indirect effects) on the quantity of abatement of pollutant $k$ in the Bay is calculated as follows:

(6)
$$\Delta Q_{jk}^{1,D} = (\widehat{TET}_j^{cc} \cdot L_{kj}^{crop} \cdot \eta_{kj}^{cc}) \cdot \ \delta_{kj} \ \text{ for enrolled farmer } j$$

$$\Delta Q_{jk}^{0,D} = (\widehat{TEU}_j^{cc} \cdot L_{kj}^{crop} \cdot \eta_{kj}^{cc}) \cdot \ \delta_{kj} \ \text{ for unenrolled farmer } j$$

Here, the quantities of abatement are expressed either in pounds (for nitrogen and phosphorus) or tons (for sediment). This direct effect estimates additionality that accounts for self-selection into cost sharing programs, but not indirect effects. We then calculate abatement in the Bay in consideration of both direct and indirect effects of environmental incentive payments, which represents the “net effect” on pounds of pollution load from cropland. When multiple practice types are used on the same acre of land, the reduction efficiencies $\eta_{kj}^{n}$ are considered multiplicative, not additive, because one practice reduces the nutrient loads available for subsequent practices to reduce. Since our survey data is at the farm-level, we do not know the spatial distribution of the acreage shares in each practice type within the farm in order to assess the degree of overlap (i.e. within farm correlation of practice types). Thus we begin by assuming practices to be placed independently on a farm (i.e. no correlation).

Let $\hat{s}_i^{cc}$, $\hat{s}_i^{cs}$, and $\hat{s}_i^{ct}$ be the estimated shares of operating acres in cover crops, contour/strip and conservation tillage, respectively, where $i = w$ indicates with cost sharing and $i = o$ without. Let $A_j$ be total farm operating acreage.[12] Since the practices under consideration are not mutually exclusive, it is conceivable that they are used on the same fields. Moreover, if $\hat{s}_i^{cc} + \hat{s}_i^{cs} + \hat{s}_i^{ct} > 1$, there must be some overlap among practices. Note that 91 (approx. 20%) of the usable observations have combined acreage shares greater than one with cost sharing. To calculate multiplicative reduction efficiencies, let $m = \{1,2,\ldots,8\}$ be an index of mutually exclusive combinations of the practices, such that a single number, $\eta_{kj}^m$, refers to the reduction efficiency from a unique combination of practices on the same field:

$m = 1 \leftrightarrow no\ BMPs$, and $\eta_{kj}^1 = 0$,

$m = 2 \leftrightarrow cc$, and $\eta_{kj}^2 = \eta_{kj}^{cc}$

$m = 3 \leftrightarrow cs$, and $\eta_{kj}^3 = \eta_{kj}^{cs}$

$m = 4 \leftrightarrow ct$, and $\eta_{kj}^4 = \eta_{kj}^{ct}$

$m = 5 \leftrightarrow cc + cs$, and $\eta_{kj}^5 = \eta_{kj}^{cc} + \eta_{kj}^{cs} - \eta_{kj}^{cc} \cdot \eta_{kj}^{cs}$

$m = 6 \leftrightarrow cc + ct$, and $\eta_{kj}^6 = \eta_{kj}^{cc} + \eta_{kj}^{ct} - \eta_{kj}^{cc} \cdot \eta_{kj}^{ct}$

$m = 7 \leftrightarrow cs + ct$, and $\eta_{kj}^7 = \eta_{kj}^{cs} + \eta_{kj}^{ct} - \eta_{kj}^{cs} \cdot \eta_{kj}^{ct}$

$m = 8 \leftrightarrow cc + cs + ct$,

and $\eta_{kj}^8 = \left(\eta_{kj}^{cc} + \eta_{kj}^{cs} + \eta_{kj}^{ct} + \eta_{kj}^{cc} \cdot \eta_{kj}^{cs} \cdot \eta_{kj}^{ct}\right) - \left(\eta_{kj}^{cc} \cdot \eta_{kj}^{cs} + \eta_{kj}^{cc} \cdot \eta_{kj}^{ct} + \eta_{kj}^{cs} \cdot \eta_{kj}^{ct}\right)$

Similarly, acreage shares $\hat{s}_{i,j}^m$ are calculated for mutually exclusive combinations of the practices. Assuming independent placement (random overlap) of practices, these are:

$m = 1 \leftrightarrow no\ BMPs$, and $s_i^1 = (1 - s_i^{cc}) \cdot (1 - s_i^{cs}) \cdot (1 - s_i^{ct})$,

