ABSTRACT

Title of Document:	AGRICULTURE, ENVIRONMENTAL INCENTIVE PAYMENTS, AND WATER QUALITY IN THE CHESAPEAKE BAY.

Patrick Michael Fleming, Doctor of Philosophy, 2016

Directed By: Professor, Erik Lichtenberg, Department of Agricultural and Resource Economics

Assistant Professor, David A. Newburn, Department of Agricultural and Resource Economics

Nonpoint sources (NPS) pollution from agriculture is the leading source of water quality impairment in U.S. rivers and streams, and a major contributor to lakes, wetlands, estuaries and coastal waters (U.S. EPA 2016). Using data from a survey of farmers in Maryland, this dissertation examines the effects of a cost sharing policy designed to encourage adoption of conservation practices that reduce NPS pollution in the Chesapeake Bay watershed. This watershed is the site of the largest Total Maximum Daily Load (TMDL) implemented to date, making it an important setting in the U.S. for water quality policy.

I study two main questions related to the reduction of NPS pollution from agriculture. First, I examine the issue of additionality of cost sharing payments by estimating 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 account for substitution effects among conservation practices. Quasi-random Halton sequences are employed to solve the system of equations for conservation practice acreage and to minimize the computational burden involved. By considering patterns of agronomic complementarity or substitution among conservation practices (Blum et al., 1997; USDA SARE, 2012), this analysis estimates water quality impacts of the crowding-in or crowding-out of private investment in conservation due to public incentive payments.

Second, I connect the econometric behavioral results with model parameters from the EPA's Chesapeake Bay Program to conduct a policy simulation on water quality effects. I expand the econometric model to also consider the potential loss of vegetative cover due to cropland incentive payments, or slippage (Lichtenberg and Smith-Ramirez, 2011). Econometric results are linked with the Chesapeake Bay Program watershed model to estimate the change in abatement levels and costs for nitrogen, phosphorus and sediment under various behavioral scenarios. Finally, I use inverse sampling weights to derive statewide abatement quantities and costs for each of these pollutants, comparing these with TMDL targets for agriculture in Maryland.

AGRICULTURE, ENVIRONMENTAL INCENTIVE PAYMENTS,
AND WATER QUALITY IN THE CHESAPEAKE BAY

By

Patrick Michael Fleming

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2016

Advisory Committee:
Professor Erik Lichtenberg, Co-chair
Professor David A. Newburn, Co-chair
Professor Maureen Cropper
Professor James Hanson
Professor Lori Lynch

Dedication

I am ever thankful that I get to share my life with the greatest woman I know. You inspire me. You fascinate me. You influence me for the better. You are the one I love and my dearest companion in life. This dissertation is dedicated to you, Elisa.

Acknowledgements

In writing this dissertation I have benefitted from the friendship, feedback and support of many people. I thank each of you for being a part of my journey.

I would like to thank my dissertation committee and the faculty, staff, and my fellow graduate students at University of Maryland who provided me with thoughtful advice and support throughout my graduate studies, both inside and outside the classroom.

I would like to give special thanks to Dr. Erik Lichtenberg, for his constant availability, his ability to find a way forward, and for pushing me to do my best and be my best. Thank you, Erik, for your genuine concern and care for students, and for making academic research a joyful and rewarding endeavor.

I would also like to give special thanks to Dr. David A. Newburn, for his incredibly detailed comments, countless phone conversations, his persistence, honesty, and insights. Thank you, Dave, for being an inspiration to me, and teaching me what it means to be an academic researcher who cares about what he does and the people he works with.

And thank you both, Erik and Dave, for your friendship.

Table of Contents

Chapter 1: Introduction and Literature Review

1. *Introduction*

This dissertation concerns the economic incentives that lead households and businesses to internalize social costs. Specifically, this research examines the effects of a public policy designed to encourage farmers to adopt conservation practices known to reduce nonpoint source (NPS) pollution into rivers, streams, and coastal waters. Agricultural runoff is currently the largest source of damage in U.S. waterways (U.S. EPA, 2009), and the Chesapeake Bay watershed is the location of the first application of the Clean Water Act's Total Maximum Daily Load (TMDL) to include NPS pollutants on a watershed scale. This makes the context of agricultural conservation in Maryland an ideal setting for research at the intersection of environmental economics and policy.

The research contained in this dissertation will examine the effect of agricultural cost sharing on both farmer behavior and water quality downstream. Cost sharing has become the primary public policy instrument in the United States to reduce NPS pollution on working farmland. From my own experience working with farmers, I have seen that the voluntary incentive payments offered through cost sharing programs have the potential to be quite effective at inducing farmers to adopt certain conservation practices, like cover crops, but also have unintended indirect effects on other conservation practices or land uses that are not subsidized. A more complete understanding of both the direct and indirect effects of cost sharing is needed to evaluate the overall effectiveness of this widely-used program, with respect to reducing agricultural runoff and achieving water quality goals such as the Chesapeake Bay TMDL.

To frame the discussion, I begin by outlining the existing literature on agricultural conservation policy. First, I begin by discussing the importance of nonpoint source (NPS) pollution on water quality in the United States, and in particular the role of agriculture. Second, I describe the recent trajectory of U.S. policy that seeks to address NPS pollution from agriculture. Third, I briefly sketch the economic policy simulation literature that seeks to model water quality impacts of agricultural NPS pollution policy. Finally, I present empirical and theoretical research that has documented the importance of farmer behavioral responses to incentive payments, in the context of both land retirement and working-land conservation programs. My research seeks to integrate these areas of research—by providing a comprehensive evaluation of farmer behavioral response to incentive payments, coupled with a policy simulation of water quality impacts—in the context of working-land conservation practices.

2. <u>Literature</u>

2.1 Agricultural nonpoint source pollution in the United States

Nonpoint sources are the most significant contributor to water pollution in the United States (U.S. EPA 2002, U.S. EPA 2009). With the passage of the Clean Water Act in 1972, point sources such as factories and wastewater treatment plants have been regulated by the Environmental Protection Agency (EPA), requiring a permit from the National Pollution Discharge Elimination System (NPDES) in order to discharge pollutants into surface waters. Since that time, U.S. rivers, streams, lakes, and coastal waters have seen substantial reductions in runoff from point sources. By 1992, point sources accounted for just 35 percent and 24 percent of pollution in impaired rivers and lakes, respectively (U.S. Forest Service, 1993). In annual water quality assessments reported to the EPA, U.S. states now report that nonpoint source pollution is the leading remaining cause of water quality problems (U.S. EPA, 2016).

Not all nonpoint sources are alike. The major nonpoint sources of water pollution include agricultural runoff of both fertilizer and animal wastes[1], urban and suburban stormwater runoff, leaks from faulty residential septic systems, and atmospheric deposition. However, as the scale and intensity of agriculture has grown over the past several decades, in many regions of the United States NPS pollution from agriculture has become the largest contributor to water quality impairment. For example, the flux of nitrogen (N) in the Mississippi River more than tripled between 1970 and 2000, and agriculture is known to be the major cause of this change (Goolsby et al, 2001). The increase in N concentrations due to agriculture has led to the large hypoxic zone in the Gulf of Mexico (Alexander et al., 2000; Howarth, 2002). In the Chesapeake Bay watershed, a recent report by the U.S. Geological Survey found that agriculture contributes more than half the N delivered from the watershed to the bay, and nearly half the phosphorus (P) contributions (USGS, 2011). Overall, NPS pollution from agriculture is the leading source of water quality impacts in U.S. rivers and streams, the third largest source for lakes, the second largest source of impairment for wetlands, and a major contributor to contamination of estuaries and coastal waters (U.S. EPA 2016).

Without taking attention away from agriculture, it is important for the sake of context to bear in mind that in many U.S. waterways, agriculture is not the primary

---

[1] However, if a livestock operation is categorized as a Concentrated Animal Feeding Operation (CAFO), it is regulated as a point source under the Clean Water Act.

nonpoint source of pollutants. For example, in assessed lakes, reservoirs and ponds, as well as bays and estuaries, the largest known source of impairment is atmospheric deposition (U.S. EPA 2016). Atmospheric deposition of oxidized N from fossil-fuel combustion was found to be the most substantial flux from nonpoint sources in estuaries in the northeastern United States (Howarth, 2002). Similarly, recent evidence has shown that in the Upper Mississippi River the largest source of fine sediment has shifted from agricultural soil erosion to accelerated erosion of stream banks and bluffs driven by increased river discharge (Belmont et al., 2011), a nonpoint source of pollution that the EPA has characterized as "hydrologic modification". As stormwater runs off paved surfaces at faster rates, scouring of sediment from stream banks has increased following rain storms. Thus, the variety of nonpoint sources adds to the challenge faced by policymakers seeking to mitigate NPS pollution.