$m = 2 \leftrightarrow cc$, and $s_i^2 = s_i^{cc} \cdot (1 - s_i^{cs}) \cdot (1 - s_i^{ct})$

$m = 3 \leftrightarrow cs$, and $s_i^3 = (1 - s_i^{cc}) \cdot s_i^{cs} \cdot (1 - s_i^{ct})$

$m = 4 \leftrightarrow ct$, and $s_i^4 = (1 - s_i^{cc}) \cdot (1 - s_i^{cs}) \cdot s_i^{ct}$

$m = 5 \leftrightarrow cc + cs$, and $s_i^5 = s_i^{cc} \cdot s_i^{cs} \cdot (1 - s_i^{ct})$

$m = 6 \leftrightarrow cc + ct$, and $s_i^6 = s_i^{cc} \cdot (1 - s_i^{cs}) \cdot s_i^{ct}$

$m = 7 \leftrightarrow cs + ct$, and $s_i^7 = (1 - s_i^{cc}) \cdot s_i^{cs} \cdot s_i^{ct}$

$m = 8 \leftrightarrow cc + cs + ct$, and $s_i^8 = s_i^{cc} \cdot s_i^{cs} \cdot s_i^{ct}$

Under this scenario in which both direct and indirect effects are considered, the change in the quantity of abatement is:

(7) $$\Delta Q_{jk}^{D+I} = A_j \cdot \left\{\left[\sum_{m=2}^{8} \hat{s}_{w,j}^{m} \cdot L_{kj} \cdot \eta_{kj}^{m}\right] - \left[\sum_{m=2}^{8} \hat{s}_{o,j}^{m} \cdot L_{kj} \cdot \eta_{kj}^{m}\right]\right\} \cdot \delta_{kj}$$

*Costs and population inferences*

The quantities of abatement in the Chesapeake Bay are then translated to abatement costs using a cost share rate of \$65 per acre, which is a typical award given in Maryland (for rye planted by October 1st). Assuming that the funding agency does not consider cover crop usage without cost sharing and thus assumes 100% additionality, the expenditure is simply

(8) $$E_j = 65 \cdot A_j \cdot \hat{s}_{w,j}^{cc}.$$

The cost per pound of abatement, or marginal abatement cost, for each pollutant is then calculated as:

(9) $$MAC_{jk} = E_j / \Delta Q_{jk}^{D+I}$$

This cost per pound of abatement is ranked in ascending order among the enrolled and unenrolled farmers in the survey, as well as among farmers in different geographic river basins in the state.

*Comparison with a standard least-cost scenario*

For the sake of comparison, we also calculate abatement and costs under the standard approach that treats all estimated cover crop acreage as due to the cost-sharing award (i.e. 100% additionality). In this scenario, the estimated cover crop acreage with cost sharing is used in place of the treatment effect.

(10) $$\Delta Q_{jk}^{N} = A_j \cdot (\hat{s}_{w,j}^{cc} \cdot L_{kj} \cdot \eta_{kj}^{cc}) \cdot \delta_{kz}$$

Since the treatment effect is calculated as $\hat{s}_{w,j}^{cc} - \hat{s}_{o,j}^{cc}$, this scenario is equivalent to assuming the acreage share of cover crops without cost sharing ($\hat{s}_{o,j}^{cc}$) is always zero. Moreover, this scenario assumes that there are no indirect effects on other conservation practices.[13] Abatement costs in this least-cost scenario are calculated as before. Similarly, when implementation costs are equal to the cost share award, note that this standard scenario is trivially equivalent to a scenario in which implementation costs are used to estimate costs of abatement.

After scaling up to the population level, this provides two sets of abatement cost curves to compare: (i) a least-cost scenario in which farmer behavioral responses are not considered; and (ii) an overall effect of cost sharing in which a wide range of behavior is accounted for (non-additional adoption and indirect effects). Previous literature on the effects of agricultural land use on water quality has focused only on (i), thus abstracting from farmer behavioral response to environmental incentive payments.

**Policy simulation results**

This section describes the policy simulation results in which the estimated treatment effects are combined with data from the CBP watershed model to obtain farm-level abatement and costs due to enrollment in the cover crop cost sharing program. We compare abatement and costs from a current standard least-cost scenario in which all enrolled acreage is assumed to be additional with a more realistic scenario which estimates additionality for the direct effect of enrollment on cover crops and indirect effects on the conservation tillage and contour/strip practices.