2.2 Policy background

The primary policy efforts to reduce NPS pollution from agriculture have mainly taken the form of voluntary subsidies for either land retirement or installation of conservation practices on working farmland. These voluntary incentive payments are administered through the United States Department of Agriculture (USDA), and the programs in the former group include the Conservation Reserve Program (CRP), and later the Conservation Reserve Enhancement Program (CREP). Federal programs focusing on working-land conservation practices include the Environmental Quality Incentives Program (EQIP) and the Conservation Stewardship Program (CSP). Over time, policy emphasis has shifted from land retirement to working-land conservation practices.

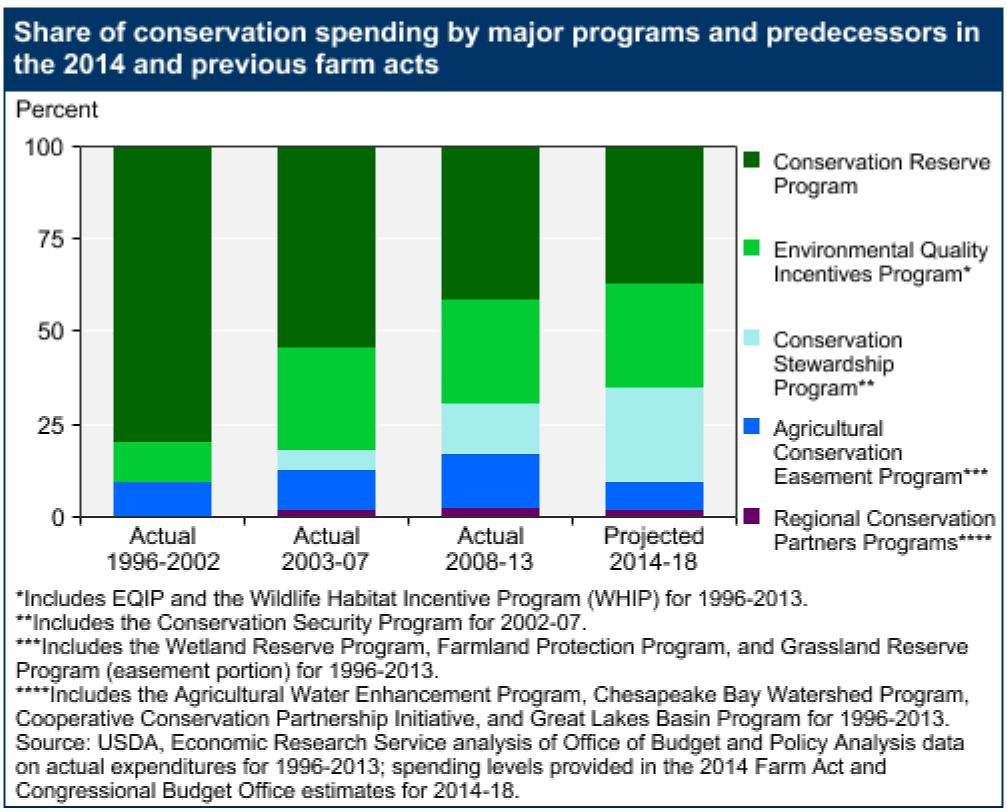
The 1985 farm bill (Food Security Act of 1985) established the CRP as we know it, authorizing the USDA to pay for the retirement of farmland in 10- and 15-year voluntary contracts. Subsequent farm bills in 1990 and 1996 expanded the list of eligible lands to be included, and allowed for early termination of CRP contracts in specific cases. The CREP program grew as an offshoot of CRP, allowing the federal program to work in cooperation with state governments in order to target high-priority conservation issues and environmentally-sensitive land. But over time, the acreage cap of the CRP has declined. Initially, the 1985 farm bill authorized up to 40 million acres of enrollment, which was reduced to 32 million acres in the 2008 Food, Conservation and Energy Act. The program cap was further reduced in the 2014 Agricultural Act, gradually lowering the cap from 27.5 million acres in 2014 to 24 million acres in 2017 and 2018, at only sixty percent of its initial level. Funding allocations for land retirement have, accordingly, been decreasing in recent years.

In contrast, emphasis on working land conservation programs has been increasing in recent U.S. farm bills. At the federal level, EQIP is the largest program that shares the cost of installing conservation practices on working land. This program was created by the 1996 farm bill, replacing and combining several older programs that were similarly aimed at promoting efficiency and conservation. The 2002 farm bill re-authorized EQIP—authorizing a six-fold increase in funding from 2002 to 2007—and also introduced a new working-land conservation program in the form of the CSP.[2] A further

[2] Initially called the Conservation Security Program, this program was succeeded by the Conservation Stewardship Program in the 2008 Farm Bill. The program offers not only cost sharing for implementation, but also annual rental payments for farmers willing to install certain conservation measures such as riparian buffers as part of their operation.

fifty percent increase in combined funding for EQIP and CSP was established in the 2008 farm bill, and funding continued to rise in the 2014 farm bill, despite funding reductions for the land retirement programs. In 2014, for example, the combined EQIP and CSP outlays were $2.4 billion, and scheduled to rise to $3.6 billion by 2018. Figure 1 below compares the share of USDA conservation spending by major programs and their predecessors, from 1996 to 2018.

Figure 1



See http://www.ers.usda.gov/topics/natural-resources-environment/conservation-programs/background.aspx

Today, efforts to reduce NPS pollution from agriculture appear to be turning a new page. 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. For the first time, efforts to limit agricultural NPS pollution may pass from the purview of the USDA to the EPA. If this landmark application of the Clean Water Act to the watershed-scale serves as a model for other U.S. watersheds such as the Mississippi River Basin—as many, including the American Farm Bureau Federation, expect—there will be wide-reaching consequences for NPS pollution from agriculture in the United States.

2.3 Policy simulations and water quality

The voluntary nature of existing agricultural conservation policies raises the question of the additionality of water quality benefits attributed to these programs. Retirement of low-productivity cropland as well as adoption of conservation practices on working farmland can be profit-maximizing choices for some farmers. Since enrollment in CRP/CREP, EQIP and CSP is voluntary, farmers self-select into these programs. Therefore one cannot assume that all of the water quality gains associated with land retirement or conservation practice adoption are directly a result of the incentive payments. There may be a substantial number of farmers who enroll in the EQIP program, for example, who would have adopted the relevant conservation practice anyway.

Understanding additionality is extremely important for prospective economic analysis intended to guide the policy formulation process. For example, a number of studies have integrated economic and water quality models to estimate the costs and benefits of policies such as subsidized land retirement and adoption of working-land conservation practices. The majority of these studies assume 100% additionality achieved with no enforcement costs. In what follows, I will briefly survey this policy simulation literature in the context of both land retirement, agricultural conservation practices, as well as other proposed (sometimes hypothetical) policy instruments.

(i) Land retirement

A number of policy simulations have evaluated the water quality effects of agricultural land retirement. Khanna et al. (2003) evaluate the cost-effective targeting of land use retirement in the CREP program in a river basin in Illinois. Secchi et al. (2007) outline a methodology to assess the economic costs and water quality benefits of a number of hypothetical land use scenarios for thirteen watersheds in Iowa. Lacroix and Thomas (2011) use a simultaneous model of crop choice, land set-asides and fertilizer use to estimate elasticities of crop price and subsidy levels on acreage decisions, in the context of French agricultural policy. On a watershed-wide scale, Wainger et al. (2013) and Rabotyagov, Valcu and Kling (2014) identify the most cost effective land use changes to reduce runoff in the Chesapeake Bay watershed and hypoxia in the Mississippi basin, respectively.

Some of these studies combine land retirement with conservation practice adoption. Rabotyagov et al. (2010) integrate a watershed based model with cost data to develop, via evolutionary algorithms, a trade-off frontier for the Upper Mississippi River Basin (UMRB) specifying the least cost of achieving different level of N and P reductions through both land retirement, conservation tillage, and use of cover crops.

Like Wainger et al. (2013), they find that meeting stricter water quality goals requires not only conservation practice adoption, but also a substantial amount of land retirement.

(ii) Conservation practice adoption

Some policy simulation studies have focused on working-land conservation practices. For example, Kling et al. (2014) evaluate the impact of a simple scenario where cover crops are incentivized with green payments over a large expanse of the Mississippi basin, using their LUMINATE model. On a more limited geographic scale, Jenkins et al. (2010) evaluate the benefits of wetland restoration in the southern part of the Mississippi corridor. Ribaudo et al. (2001) compare the cost-effectiveness of a fertilizer standard with wetland restorations as N reduction methods in the Mississippi basin. Finally, Wu and Babcock (1998) evaluate the water quality impact of tillage, crop rotation, and soil testing practices in the Central Nebraska Basin.