*Farm-level abatement and costs*

Table 4 shows weighted-average abatement per farm and per acre in the survey sample, with weights based upon the inverse sampling weights. Results are reported for each pollutant for farmers who are both enrolled and not enrolled in the cover crop program. Columns [1] and [2] of the table show average abatement, with the first row showing the standard scenario in which all incentive payments are additional and there are no indirect effects, calculated based on equation (10). The second row shows the level of abatement based on the direct effect on cover crops, which accounts for self-selection and non-additional adoption, calculated based on equation (6). The third and final row shows the net effect on abatement (net = direct and indirect effects) that accounts for both additionality with regard to cover crops and indirect effects on the contour/strip and conservation tillage practices, calculated based on equation (7).

For enrolled farmers, we find that the current standard approach gives highly optimistic estimates of reductions in all three pollutants. For example, nitrogen abatement is reduced from 7 pounds per acre to 5.6 pounds per acre after accounting for non-additional abatement, and down slightly further to 5.5 pounds per acre after accounting for indirect effects on other practices. This represents a 22 percent decline from the standard scenario. Similarly, phosphorus abatement declines by 53% and sediment abatement declines by 18% after considering non-random enrollment. (Note that although the average indirect effects on acreage in contour/strip and conservation tillage tended to be negligible or positive (as shown in Table 3), when the effect on acreage shares was translated to abatement for each farmer, abatement shifted in a negative direction due to variation in the distribution of effects for each farmer.[14]

Column [3] of Table 4 shows weighted average abatement costs. We find that average farm abatement costs increase significantly after considering non-additional abatement (direct effects), rising from only $11.42 per pound nitrogen reduced in the standard scenario to $15.90 when accounting for non-additional adoption of cover crops due to nonrandom enrollment in the program, a nearly 40% increase in cost. Estimated farm-level nitrogen abatement costs increased another 5% after considering potential substitution with contour/strip and conservation tillage. (Note that in some cases the changes in average costs between scenarios do not correspond with the changes in abatement. For example, there is steep decrease in the cost of phosphorus abatement among enrolled farmers after considering indirect effects, despite lower abatement per acre. This is due once again to the underlying distribution of estimates for each farm. When indirect effects lead to negative estimates of net abatement, the cost per pound abatement calculated using equation (9) also becomes negative, thus skewing average costs downward.)

The right side of Table 4 shows the same set of results for the group of unenrolled farmers. As before, the standard least-cost scenario overestimates abatement and underestimates costs. However, for the unenrolled group the differences between the standard and behavioral scenarios are stark. For example, the cost of nitrogen abatement increases by 52% (from $15.88 per pound to $24.16 per pound) after accounting for non-random enrollment. In comparison to enrolled farmers, this suggests that the implied costs of non-additional adoption will be increasingly high if the cover crop program seeks to increase participation across the state. In contrast, indirect effects among the group of unenrolled farmers are beneficial when translated to abatement. For nitrogen, indirect effects are beneficial but do not compensate for non-additional enrollment. However, for phosphorus and sediment the beneficial indirect effect on other practices more than compensates for non-additional enrollment, leading to abatement per farm that is 38% and 82% greater than in the standard least-cost scenario. In short, the crowding-in of contour/strip and conservation tillage practices as a result of cost sharing greatly lowers the estimated per-farm costs of phosphorus and sediment abatement among the unenrolled group.

*Policy simulation results at regional watershed level*

The question remains: what do these farm-level sample averages reveal about total abatement in the population? Moreover, to construct abatement supply curves, it is necessary to translate the econometric analysis from the survey sample to the population level for the entire state of Maryland. The inverse sampling weights provide by MASS, $w_j$, allow us to estimate the total pollution abatement obtainable in the state of Maryland, as represented by each surveyed farm. The total quantity of abatement of pollutant $k$ for various groups, $g = \{enrolled, unenrolled\}$, is calculated as,

(11) $$TQ_k^g = \sum_j^{J_g} \Delta Q_{jk}^{D+I} \cdot w_j \text{ for farmer } j \text{ in group } g$$

$$\text{where } \sum_{j=1}^{J_g} w_j = 1.$$

Here, $Q_{jk}^{D+I}$ is calculated as in equation (7). To find the cost associated with obtaining this total quantity of abatement, we utilize the marginal cost of abatement calculated for each farm from equation (9), $MAC_{jk}$. The estimated total cost for achieving $TQ_k^g$ is then calculated as:

(12) $$TC_k^g = \sum_j^{J_g} (MAC_{jk} \cdot (\Delta Q_{jk}^{D+I} \cdot w_j)) \text{ for farmer } j \text{ in group } g$$

$$\text{where } \sum_{j=1}^{J_g} w_j = 1.$$

These results are shown in Table 5 for the population of enrolled and unenrolled farms in Maryland. The total abatement of nitrogen obtained due to enrollment in cover crop cost sharing is estimated to have been approximately 1.01 million pounds after accounting for non-additionality and indirect effects. This is in contrast to an estimate of 1.38 million pounds when behavioral response is not considered. In general, only 73% (1.01 of 1.38 million pounds) of nitrogen abatement due to cover crop cost sharing across the state can be attributed to the treatment effect on enrolled farmers. Abatement is similarly reduced among enrolled farmers for phosphorus and sediment after considering nonrandom enrollment. Respectively, about 71% and 80% of phosphorus and sediment abatement across the state is additional.

The estimated state-level indirect effects on contour/strip and conservation tillage appear to have negligible or deleterious effects for the enrolled group. Total net abatement of nitrogen is virtually unchanged after considering the subsidy's effect on other practices. Total net abatement of phosphorus and sediment, in contrast, is estimated to have been respectively 21% and 37% lower than the direct effect estimate of additionality, showing the importance of indirect effects for these two pollutants.

The total cost of achieving this level of abatement is estimated to have been about $13.7 million[15], which is the same for all pollutants. Dividing total cost by total abatement leads to an implied marginal cost for each pollutant, which can be interpreted as the average marginal cost across a group of farmers, in this case the enrolled farmers. Average state-wide marginal costs for abatement already obtained through currently enrolled farmers increases by 37% after accounting for nonrandom enrollment and indirect effects (from $9.91 per pound nitrogen abatement to over $13.50 per pound). Phosphorus abatement obtained through enrollment increased by 40% per pound after accounting for nonrandom enrollment (from $534 to $750). It increased another 26% after considering indirect effects (to about $945 per pound). The steeper increase in average state-wide marginal costs for phosphorus is due to the relatively larger effect that contour/strip and conservation tillage practices have on phosphorus runoff in comparison to nitrogen. A similarly steep incline is observed for average state-wide costs of sediment abatement obtained through current enrollment in cover crop cost sharing.

For unenrolled farmers, the population level results reflect potential abatement obtainable from expanding the cover crop program to include those farmers who do not yet participate. The estimated average state-wide costs assume that these farmers can be incentivized to join the program at current cost share rates, but they account for differential levels of additionality and varying indirect effects on conservation behavior among the unenrolled group.

Despite the smaller average size of the unenrolled farms, the potential abatement obtainable from this group is higher than the abatement obtained from currently enrolled farms. This is due to the larger quantity of unenrolled farms in the state. However, the percentage additionality of abatement is lower for unenrolled farms in comparison to the enrolled group, at about 54% (1.22 million in comparison to 2.26 million) due to the fact that some of the unenrolled farms may already use cover crops without incentive payments. Total net nitrogen abatement obtainable (direct and indirect effects) is estimated to be about 20% higher than in the direct scenario that does not consider the possibility of indirect effects (1.5 million pounds). Among unenrolled farms, indirect effects play an unambiguously positive role. For phosphorus and sediment runoff, positive indirect effects increase net abatement to levels higher than that found even in the standard scenario of implementation costs / 100% additionality.

The total cost of achieving these levels of state-wide abatement on unenrolled farms is almost 70% higher than that already required for the enrolled group ($22.8 million in comparison to $13.7 million). Note that the implied average marginal costs are higher in the unenrolled farms than among currently enrolled farms for all three pollutants, after accounting for lack of additionality due to nonrandom enrollment (direct effect). This suggests that efforts to expand the cover crop program to currently unenrolled farmers will likely require enrolling non-additional acres, as some of these farms already adopt cover crops without incentive payments.

After considering the possibility of non-additional adoption among unenrolled farmers, average marginal cost of abatement across the state increases substantially. For nitrogen, implied marginal costs increase on average by 85%. For phosphorus and sediment, the increases in average marginal costs are similarly steep after considering non-additional adoption (74% and 45%, respectively).

However, due to the estimated “crowding-in” of other practices, the cost of total net abatement in the state is lower than the cost of direct abatement for the unenrolled group. For nitrogen, the cost of net abatement declines slightly, by about 19%, to $15.21 per pound. This remains higher than the estimated state-wide cost of net abatement for enrolled farmers, suggesting that the cover crop program has successfully targeted lower cost abatement for nitrogen, even after incorporating behavioral response. In contrast, state-wide net abatement costs are significantly lower in the unenrolled group for phosphorus and sediment, in comparison to currently enrolled farmers. This suggests that the targeting of unenrolled farmers may represent a low cost way to improve water quality in regions of the state where phosphorus and sediment runoff are a primary concern.