(iii) Other policy combinations

Other policy simulations have evaluated the water quality impact of fertilizer taxes, ethanol policy, water quality trading, or combinations of these with land retirement and conservation practice adoption. Wu and Tanaka (2005) estimate the costs and water quality impact of adopting two different conservation practices, along with the possibility of land retirement and a tax on the use of fertilizer in the Upper Mississippi River Basin (UMRB). They integrate an econometric analysis of farmer adoption decisions with a biophysical model using the Soil and Water quality Assessment Tool (SWAT). The econometric model predicts farmers' choice of crops, tillage practices and participation in the Conservation Reserve Program (CRP) at over 40,000 Natural Resource Inventory (NRI) sites—as opposed to particular farms—in the UMRB. SWAT then simulates the level of nitrate concentrations in the Mississippi River based on the predicted changes in land use and farming practices. An earlier study, Wu et al. (2004), forms the econometric basis of Wu and Tanaka (2005). This study predicts crop rotations and conservation tillage choice in response to expected profit in corn, hay and soybeans. Unlike Wu and Tanaka (2005), this earlier paper does not conduct a detailed simulation of water quality impacts.

Secchi et al. (2011) assess water quality changes in the context of an increase in corn acreage due to an ethanol policy in the Upper Mississippi river basin. Doering et al. (2001) provide an economic analysis for reducing N on a large scale under five policy scenarios, including restricted N fertilizer application, reduced field losses of N, wetland restoration, streamside buffers, and combined wetland restoration with N fertilizer reduction.

Finally, several papers have evaluated the possibility of water quality trading programs using empirical data to inform a proposed theoretical framework. Rabotyagov, Valcu and Kling (2013) compare the effectiveness of three second-best policy options (command-and-control, trading program, and a performance standard) with a first-best cost-efficient solution using data from the Boone Watershed in Iowa. Lankoski, Lichtenberg and Ollikainen (2010) examine the compliance to alternative agri-environmental policies in a heterogeneous landscape. Lankoski, Lichtenberg and Ollikainen (2008) examine point/nonpoint effluent trading in a spatially heterogeneous environment, with a simulation based in Finland. Hanson and McConnell (2008) simulate trading between high-cost sewage treatment plants and low-cost winter cover crops.

(iv) Policy simulation literature and farmer behavioral response

The overwhelming majority of the studies in groups (i) to (iii) mentioned above do not consider farmer behavioral response to incentives. For example, the cost-effectiveness papers of Rabotyagov et al. (2010), Rabotyagov, Valcu and Kling (2014), and Wainger et al. (2013) are based on implementation costs of conservation practices. Thus, they abstract from the issues of additionality. Wu and Tanaka (2005)—building upon the econometric methodology in Wu et al. (2004)—do integrate farmer behavioral response with a biophysical water quality model. However, their consideration of behavioral response is limited to additionality at certain NRI sites, thus abstracting from farmer characteristics that affect self-selection into voluntary conservation programs, as well as other aspects of additionality such as slippage and correlation in practice adoption, which will be discussed below.

2.4 Additionality and land retirement

Several strands of literature have analyzed the problem of additionality in U.S. agricultural conservation policy. This dissertation focuses on working-land conservation practices, as opposed to farmland retirement or land set-asides. However, there has been an extensive economic literature on land retirement programs (CRP/CREP), and since land retirement was initially the main policy instrument used to address agricultural NPS pollution I will begin here. While many studies of land retirement focus on farmers' willingness-to-accept in order to induce participation (Cooper and Keim, 1996; Lynch, Hardie and Parker, 2002), there are two primary issues to consider in regard to the additionality associated with these programs: the problem of slippage, and the estimation of how much CRP acreage would have been taken out of production even in the absence of payments.

(i) Slippage in the CRP

In the context of land retirement programs, slippage refers to the conversion of non-cropland into cropland production. This can occur either because a farmer substitutes for other acres on his or her farm that were retired through CRP enrollment, or as other producers expand production in anticipation of supply reduction and price increases induced by land retirement. If farmers expand crop production to previously un-cultivated acreage, the net environmental benefits of enrollment will be reduced. For example, Junjie Wu (2000) found that for each 100 acres of cropland retired under the CRP, twenty acres of non-cropland were converted to cultivated farm uses, due to substitution and the potential for higher output prices. This had the potential to offset 9 to 14% of CRP erosion-reduction benefits. In response to this study, Roberts and Bucholtz (2005) pointed out the endogeneity of CRP enrollments. Regional variation in CRP enrollments—upon which Wu's empirical results depend—is a choice variable, influenced by many unobserved factors that also affect noncropland to cropland conversions, and therefore the econometric specification is subject to bias. Moreover, they point out that the cross-sectional dataset used by Wu is unable to identify slippage arising from the price feedback effect. In response, Wu (2005) argues that the contention of endogeneity is inconsistent with CRP program rules: although individual farmers' participation decisions may be made jointly with land use decisions, program administrators ultimately determine the regional allocation of CRP acreage, which is based on political preferences and other factors exogenous to the non-cropland to cropland conversion decision. In accord with this theoretical argument, Wu conducts a Hausman test for exogeneity and determines that empirically the null hypothesis of exogeneity of the regional variation in CRP acreage cannot be rejected. In short, slippage in the CRP/CREP program cannot be ruled out as a theoretical possibility, and some empirical evidence for its existence remains.

(ii) Non-additional CRP enrollment

Land retirement programs produce environmental gains only when the land taken out of production would not have been retired without the incentive provided by the program. In CRP, farmers who seek to enroll new acreage in a CRP contract must show that it had a history of crop production. Farmers who already have CRP contracts are eligible to re-enroll, but must compete for contracts through the general sign-up process (Claassen, Cattaneo, and Johansson, 2008). Whether environmental gains are additional can be estimated by comparing actual land retirement to a counterfactual baseline that attempts to account for output and production changes that would have happened in the absence of the program. While construction of the baseline is difficult, several studies have estimated non-additional enrollment in the CRP/CREP program by analyzing prevailing trends in land use changes. Lubowski, Plantinga and Stavins (2003) estimate that about 15% of the land enrolled in CRP would have shifted to a non-crop use even without the program.

Moreover, with respect to CRP re-enrollments, the relevant question is whether this land would actually be returned to production without additional incentive payments. Sullivan et al. (2004) analyze contract re-enrollments and project that almost 50% of CRP land would not be returned to crop production even in the absence of payments. Roberts and Lubowski (2007) argue that 42% of CRP land would not have been returned to crops in the late 1990s even if the CRP program had expired. However, they interpret this finding as demonstrating the enduring impact of the CRP program, rather than a lack of additionality in CRP re-enrollments. Their contention is that targeted signing bonuses of first-time enrollees may improve environmental gains due to the longer-term impacts of CRP on land retirement. However, due to the voluntary nature of U.S. land retirement programs, it is impossible to eliminate the possibility of non-additional land set-asides at either the first enrollment or the re-enrollment phase.

2.5 Additionality and conservation practice adoption

More recently, emphasis in U.S. agricultural conservation policy has shifted to cost sharing the installation of conservation practices on working farmland. Federal and state-level cost sharing programs encounter the problem of additionality in three ways: the issue of slippage; the adoption of conservation practices that would have occurred absent program payments; and impacts on other conservation measures due to patterns of complementarity and substitution in practice use (crowding-in or crowding-out of private investment in conservation due to public investment). This last issue is unique to working-land conservation programs, and does not arise in the context of land retirement.

(i) Slippage in conservation cost sharing

One theme of theoretical literature has analyzed the potential for slippage in cost sharing. Khanna et al. (2002) compare the cost effectiveness of cost sharing with an efficient pollution tax. A pollution tax achieves abatement through three mechanisms: (1) encouraging reduced use of polluting inputs ("negative intensive margin"); (2) encouraging reduced output ("negative extensive margin"); and (3) encouraging use of more efficient technologies ("technology switching effect"). Cost sharing, however, only encourages the latter—i.e. technology switching—while at the same time creates incentives to expand the acres of land under production ("positive extensive margin", or "slippage").

In another article, Lichtenberg (2004a) uses a Ricardian land market equilibrium model to analyze the pressure for more extensive production under green subsidies. Because of this pressure for more production, green payments may actually worsen environmental outcomes. While this adverse effect may be avoided by targeting of green payments, such targeting is difficult and requires careful study.

Similarly, there is some empirical evidence of slippage in agricultural cost sharing. Lichtenberg and Smith-Ramirez (2011) use an endogenous switching regression to find evidence for slippage. They show that farmers receiving cost sharing (for any one of a group of eight erosion-control practices) allocated almost 50% fewer acres to vegetative cover than they would have in the absence of cost sharing.

(ii) Non-additional conservation practice adoption

Horowitz and Just (2013) argue that some non-additional abatement will inevitably arise as the programs seeks to incentivize farmer participation. Along with analyzing slippage, Lichtenberg and Smith-Ramirez (2011) also find evidence of additional cover crop and contour / strip cost implementation, practices to which farmers allocated 8% and 15% more acres, respectively, than they otherwise would have. This increase in acreage can be decomposed into both new adoption, as well as increased acreage of adoption even if the farmer would have placed some acreage in the practice absent incentive payments. This study finds statistically significant results only in the increase in probability of adoption due to enrollment (a 35% and 38% increase in probability of adoption for cover crops and contour/strip, respectively), and not in the amount of acreage given adoption. This suggests that additionality is primarily composed of new adopters as opposed to increasing acreage served.

Other empirical studies have found higher levels of additionality for similar conservation practices using a propensity score matching approach and data from different geographic regions. Mezzatesta, Newburn, and Woodward (2013) find that farmers from southwestern Ohio who receive cost sharing for cover crops and hay fields allocate 24% and 23% more acres to these practices than they would have in the absence of cost sharing (which translated to a percent additionality of 91% and 93%, respectively).[3] Of the six BMPs that were studied, the lowest percent additionality was found for conservation tillage, to which farmers allocated only 15% more acres than they would have without cost sharing. Mezzatesta, Newburn, and Woodward (2013) also find limited evidence for

[3] Note that the results of Mezzatesta, Newburn, and Woodward (2013) are primarily framed in terms of percent additionality. Percent additionality "can be interpreted as the percentage of the observed conservation practices for enrolled farmers that can be attributed to the treatment effect" (p.19). Thus, it allows comparisons of additionality across practices designed to cover entire fields (like no-till) and practices designed to cover small areas (like filter strips or riparian buffers).

slippage, though there is no reason to expect that the degree of slippage found in Maryland would be same as that found in Ohio, given the different composition of agriculture in the two regions. In another paper, Claassen and Duquette (2012) use a nationwide dataset to show very high levels of additionality for four of the five conservation practices studied. They find a percent additionality of near 90 percent for four of the five conservation practices studied. However, it is unclear if the higher additionality calculated in these studies—in comparison to Lichtenberg and Smith-Ramirez (2011)—is a result of the different datasets (and geographic regions) studied, or of the differing econometric methodologies.

As mentioned in the context of Lichtenberg and Smith-Ramirez (2011), it is also possible to decompose additionality into its component parts: increased practice acreage from those who would not adopt without cost sharing ("new adopters"), and increased acreage associated with those who would adopt even without cost sharing but with fewer acres. This decomposition falls out directly from the Tobit marginal effect, and is also derived in the propensity score matching framework by Mezzatesta, Newburn, and Woodward (2013).

In the context of European Agro-environmental schemes (AES), Chabé-Ferret and Subervie (2013) use difference-in-difference (DID) matching to distinguish additionality from windfall effects brought about by incentive payments for several conservation practices: including crop rotation, cover crops, grass buffer strips, and conversion to organic farming. By matching, they are able to control for selection bias in a similar manner to Lichtenberg and Smith-Ramirez (2011), and Mezzatesta, Newburn, and Woodward (2013)—by using observed covariates to compare recipient farmers to similar non-recipients. However, with access to data prior to the implementation of the AES, they are also able to calculate differences in practice acreage in order to account for time-invariant unobservable factors. They find that the payment for cover crops is not cost effective, partly because the additionality is relatively low. In terms of percent additionality (calculated as average treatment effect on the treated (ATT) for cover crops / total acreage in cover crops), they find about 58 percent additionality for cover crops, which is significantly lower than the 91 percent additionality for cover crops found by Mezzatesta, Newburn, and Woodward (2013) in the context of Ohio. In general, Chabé-Ferret and Subervie (2013) find that cost sharing incentive payments which combine restrictive requirements with large payments—such as those available in Europe for conversion to organic farming—have the highest additionality.

Also in the context of European agri-environmental payments, Laukkanen and Nauges (2014) estimate a six-equation system of land allocation and input use equations, using a farmer survey in Finland. Participation in the EU agri-environmental programs is almost universal in Finland, so instead of estimating "treatment effects", the authors use parameters from their structural econometric model to make inferences about what would have happened in the absence of the payments. They then connect predicted land allocation and fertilizer use to environmental production functions to quantify the change in nutrient loadings.

(iii) Correlation in agricultural conservation practice adoption

Correlation in the adoption of conservation practices is relevant for the effectiveness of cost sharing and for ultimate nutrient reduction in coastal waters. In many regions of the

United States, conservation practice adoption displays patterns of substitution or complementarity. For this reason it is helpful to identify practices whose adoption is likely to induce adoption of other practices or crowd out adoption of substitute practices.

The analysis of correlation in conservation practice use begins to involve some interesting problems from an applied econometrics perspective. The empirical literature has approached this problem in three ways: random utility models involving multinomial logit, polychotomous choice models involving multinomial probit, and dual models involving single probit estimation. To begin with the example of random utility models, Wu & Babcock (1998) estimate joint adoption decisions of conservation tillage, crop rotation, and soil nitrogen testing using a multinomial logit framework, treating each of the eight possible combinations of practices as a mutually exclusive alternative. They then estimate the impact of each conservation package on crop yields, input use, and soil erosion.

Due to the restrictiveness of the Independence of Irrelevant Alternatives (IIA) assumption, many economists have analyzed the joint adoption decision as some form of multinomial probit (MNP), in which there is correlation in the unobservable components of each equation. Khanna (2001) uses a modified MNP to model a sequential adoption decision of two BMPs—soil testing and precision fertilizer application. She finds that adoption leads to significant gains in nitrogen productivity in farms with poor soil quality, but insignificant gains in farms that already have above average soil quality. Similarly, Cooper (2003) models a simultaneous choice of whether or not to adopt any of five BMPs, and accordingly uses a multinomial probit (MNP) with an unrestricted variance-covariance matrix. His MNP model requires the solution of five-fold integrals, and therefore encounters the "curse of dimensionality" in computation techniques, whereby the number of computations required increases exponentially with the number of dimensions of the problem. For this reason, he takes advantage of simulated maximum likelihood techniques.[4] Simulated ML estimation is a useful method for breaking the "curse of dimensionality", relying on large numbers of iterations and knowledge (or assumptions) regarding the underlying distribution of data. However, it does not always work well when BMP adoption frequencies are low, as parameter estimates may fluctuate around zero and thereby prevent convergence. Moreover, Cooper does not consider self-financed adoption of BMPs in his presentation of results, but only looks at a survey of farmers' hypothetical willingness-to-accept for adoption of BMPs.

Finally, in a paper on the responsiveness of BMP adoption to BMP costs, Lichtenberg (2004b) estimates latent demand models for seven conservation practices. Using county-level BMP reimbursement rates as a proxy for installation costs, he calculates cross-price elasticities to indicate complementarity or substitution between practices, using a dual approach. The results indicated strong complementarity between several BMPs, including cover crops, critical area seeding, and grass waterways. The study did not have information on the acres of land allocated to BMPs, and so it calculated the *change in probability of adoption* due to a 1% change in unit costs. The model also did not account for the endogeneity of cost sharing, treating farmers enrolled in cost sharing programs within the same decision framework as those not enrolled (i.e. no endogenous switching).

[4] Before Cooper, Dorfman (1996) used a similar approach, showing how Gibbs sampling can be used to lower the computational burden of MNP models. This is the general econometric approach taken by Smith-Ramirez (2005).

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 in order 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 2013), 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 outweigh the diminishing returns shown by the RUSLE. In short, for both economic and agronomic reasons it is likely that the subsidies devoted to a working-land practice will have indirect effects on other practices.

One common feature of the empirical economic studies that have examined correlation in the adoption of multiple conservation practices is that 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 dissertation helps to fill this gap by providing an analysis of correlation in conservation practice adoption that estimates the separate effect of cost sharing for each of the practices, and the corresponding effect on acreage in each practice. This opens the possibility of crowding-in or crowding-out of private conservation effort in response to public conservation incentives, as discussed for example by Albers, Ando, and Chen, (2008) in the context of land set-asides.