## Conclusion

This study has demonstrated the importance of incorporating farmer behavioral responses when studying the water quality impacts of environmental incentive payments. We compared estimated abatement levels and cost-effectiveness under the standard assumption of perfect additionality / implementation costs used in the existing literature with a more realistic scenario in which a wide range of known behavioral responses to cost sharing are considered. These behavioral responses include the possibility of non-additionality of incentive payments due to nonrandom enrollment, and indirect effects of incentive payments on other practices. Inverse sampling weights from the survey sample allowed us to extend these policy simulation results to the regional watershed level.

We find that the standard policy simulation scenario is highly optimistic. While estimated additionality for the cover crop program is high, only 73% of state-wide nitrogen abatement can be attributed to the effect of enrollment in cost sharing among currently enrolled farms, and only 54% can be attributed to enrollment in the counterfactual scenario in which unenrolled farms across the state participate. At the state-level level, this translates to an increase of average marginal abatement costs of 37% and 85%, respectively. However, we find that among currently unenrolled farmers the potential "crowding in" of other conservation practices due to the incentive payment substantially improves the potential cost effectiveness of extending incentive payments to this group. The influence of indirect effects on abatement is particularly strong for phosphorus and sediment, for which contour/strip and conservation tillage play a more decisive role than cover crops.

Consideration of farmer behavioral response to environmental incentive payments presents both challenges and opportunities to policymakers. When considering farmer behavior, the total abatement achievable not only depends on varying geographic and hydrologic conditions—as implied by water quality models—but also on the underlying heterogeneity of the population of farmers. Thus, the overall variation in estimates of abatement and marginal abatement costs increase significantly. But this challenge also presents at least two opportunities. First, heterogeneity in farmer behavioral response points to the possibility of targeting additional cost share funds where they will have the largest behavioral impact. Second, this heterogeneity also leads to increased room for gains from trade in potential water quality trading programs.

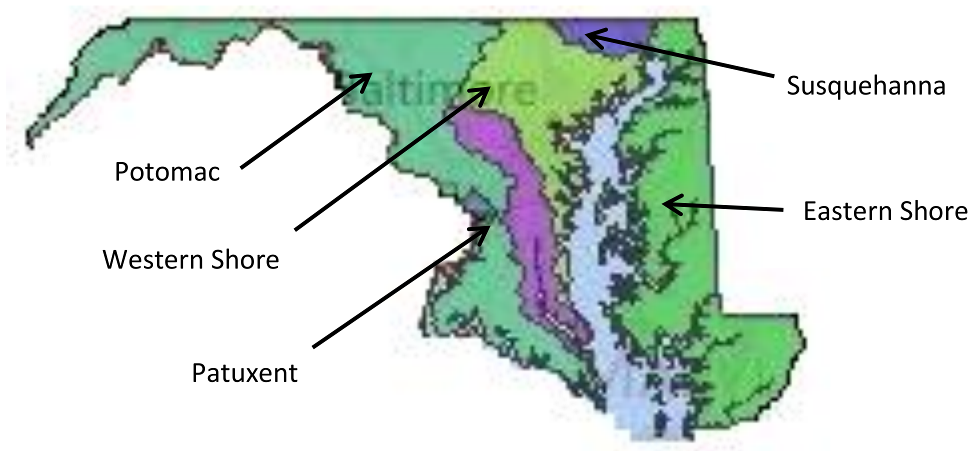


**Figure 1. Major river basins in Chesapeake Bay watershed in Maryland**

**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 | Adoption without cost share | Adoption with cost share | Adoption without cost share | Adoption with cost share |
| | [1] | [2] | [3] | [4] | [5] |
| Cover crops | 285 | 46 | 93 | 23.6% | 32.2% |
| Conservation tillage | 213 | 185 | 26 | 55.9% | 54.9% |
| Contour/Strip | 351 | 64 | 9 | 28.2% | 22.4% |