3. This dissertation in the context of the literature

In any voluntary agri-environmental program, such as cost sharing or land retirement, it is impossible to eliminate the potential for unintended behavioral effects that lead to less than 100% additionality. As opposed to an efficient pollution tax or tradable permit program—which provides a transparent incentive for farmers to reduce pollution to the point at which marginal abatement costs equal the level of the tax or the price of the permit—cost sharing programs are not able to elicit a farmer's hidden information on marginal abatement costs, nor do they attach a price to the pollutant itself. This dissertation complements the existing literature by providing a more comprehensive analysis of additionality than previous work. No study to my knowledge has considered the implications of indirect effects (crowding-in or crowding-out of other conservation practices) for conservation cost sharing. And no study has considered non-additional adoption, indirect effects, and slippage effects simultaneously, estimating an overall effect of cost sharing payments on farmer behavior. Along with this, this study goes beyond previous work by integrating the empirical analysis of farmer behavior with a water quality model, in order to identify the implications of behavioral response for NPS pollution in one of the most important policy settings in the U.S. today, the Chesapeake Bay watershed.

In Chapter 2 of this dissertation, I identify the indirect effects of cost sharing policies on other non-subsidized practices. In doing so, I empirically estimate the effect of crowding-in (due to practice complementarity) or crowding-out (due to practice substitution) for three working-land practices.

In Chapter 3, I integrate the econometric model of cost sharing with a biophysical water quality model to show the relative importance of farmer behavioral responses in terms of NPS pollution abatement and marginal abatement costs. As discussed, most agri-environmental policy simulations have relied upon practice implementation costs, a method that implicitly abstracts from farmer behavioral responses. To the extent that non-additional adoption, indirect effects, and slippage effects exist, these baseline policy simulations will be inaccurate. The policy simulation model incorporates not only self-selection and indirect effects (as shown in Chapter 2), but also includes an expanded econometric system of equations to consider the potential loss of vegetative cover (i.e. slippage effects), as well as consideration of the spatial extent or conservation acreage at the farm level. This allows for measurement of the dollar-value impact of each potential layer of behavioral response to cost sharing.

In Chapter 4, I conclude with a discussion of the implications of this research for TMDL regulations in the Chesapeake Bay watershed. Anyone who works in agriculture will quickly discover that farmers are a diverse group, and each farmer responds to cost sharing incentive payments differently. Behind the average results presented by economists in policy simulation models, there is a distribution of behavioral responses to incentive payments. A wise policy approach will seek to benefit from this diversity in farmer NPS pollution abatement costs.

Chapter 2: Estimating Indirect Effects of Environmental Payments

1. Introduction

Nonpoint source (NPS) pollution from agriculture is the single largest source of impairment in U.S. rivers and streams (U.S. 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).[5]

There is limited evidence regarding substitution and complementarities between conservation practices. Lichtenberg (2004a), for example, finds empirical evidence for

[5] A related problem is that of slippage (Lichtenberg and Smith-Ramirez 2011; Lichtenberg 2004b; Khanna, Isik, and Zilberman 2003), 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.

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. They find 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. She 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 CBP's modeled nitrogen and phosphorus loads with BMP costs and pollution abatement efficiencies to calculate a cost per pound of pollution 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 by 0.269, while the acreage share in conservation tillage increased by 0.314. 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. Evidence of crowding in of private conservation in response to public programs has been found in certain regulatory contexts, such as land preservation in California (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 53 and 69 percent 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 by 0.263. 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 in 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, as found in the context of land set-asides by Albers, Ando and Chen (2008). Specifically, additional nitrogen abatement is between 22 and 38 percent 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.

2. 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 percent of nitrogen, 44 percent of phosphorus, and 65 percent 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 almost 30 years, in addition to federal government cost sharing programs. In recent years, the State has aggressively promoted cost sharing for cover crops in particular. Initially founded in 1984, the Maryland Agricultural and Water Quality Cost Sharing (MACS) program has more than quadrupled spending since 2005, with an annual budget of $26.7 million in 2013. In recent years, nearly 80 percent of this budget has been allocated to cover crops. In the 2013-14 season, 423,000 acres of cover crops were planted with the help of MACS funding, representing about a third of harvested cropland in the state. Base payments for traditional cover crops begin at $45 per acre. Like other cost share programs, enrollment in MACS is voluntary. Other cost share programs—such as the EQIP program—have also been available in the state, providing funding for cover crops and other erosion-control practices. Thus, the state of Maryland itself—due to its aggressive promotion of cost sharing and the variable production conditions which make it likely 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. 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.[6] 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.

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. He 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

---

[6] 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.

demonstrates that cover crops are especially important in conservation tillage systems because of the increased need for crop rotation in order 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 2013), 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 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.

3. Data

I 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. Farmers were asked whether they implemented any of the conservation practices studied, the acreage on which each practice was used, and whether or not cost sharing was received for each practice. Of the 523 responses received, 461 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 445 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—93 respondents adopted cover crops with cost sharing compared to 49 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 a third of a farm's operating acreage is in cover crops among farmers who adopted with cost sharing compared to less than a 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, cattle, distance to nearest surface water body), and farmer characteristics (e.g., education, income share from farming). Topography variables include the proportion of operating acres by slope class: flat slope (less than two percent grade), moderate slope (two to eight percent), and steep slope (greater than eight percent). 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 bay.

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. 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

[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 (2009). 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. See http://www.kingsagriseeds.com/.

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 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. The 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.

4. *Specification and Estimation of the Econometric Model*

This section describes the specification and estimation of the econometric model. I use a two-stage approach to estimate the effects of cover crop cost sharing on conservation practice use. I concentrate on cover crop cost sharing since it has been the largest, most aggressively promoted program in Maryland 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

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

stage are included in the second stage to correct for self-selection into cost sharing programs (Wooldridge 2014). In the second stage, several core explanatory variables are allowed to have different effects based on whether or not a farmer receives cost sharing for cover crops. This switching regression model allows for estimation of separate treatment effects for enrolled farmers in the cover crop cost sharing program and unenrolled farmers.

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.

4.1 Cost sharing

Consider first 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:

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

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

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 (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, p. 931-933) 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.

4.2 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 (Mezzatesta, Newburn, and Woodward 2013; Claassen and Duquette 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. Specifically, the generalized residual for conservation practice m is estimated as:

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

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

where superscripts w and o indicate 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 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. 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 $i = \{w, o\}$ respectively indicate with or without enrollment in the cover crop cost sharing program. The dependent variable is considered to be censored from below at zero, since it is not possible to allocate fewer than zero acres to a practice type.[9]

Accordingly, the observed acreage share s_{jm} can be defined as a multivariate tobit model, based upon a latent variable s_{jm}^* with the following empirical specification:

(4) $$s_{jm}^* = X_{jm}\beta_m^i + \sum_{m=1}^{3} \hat{\lambda}_{jm}^i \delta_m^i + \varphi_m C_{j2} + \tau_m C_{j3} + \varepsilon_{jm} \; ;$$

$$\text{where } s_{jm} = s_{jm}^* \text{ if } s_{jm}^* \geq 0,$$

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

$$s_{jm} = 0 \text{ otherwise,}$$

$$\text{and where } i = w \; if \; C_{j1} = 1\text{; and } i = o \; if \; C_{j1} = 0.$$

In equation (4), X_{jm} are variables that influence the acreage share decision. The set of variables Z_{jm} from equation (1) contains many of the same variables included in X_{jm}, such as farmer education and farm characteristics such as slope and farm size. However, for purposes of identification, the matrix Z_{jm} contains 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 water body is a proxy for potential risk of water quality impairment, which matters to the government funding agency but not necessarily to the farmer. I also use the share of a family's income from farming as an exclusion restriction. Households that receive a higher share of their income from farming are more likely to use government programs, and are therefore likely to have more familiarity with negotiating the bureaucratic procedures involved in obtaining subsidies. The share of family income from farming can thus be viewed as a proxy for the transaction costs of applying for cost share funding. The share of income derived from farming should not influence profit maximization, however, and should therefore not influence the acreage share decision. Thus the acreage equations are identified by these restriction as well as by the nonlinearity of the cost share equations.

Note that $\hat{\lambda}^{i}_{jm}$ 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_{j2} and C_{j3} represent enrollment in cost share programs for conservation tillage and contour/strip, respectively. The estimated coefficients φ_m and τ_m therefore represent the effect of conservation tillage cost sharing and contour/strip cost sharing, respectively, on practice m. While the primary purpose of this econometric model is to analyze the effect of the large cover crop cost sharing program, it is also possible that conservation tillage and contour/strip cost sharing have effects on cover crops. The structure of the model thus accounts for the possibility of "reverse causality", in the sense of crowding in of cover crops by conservation tillage cost sharing. This reverse causality should not be ruled out on simply theoretical grounds, and is therefore also estimated in the econometric model.