**Table 2. Descriptive Statistics for Farmer Survey Data**

| **Variable** | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Distance to the nearest water body (miles) | 0.45 | 1.3 | 0 | 11 |
| Proportion income from farming | 0.51 | 0.4 | 0 | 1 |
| Proportion acres in slope class<br>Flat (< 2% grade) | 0.49 | 0.4 | 0 | 1 |
| Moderate (2-8% grade) | 0.43 | 0.4 | 0 | 1 |
| Steep (>8% grade) | 0.08 | 0.2 | 0 | 1 |
| Operating acres (thousands) | 0.49 | 0.9 | 0.002 | 9.78 |
| Animal Units (thousands) | 0.31 | 1.5 | 0 | 20.64 |
| Highest level of education attained<br>Did not graduate high school | 0.16 | 0.4 | 0 | 1 |
| High school grad or some college | 0.60 | 0.5 | 0 | 1 |
| Bachelor's or graduate degree | 0.24 | 0.4 | 0 | 1 |

N=424

**Table 3. Estimated Acreage Shares With and Without Enrollment in Cover Crop Cost Sharing Program**

| | All surveyed farms | |
|---|---|---|
| | Enrolled (N=93) | Unenrolled (N=331) |
| | [1] | [2] |
| Cover Crop (Operating acreage share) | | |
| Without Enrollment | 0.046 | 0.050 |
| With Enrollment | 0.262 | 0.251 |
| Direct Effect | 0.216** | 0.202* |
| Contour/Strip (Operating acreage share) | | |
| Without Enrollment | 0.192 | 0.055 |
| With Enrollment | 0.200 | 0.204 |
| Indirect Effect | 0.008 | 0.149 |
| Conservation tillage (Operating acreage share) | | |
| Without Enrollment | 0.355 | 0.166 |
| With Enrollment | 0.430 | 0.292 |
| Indirect Effect | 0.076** | 0.126* |

**Significant at the 99% level. *Significant at the 95% level.

**Table 4. Average Abatement and Marginal Abatement Costs Due to Enrollment in Cover Crop Cost Sharing Program**

| | Farm-level averages in Maryland | | | | | |
|---|---|---|---|---|---|---|
| | Enrolled (N=93) | | | Unenrolled (N=331) | | |
| | Abatement per farm | Abatement per acre | Cost per pound (or ton) abated | Abatement per farm | Abatement per acre | Cost per pound (or ton) abated |
| | [1] | [2] | [3] | [4] | [5] | [6] |
| **Nitrogen (pounds)** | | | | | | |
| Scenarios | | | | | | |
| Standard (100% additional, no indirect effects) | 1,094 | 7.0 | $11.42 | 275 | 6.6 | $15.88 |
| Direct Effect | 798 | 5.6 | $15.90 | 149 | 4.8 | $24.16 |
| Net Effect (Direct and indirect effects) | 800 | 5.5 | $16.66 | 183 | 6.2 | $12.88 |
| **Phosphorus (pounds)** | | | | | | |
| Scenarios | | | | | | |
| Standard (100% additional, no indirect effects) | 20.3 | 0.14 | $542.27 | 5.7 | 0.14 | $599.72 |
| Direct Effect | 14.4 | 0.11 | $778.98 | 3.3 | 0.10 | $943.12 |
| Net Effect (Direct and indirect effects) | 11.5 | 0.06 | $335.21 | 7.9 | 0.30 | $305.27 |
| **Sediment (tons)** | | | | | | |
| Scenarios | | | | | | |
| Standard (100% additional, no indirect effects) | 13.5 | 0.09 | $1,520.64 | 4.1 | 0.12 | $1,112.84 |
| Direct Effect | 10.7 | 0.08 | $2,749.42 | 2.9 | 0.09 | $2,252.39 |
| Net Effect (Direct and indirect effects) | 6.7 | 0.08 | $3,519.92 | 7.6 | 0.28 | $846.44 |

**Table 5. State-wide Total Abatement and Costs Due to Enrollment in Cover Crop Cost Sharing Program**

| | Total in Maryland | | | |
|---|---|---|---|---|
| | Enrolled (Cost of achieving total = $13.7 M) | | Unenrolled (Cost of achieving total = $22.8 M) | |
| | Total abatement (pounds or tons) | Implied average marginal cost | Total abatement (pounds or tons) | Implied average marginal cost |
| | [1] | [2] | [3] | [4] |
| **Nitrogen (pounds)** | | | | |
| Scenarios | | | | |
| Standard (100% additional, no indirect effects) | 1,381,071 | $9.91 | 2,260,237 | $10.11 |
| Direct Effect | 1,008,105 | $13.57 | 1,221,824 | $18.70 |
| Net Effect (Direct and indirect effects) | 1,010,247 | $13.55 | 1,501,879 | $15.21 |
| **Phosphorus (pounds)** | | | | |
| Scenarios | | | | |
| Standard (100% additional, no indirect effects) | 25,613 | $534.29 | 47,159 | $484.44 |
| Direct Effect | 18,232 | $750.57 | 27,121 | $842.35 |
| Net Effect (Direct and indirect effects) | 14,487 | $944.59 | 65,036 | $351.28 |
| **Sediment (tons)** | | | | |
| Scenarios | | | | |
| Standard (100% additional, no indirect effects) | 16,993 | $805.30 | 34,096 | $670.04 |
| Direct Effect | 13,542 | $1,010.55 | 23,526 | $971.07 |
| Net Effect (Direct and indirect effects) | 8,518 | $1,606.56 | 62,170 | $367.47 |

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## Appendix

**Table A1. Coefficient Estimates for Multivariate Probit Model of Enrollment in Cost Share Programs by Practice Type**

| | Cost share enrollment (MV Probit) | | |
|---|---|---|---|
| | Cover crops | Contour/strip | No-till |
| Distance to the nearest water body (miles) | -0.1491** | 0.1037 | -0.1252 |
| | (0.0683) | (0.1190) | (0.1068) |
| Proportion income from farming | 1.0823*** | -0.0618 | 0.5153** |
| | (0.2246) | (0.3066) | (0.2482) |
| Erosion reduction cost ($ / lb. reduced) | | | |
| Cover crops | -3.2942 | -280.0572** | -120.2613 |
| | (41.5714) | (117.2419) | (76.7022) |
| Contour/strip | 17.434 | 229.2071*** | 104.8156** |
| | (29.8943) | (83.9563) | (42.7833) |
| No-till | -14.1286 | -47.7072 | 7.4117 |
| | (30.7311) | (70.2405) | (78.4309) |
| Highest level of education completed | | | |
| High school or Community college | -0.0989 | 0.2113 | 0.1075 |
| | (0.2275) | (0.3844) | (0.2795) |
| Bachelor's degree or higher | 0.4228* | 0.2306 | 0.2203 |
| | (0.2265) | (0.3643) | (0.2479) |
| Proportion acres in slope class | | | |
| Moderate (2-8% grade) | 0.6837** | 2.3855*** | 0.9525*** |
| | (0.2995) | (0.8312) | (0.2963) |
| Steep (> 8% grade) | 0.0879 | 0.3176 | -0.1897 |
| | (0.5496) | (0.9913) | (0.8669) |
| Operating acres (thousands) | 0.5006*** | 0.2449* | -0.0279 |
| | (0.1783) | (0.1268) | (0.1217) |
| Observations | 424 | 424 | 424 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## Appendix

## Table A2. Coefficient Estimates for Multivariate Tobit Model of Acreage Shares With and Without Cover Crop Cost Sharing by Practice Type