Moreover, note that the generalized residuals from each cost share enrollment equation are included in each acreage share equation, sweeping away the cross-practice selection bias that would occur if a farmer with one practice type is more likely to enroll in a cost sharing program for another practice type. For example, consider a second mechanism for "reverse causality", in which adoption of conservation tillage leads to wider enrollment in the cover crop program. This potential source of selection bias is accounted for by including the generalized residual from the cover crop enrollment equation in the conservation tillage acreage share equation. In short, every combination of cross-practice correlation between acreage share and cost share enrollment are incorporated in equation (4), and therefore the estimates for crowding in due to enrollment in the cover crop program are consistent.

Certain parameter estimates in equation (4) may switch based upon observed enrollment in the cover crop cost sharing program, C_{j1}. Thus, $\theta_m^i = \{\beta, \delta, \varphi, \tau\}, i = \{w, o\}$ 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 $\hat{\theta}_m^w \neq \hat{\theta}_m^o$ should not be precluded in advance for regressors related to the cost 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., $\hat{\theta}_m^w = \hat{\theta}_m^o$) 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[10].

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 right hand variables.

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:

[10] The constant term, as well as variables specifically related to the cost of BMP implementation—BMP cost, the propensity to receive cost sharing for each of the three practices, and indicators of cost share enrollment for contour/strip and conservation tillage—would 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've also received cost share for conservation tillage.

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

The off-diagonal elements represent the covariance between acreage share decisions for each of the practice types. Due to the fact that Ω_s is unrestricted, the system of acreage share equations shown in equation (4) accounts for unobserved factors that lead to correlation in the acreage share decisions across practices. The correlation terms in the covariance matrix capture the average impact of all unobservables that affect both practices in a given pair. The unobserved characteristics causing a farmer with one practice to be more (or less) likely to adopt another practice are reflected in the estimated elements of Ω_s. However, note that the covariance matrix does not identify the effects of any single unobservable. For instance, there could be unobservables with both positive and negative correlations that cancel each other out on average, creating an outcome consistent with a correlation coefficient not statistically significantly different from zero. Nonetheless, by allowing for unrestricted correlation in the acreage share equations, the econometric model identifies the effect of cover crop enrollment on acreage in each practice, apart from the average impact of unobserved characteristics that lead to correlation in the adoption of these practices.

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. 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, in order 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 $R = 20$.

5. *Estimation Results*

The primary interest in 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.

5.1 Cost Sharing Estimation using Multivariate Probit

Results for the trivariate probit in table 3 show marginal effects for the explanatory variables that influence cost share enrollment. A log-likelihood ratio test indicates that the explanatory variables are jointly significant at the 0.01% level, with a chi-squared test statistic of $\chi^2_{(27)}$ =183.3. A likelihood ratio test that the correlation coefficients are jointly equal to zero ($\hat{\rho}_{12} = \hat{\rho}_{13} = \hat{\rho}_{23} = 0$) was rejected at the 1.2% level, with $\chi^2_{(3)}$ =11.1. This indicates that statistically significant correlation exists in the cost share enrollment decisions for the three practices, and the goodness-of-fit is significantly improved by allowing for such correlation.

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 one of the exclusion restrictions 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 marginal effect 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 serves as a proxy for the transaction costs of cost share application for the farmer, which is the second exclusion restriction used to identify cost share enrollment with respect to BMP acreage.[11] 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

[11] A Hausman test was performed to test for a possible weak instrument problem. Results showed no systematic difference in coefficient estimates between a model that included proportion income from farming and one that did not. Thus the more efficient model that includes both instrumental variables is preferred.

sloped land does not have a statistically significant influence on cost share enrollment for any of these three practices.

The marginal effects 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 independent variables appear in the trivariate probit, including farm size, farmer education, and a dummy variable indicating if a farm has 50 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, 17 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.[12] The "missing farm income" variable has negative and statistically significant effects for all three practices, indicating that farmers who did not report proportion income from farming were on average less likely to be enrolled in cost sharing programs.

[12] I initially included imputed values for proportion income from farming for these 17 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 2499, 2500 to 4999, 5000 to 9999, etc.). However, the "missing farm income" dummy variables were still negative and statistically significant when imputing values, indicating bias in the attempted imputation technique.

The pseudo R-squared of this model is 0.255 (with a restricted log likelihood of negative 358.7 and an unrestricted log likelihood of negative 267.2). According to McFadden (1979), a pseudo R-squared value between 0.2 and 0.4 indicates very good model fit.

Figure 1 below compares predicted enrollment with actual enrollment in the survey. The columns show actual (observed) enrollment by practice type, and correspond to the descriptive statistics summarized in Table 1. The rows correspond to predictions. When making model predictions based upon the probability of enrollment for each practice type, the choice of a cutoff probability is decisive. The cutoff probability refers to the threshold above which the observation is considered “enrolled”, and below which the observation is considered “not enrolled”. It is known that when a sample has large imbalances between “successes” and “failures” (in this case, being enrolled or not), a default cutoff threshold of 0.5 is not practical.[13] Therefore, due to the heavily imbalanced nature of enrollment for contour/strip and conservation tillage in this survey—for which very few farmers are enrolled in cost sharing—cutoff probabilities had to be chosen in a different way. Figure 1 below shows predictions based on cutoff thresholds for each practice that jointly minimize Type I and Type II Errors. The figure shows that about 60 percent of the farmers enrolled in the cover crop program were correctly predicted to be enrolled (56 out of 93), and nearly 90 percent of the unenrolled (315 out of 352). A similar pattern is observed for

[13]While a substantial share of surveyed farmers had an estimated probability to enroll in the cover crop program that was greater than 0.5, the range of predicted probabilities for conservation tillage and contour/strip enrollment were between approximately 0 and 0.4, and 0 and 0.3, respectively, given the small number of enrollees in cost sharing for these two practice types. Thus, for these two practices the predicted probabilities did not rise above 0.5.

conservation tillage and contour/strip enrollment, with a very high share of correct predictions among the unenrolled, and greater than 50 percent correct among the enrolled.

Figure 1

	Observed enrollment by practice type					
	Cover crops		Conservation tillage		Contour/strip	
	Unenrolled	Enrolled	Unenrolled	Enrolled	Unenrolled	Enrolled
Predictions						
Unenrolled	315	37	348	12	401	4
Enrolled	37	56	71	14	35	5
Total	352	93	419	26	436	9

Cutoff point for predicted probability was chosen to jointly minimize both Type I and Type II Errors.

5.2 BMP 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 the explanatory variables, and cost share enrollment for conservation tillage and contour/strip cropping are included as endogenous right-hand side variables. A log-likelihood ratio test indicates that the explanatory variables are jointly significant at the 0.01% level, with a chi-squared test statistic of $\chi^2_{(48)}$ =323.6. A likelihood ratio test that the correlation coefficients are jointly equal to zero was rejected at the 0.01% level, with $\chi^2_{(3)}$ =44.1, indicating that the goodness-of-fit is significantly improved by allowing for correlation in the acreage share decisions for each of the three practices.

Generalized residuals, as specified in equation (3), are included to correct for a farmer self-selection into cost share programs. While the marginal effects of the generalized residuals shown in table 4 do not provide strong statistical evidence for selection bias in cost sharing enrollment for certain programs, a Wald test for joint significance of the generalized residuals 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 nonrandom enrollment in cost sharing programs—along with this joint statistical significance of the first-stage generalized residuals—it remains justified to use a Heckman selection model in order to remove potential selection bias, by allowing for correlation in the enrollment and acreage share decisions.

The marginal effects 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 marginal effects of the indicators for conservation tillage and contour/strip cost sharing programs show in general a negative relationships 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 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.

The pseudo R-squared of this model is 0.234 (with a restricted log likelihood of negative 727.6 and an unrestricted log likelihood of negative 557.4), indicating relatively good fit (McFadden 1979). The estimated standard deviation in a tobit equation is comparable to the mean squared error in a linear regression. For cover crops, conservation tillage, and contour/strip acreage shares, the estimated standard deviations were 0.085, 0.229, and 0.163, respectively. This indicates that the model predictions were most accurate for cover crops, and least accurate for conservation tillage.

5.3 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 for calculation of 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 Vyclatil 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.

The treatment effects are initially calculated for each farmer j and practice m. Let J^w and J^o represent the set of enrolled and unenrolled farmers, respectively. Then the treatment effect on an enrolled farmer is the expected acreage share in a practice given enrollment in cover crop cost sharing, minus the expected acreage share in the practice if the farmer were not enrolled in cover crop cost sharing. This second term represents a counterfactual that is not actually observed. The treatment effect on an unenrolled farmer is estimated similarly, except in this case the counterfactual is the first term, the expected acreage share in a practice given enrollment in cost sharing. Using notation as in equations (1) and (4), the treatment effects can be defined formally:

(6) $$\widehat{TET}_{jm} = E\left(s^w_{jm} \,|C_{j1} = 1, X_{jm}, Z_{jm}\right) - E\left(s^o_{jm} \,|C_{j1} = 1, X_{jm}, Z_{jm}\right), j \epsilon\, J^w,$$

$$\widehat{TEU}_{jm} = E\left(s_{jm}^{w} \,\middle|\, C_{j1} = 0, X_{jm}, Z_{jm}\right) - E\left(s_{jm}^{o} \,\middle|\, C_{j1} = 0, X_{jm}, Z_{jm}\right),\ j \epsilon J^{o}.$$

These treatment effects are expressed in terms of changes in acreage shares, as in equation (4). The average treatment effects for each practice are then averages of the estimated treatment effects for each farmer, weighted by the sampling weights, ω, from the farmer survey, such that,

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

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

Table 5 shows an ATT of 0.269 acres for farmers who received cost sharing for cover crops, indicating that on average farmers allocated 26.9 percent more of their acreage to cover crops with the incentive payment than they would have under 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' land in conservation tillage by 31.4 percent. 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 ATU of 0.263 indicates that the unenrolled farmers would increase their acreage in cover crops by an average of 26.3 percent when included in the cover crop program. This suggests potential for a substantial increase in cover crop adoption by further targeting the cost share program to those who are currently unenrolled.

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 farms without annual crops (i.e. corn, soybeans, small grains or vegetables) are excluded. 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.

6. *Water Quality and Policy Implications*

The question then remains: what does this mean for agricultural NPS pollution in the Chesapeake Bay? 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) $$\Delta_{jp}^{w,D} = A_j \cdot (\widehat{TET}_{j1} \cdot \bar{z}_{ps} \cdot \eta_{1ps}) \cdot \delta_{ps}, \text{ for enrolled farmer } j,$$

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

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

(9) on other field practices. Letting the superscript *D+I* indicate the sum of the direct and indirect effects, or the "overall" effect,

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

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

Average abatement per farm is then calculated as the weighted average of Δ_{jp}^{w} and Δ_{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. A map of river basins is shown in figure 1. 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 1,927 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 22 and 38 percent after considering indirect effects, while phosphorus abatement increases between 165 and 246 percent. Mechanically, the indirect effect on phosphorus runoff is larger than due to the fact 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 15 to 19 percent 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.[14] After considering the indirect effects of cost share payments, nitrogen reduction becomes less expensive among already-enrolled farmers: decreasing by 18 percent on the Eastern Shore, 12 percent in the Potomac, and 26 percent 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 53 and 69 percent in Maryland's major river basins after accounting for indirect effects.[15]

[14] $45 per acre is the base payment for cover crops planted in rye, a typical incentive payment offered by MACS.

[15] 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 (USGS, 2003).

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 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 in 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 in comparison to those who are not yet enrolled.

7. 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 to analyze 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 effort 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 12 and 26 percent, and phosphorus abatement by between 53 and 69 percent. 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. 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. 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, so that accurate anticipation of their results requires 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 which only account for direct effects. It is necessary for any program that seeks to encourage 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.

Figures

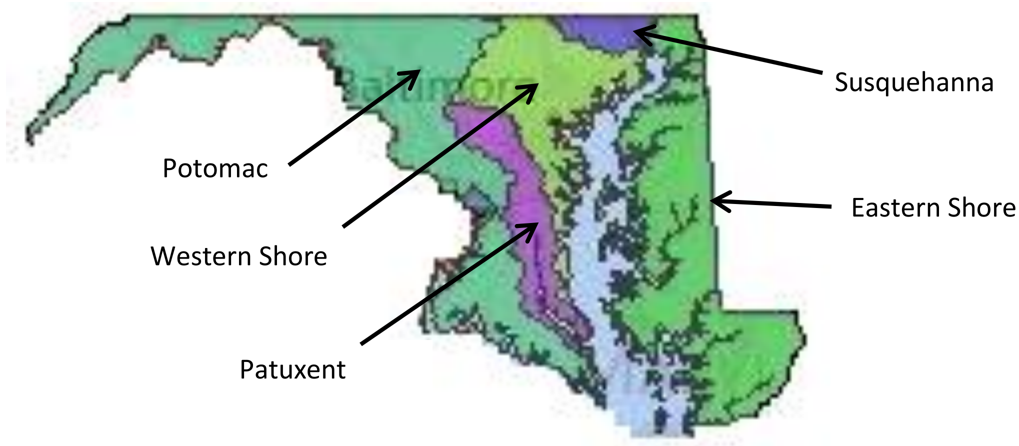


Figure 1. Major river basins in Chesapeake Bay watershed in Maryland

Tables

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	303	49	93	24.0%	32.2%
Conservation tillage	228	191	26	55.7%	54.9%
Contour/Strip	370	66	9	28.3%	22.4%

Table 2. Descriptive Statistics for Maryland Farmers, 2010

Variable	Mean	Std. Dev.	Min	Max
Distance to the nearest water body (miles)	0.45	1.4	0	11
Proportion income from farming	0.58	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
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
Erosion reduction per cost (tons reduced / $) Cover crops	0.033	0.017	0.009	0.118
Conservation tillage	0.081	0.044	0.021	0.256
Contour/Strip	0.037	0.027	0.006	0.152

N=445

Table 3. Estimated Marginal Effects on Probability of Cost Share Enrollment, Multivariate Probit

	Cost Share Enrollment		
	Cover crops	Cons. tillage	Contour/strip
Erosion benefit (tons reduced / $)			
Cover crops	-0.1126*	-	-
	(0.063)		
Cons. tillage	-	-0.0193	-
		(0.024)	
Contour/strip	-	-	0.0204
			(0.014)
Distance to the nearest water body (miles)	-0.0149*	-0.0158	0.0005
	(0.008)	(0.010)	(0.003)
Proportion income from farming	0.0429	0.0428*	-0.0177
	(0.033)	(0.025)	(0.014)
50 or more acres in corn, soybeans or small grains (= 1 or 0)	0.1682***	0.037	0.0157
	(0.039)	(0.028)	(0.013)
Proportion acres steeply sloped			
Moderate (2 - 8% grade)	0.0746***	0.0174	0.0286**
	(0.025)	(0.020)	(0.014)
Steep (> 8% grade)	0.0367	-0.081	-0.0246
	(0.073)	(0.074)	(0.022)
Log operating acres	0.0276**	-0.0032	0.0067
	(0.012)	(0.008)	(0.006)
Completed high school	0.0921***	0.0683**	0.0026
	(0.032)	(0.033)	(0.013)
Missing farm income	-0.5231***	-0.2853***	-0.1164***
	(0.049)	(0.025)	(0.011)
Observations	445	445	445

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

Table 4. Estimated Marginal Effects on Practice Acreage Share, Multivariate Tobit with Endogenous Switching

	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	-0.1936	0.0437*	-		-	
	(0.162)	(0.025)				
Conservation tillage	-		-0.0836	0.0021	-	
			(0.125)	(0.032)		
Contour/strip	-		-		0.1493	0.0335
					(0.110)	(0.020)
Generalized residual (covar. w/ 1st stage)						
Cover crop enrollment	-0.0351	-0.004	-0.1358	-0.1204	0.0264	0.0091
	(0.101)	(0.027)	(0.160)	(0.091)	(0.053)	(0.031)
Cons. tillage enrollment	0.0143	-0.0293	0.1438	0.1229	0.0747	0.0147
	(0.227)	(0.043)	(0.266)	(0.118)	(0.136)	(0.050)
Contour/strip enrollment	0.0375	-0.0092	0.5593	0.3316	0.2265**	0.1062**
	(0.298)	(0.060)	(0.406)	(0.206)	(0.102)	(0.051)
No-till enrollment (1=yes; 0=no)	-0.015		-0.1418		-0.0464	
	(0.123)		(0.282)		(0.124)	
Contour/strip enrollment (1=yes; 0=no)	-0.0768		-0.7248		-0.1842	
	(0.182)		(0.491)		(0.125)	
50 or more acres in corn, soybeans or small grains (= 1 or 0)	0.028		0.229***		0.0392*	
	(0.021)		(0.051)		(0.021)	
Proportion acres moderately sloped (2-8% grade)	-0.0001		0.0828**		0.01	
	(0.017)		(0.040)		(0.014)	
Proportion acres steeply sloped (> 8% grade)	-0.0978*		-0.0144		0.0425	
	(0.045)		(0.081)		(0.026)	
Log operating acres	-0.0024		-0.0067		0.0096*	
	(0.006)		(0.015)		(0.005)	
Completed high school	-0.0279		0.0136		-0.0073	
	(0.022)		(0.047)		(0.017)	
Observations	93	352	93	352	93	352

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

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 annual crops only (corn, beans, etc.)**	
Sample size:	**N=445**		**N=331**	
	Enrolled	Unenrolled	Enrolled	Unenrolled
Cover crops (cc)				
Without	0.023	0.025	0.056	0.042
With	0.292	0.287	0.292	0.319
Change	0.269***	0.263**	0.236***	0.278*
	(0.079)	(0.176)	(0.071)	(0.191)
Cons. tillage (ct)				
Without	0.141	0.152	0.217	0.226
With	0.455	0.354	0.474	0.390
Change	0.314***	0.203	0.257**	0.164
	(0.180)	(0.228)	(0.166)	(0.141)
Contour/strip (cs)				
Without	0.072	0.028	0.091	0.046
With	0.088	0.034	0.088	0.041
Change	0.016	0.006	-0.003	-0.006
	(0.158)	(0.065)	(0.042)	(0.033)

Note: Asterisks *** , ** and * denote significance at 1%, 5% and 10% levels, respectively.
Standard errors in parentheses calculated by the Delta Method.