| | Acreage share (MV Tobit) | | | | | |
|---|---|---|---|---|---|---|
| | Cover crops | | Contour/strip | | No-till | |
| | With | Without | With | Without | With | Without |
| Erosion reduction cost ($ / lb. reduced) | -0.1439 | -0.3429 | -0.1637 | 0.3477 | -0.7241** | -0.7686** |
| Cover crops | (0.2197) | (0.3819) | (0.3817) | (0.5255) | (0.2838) | (0.2994) |
| Contour/strip | 0.1622 | 0.3072 | 0.0589 | -0.1839 | 0.6745*** | 1.0448*** |
| | (0.1499) | (0.2958) | (0.3077) | (0.3717) | (0.2059) | (0.2285) |
| No-till | 0.0223 | -0.2439 | -0.0251 | -0.5825* | -0.0926 | -1.0942*** |
| | (0.1532) | (0.1782) | (0.1907) | (0.3348) | (0.2427) | (0.1798) |
| Cost share enrollment (1=yes; 0=no) | 0.735 | -4.0907** | -1.0255 | -2.0028 | 0.0253 | -1.2294 |
| Contour/strip | (0.7195) | (1.6376) | (0.8987) | (1.3511) | (1.0039) | (1.1592) |
| No-till | -0.1412 | -1.0026 | -1.8865* | 2.8189 | -1.9398*** | -2.0168 |
| | (0.4492) | (2.4404) | (1.1027) | (2.5666) | (0.7300) | (1.7557) |
| Highest level of education completed | 0.1638** | -0.176 | 0.1831 | -0.1764 | 0.4877*** | -0.2349* |
| High school or Community college | (0.0671) | (0.1102) | (0.1861) | (0.1573) | (0.1212) | (0.1199) |
| Bachelor's degree or higher | 0.1512 | -0.0479 | -0.0456 | -0.4184*** | -0.1688 | -0.042 |
| | (0.0951) | (0.0985) | (0.1674) | (0.1062) | (0.1524) | (0.0849) |
| Proportion acres in slope class | 0.0217 | 0.1111 | 0.1393 | -0.3128 | 0.3931 | 0.5935*** |
| Moderate (2-8% grade) | (0.1744) | (0.2135) | (0.3378) | (0.2236) | (0.2712) | (0.1652) |
| Steep (> 8% grade) | 0.6243*** | -1.1614*** | 0.6056 | 0.1975 | 0.9390** | 0.4626** |
| | (0.2109) | (0.3973) | (0.5126) | (0.2218) | (0.4085) | (0.1937) |
| Operating acres (thousands) | -0.0959* | 0.1255 | 0.0113 | 0.0651 | -0.1227 | -0.2537* |
| | (0.0576) | (0.1501) | (0.0725) | (0.1950) | (0.0846) | (0.1430) |
| Lambda (covariance w/ cover crop | 0.0274 | -0.1127 | -0.0149 | -0.3732 | -0.3891* | -1.0233*** |
| cost share) | (0.1519) | (0.3855) | (0.2523) | (0.4895) | (0.2066) | (0.3404) |
| Lambda (covariance w/ contour/strip | -0.3791 | 1.2915 | 0.6185* | 1.5185** | -0.0043 | 0.6806 |
| cost share) | (0.2815) | (0.7921) | (0.3250) | (0.6751) | (0.3642) | (0.6108) |
| Lambda (covariance w/ no-till | 0.0269 | -0.7872 | 0.9684* | -1.4692 | 0.9335*** | 1.1513 |
| cost share) | (0.2207) | (1.1014) | (0.5205) | (1.2957) | (0.3485) | (0.8693) |
| Observations | 424 | | 424 | | 424 | |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## Endnotes

[1] http://stat.chesapeakebay.net/?q=node/130&quicktabs_10=1

[2] Conversation with MACS program administrator Norman Astle, 7/5/2012.

[3] 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.

[4] Data from the most recent Phase 5.3 CBP watershed model is publicly available: http://www.chesapeakebay.net/data .

[5] While the CBP watershed model does not explicitly account for nonlinearities in the NPS pollution production function, there are other models—such as the land use model integrating agriculture and the environment (LUMINATE) of Kling et al. (2014)—that do. However, for the purposes of the present study, we use a linear approximation of the fate and transport of pollution downstream through delivery coefficients, as in Rabotyagov, Valcu and Kling (2013).

[6] Contour farming and strip cropping were identified separately in the survey, but due to limited adoption for these two practices, they were aggregated into a single practice in the econometric analysis.

[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 by Wieland et al. (2009).

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

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

[10] This simply converts the treatment effects shown in equation (5) to acreage units rather than acreage shares.

[11] Loads are provided for each land use with and without nutrient management plans (NMPs). NMP crop land uses include nutrient management high-till with manure ("nhi") and nutrient management high-till without manure ("nho"). Non-NMP crop land uses include high-till with manure ("hwm") and high-till without manure ("hom"). Hay land uses include hay without nutrients ("hyo"), hay with nutrients ("hyw"), and nutrient management hay ("nhy"). Pasture land uses include nutrient management pasture ("npa") and pasture ("pas").

[12] As noted, the treatment effects described above are derived from the estimated shares such that,

$$\widehat{TET}_j^n = A_j \cdot \{s_{j,w}^n - s_{j,o}^n\} \text{ for enrolled farmer } j,$$

$$\widehat{TEU}_j^n = A_j \cdot \{s_{j,w}^n - s_{j,o}^n\} \text{ for unenrolled farmer } j.$$

[13] Any spatial patterns of variation in cost will be trivially the same between this standard scenario and one based on implementation costs.

[14] For example, consider a hypothetical scenario in which cost sharing is estimated to have the following indirect effects on practice acreage on four farms: 10 acres, 5 acres, -2 acres and -4 acres. When these acreage estimates are matched with pollution loads and delivery coefficients for each farm, the estimated change in abatement in the Bay are 4 pounds, 2 pounds, -5 pounds and -10 pounds, respectively. In this case, the positive average effects on acreage would translate to negative average effects on abatement.

[15] This is a similar magnitude as the actual MACS budget in 2009 and 2010 (approx. $19 million in 2009, and $17 million in 2010).