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	Overall	Direct	Overall
	[1]	[2]	[3]	[4]
Nitrogen (pounds)				
Eastern Shore	1,927	2,343	1,059	1,221
Potomac	1,105	1,394	295	352
Patux./Susque./Western	880	1,212	156	187
Phosphorus (pounds)				
Eastern Shore	38	105	22	48
Potomac	22	57	7	16
Patux./Susque./Western	15	53	3	8

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.

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 per farm			
	Enrolled		Unenrolled	
	Direct	Overall	Direct	Overall
	[1]	[2]	[3]	[4]
Nitrogen (pounds)				
Eastern Shore	$7.08	$5.84	$6.85	$5.88
Potomac	$8.33	$7.35	$10.92	$9.20
Patux./Susque./Western	$11.74	$8.63	$17.09	$14.21
Phosphorus (pounds)				
Eastern Shore	$384.88	$182.07	$372.45	$163.41
Potomac	$369.84	$121.13	$352.17	$155.71
Patux./Susque./Western	$581.25	$177.82	$679.35	$302.18

Note: Cost share award of $45 per acre for cover crop planted in rye.

Chapter 3: Incorporating Behavioral Response in Cost Sharing Policy Simulation

1. *Introduction*

Nonpoint source (NPS) pollution from agricultural and other sources has contributed to hypoxic zones in the Gulf of Mexico, Lake Erie, Chesapeake Bay and other regions globally (Diaz and Rosenberg, 2008). Policies aimed at reducing NPS pollution from agriculture have involved paying farmers to either retire cropland or to adopt runoff-reducing conservation practices on working lands. Since 2002, the federal government has turned increasingly to the latter through increased funding for cost sharing programs. In 2014, for example, the federal Environmental Quality Incentive Program (EQIP) and Conservation Stewardship Program (CSP) spent $2.4 billion to subsidize agricultural conservation practices, with spending on these programs authorized to rise to $3.6 billion by 2018.

Evaluating the actual effectiveness of cost sharing is complicated by several factors. First, enrollment in cost sharing is voluntary, such that estimates of additionality need to account for selection bias due to nonrandom enrollment (Lichtenberg and Smith-Ramirez 2011; Mezzatesta, Newburn, and Woodward 2013). Additionality is defined here as the adoption of conservation practices and associated nutrient reductions above and beyond what the farmer would have done in the absence of cost sharing. 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). For example, Lichtenberg (2004a) and chapter 2 in this dissertation finds empirical evidence for substitution and complementarity within groups of conservation practices on working land. Third, incentive payments for certain conservation practices may lead to slippage, thus reducing the expected environmental benefit of the subsidy (Khanna, Isik and Zilberman 2002; Lichtenberg and Smith-Ramirez 2011). Lichtenberg and Smith-Ramirez (2011) show that receipt of cost sharing for conservation practices was associated with large reductions in vegetative cover.

Most evaluations of the water quality impact of NPS pollution policies ignore behavioral responses. For example, Wainger et al. (2013) identify the most cost effective land use changes to reduce NPS pollution from agriculture in the Chesapeake Bay watershed, focusing on the implementation costs of various practices. 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. The focus on integrating economic and biophysical models allows these studies to shed light on the complex nonlinear relationships between agricultural land use and water quality. However, these studies are based on the implementation costs of conservation practices, not the individual agent's observed behavioral responses. Due to the absence of data that permit estimation of behavioral response, they are forced to ignore nonrandom enrollment, as well as the potential indirect effect and slippage effect associated with environmental payments, and instead implicitly assume adopted practices result in complete additionality.

In this study, we investigate the importance of incorporating farmer behavioral responses to environmental 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 cost sharing payment on the acreage share in cover crops, conservation tillage, and vegetative cover, using farmer survey data in Maryland. As in Chapter 2, I estimate both cost sharing enrollment and practice acreage shares 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 effects of cost sharing are used to derive farm-level and river-basin-level abatement and costs.

We compare estimated cost-effectiveness under the baseline assumption of perfect additionality used in the existing literature with a more realistic scenario in which a range of known behavioral responses to cost sharing are considered, including the problem of self-selection and non-additionality of cover crop payments, indirect effects of cover crop incentive payments on other practices, and slippage. We measure the relative magnitude of these behavioral factors in terms of their effect on overall nitrogen, phosphorus, and sediment abatement and cost.

We find that ignoring behavioral responses to conservation cost sharing has the potential to lead to substantial errors in estimating the cost effectiveness of these programs in the context of NPS pollution abatement. Estimates of additional acreage due to the cover crop program are high, and we find that 93 percent of nitrogen abatement can be attributed to the effect of enrollment among currently enrolled farms, and 81 percent 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 8 and 23 percent. Similar effects are seen when applying estimates of additionality to phosphorus and sediment. Second, the estimated indirect effects show qualitative evidence for "crowding in" of conservation tillage in response to the cover crop incentive payment. This "crowding in" has especially large effects on the predicted water quality improvements already achieved among the enrolled group of farmers. Among currently unenrolled farmers, the change in abatement and costs due to indirect effects is qualitatively the same, but not as large. At the same time, estimated slippage is estimated to be very large among currently unenrolled farms, indicating that many of the expected benefits of extending cost sharing to this group of farmers could be offset by the subsequent reduction in vegetative cover. Overall, we find that the baseline scenario in which all incentive payments for cover crops lead to additional adoption is highly optimistic. Moreover, a scenario that only considers nonrandom enrollment, and not the additional behavioral responses of crowding-in and slippage, is also optimistic, especially among the currently unenrolled farmers. The potential water quality gains among currently unenrolled farms are lower primarily because of the expected loss of vegetative cover due to incentive payments. Overall, rather than placing emphasis on the precise estimates, we emphasize the general importance of considering farmer behavioral response in water quality models that seek to estimate the effects of cost sharing policies.This analysis highlights several key findings and contributions to the literature. First, building upon the methodology in chapter 2 of this dissertation, 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 has the potential to lead to substantial 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, in comparison to previous literature on farmer response to policy incentives—such as Wu and Tanaka (2005)—this study is capable of considering a wider range of behavioral response. By using farmer-level survey data, we incorporate responses to policy incentives that go beyond the participation / adoption decision. This includes not only the possibility of slippage and indirect effects, but also a consideration of the spatial extent or conservation acreage on a given farm. Utilizing an econometric methodology capable of simultaneously accounting for self-selection and correlation among the acreage decisions for conservation practice use, we provide estimates of the overall effect of environmental incentive payments on agricultural NPS pollution downstream.

2. Background

Agriculture contributes substantially to NPS pollution in U.S. rivers, streams and coastal waters. 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.[16] 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.

The State of Maryland and the federal government have used cost sharing for almost 30 years to reduce agricultural NPS pollution into the Chesapeake Bay. At the state level, the Maryland Agricultural Water Quality Cost Share (MACS) program has been providing farmers with financial assistance since 1984. In 2013, MACS spent about $26.7 million to incentivize the adoption of conservation practices, approximately 78% of which was directed towards cover crops. This represents a four-fold increase in the program's budget since 2005. The cover crop program in Maryland has been extensive, with approximately one-third of all harvested cropland in the state treated with cover crops through MACS funding in 2014. Enrollment in cost sharing programs is voluntary, resulting in the potential for non-additional practice adoption (Chabé-Ferret & Subervie, 2013). Base payments in the MACS program begin at $45 per acre for traditional cover crops.[17] Other cost share programs—such as the EQIP program—have also been available in the state, providing funding for cover crops and other conservation practices. Total EQIP obligations in Maryland were about $9 million in 2013.

For these reasons, the state of Maryland is favorable for the study of cost sharing programs and farmer behavioral response. With its aggressive promotion of cost sharing for cover crops, there is a large share of farmers who participate in the program, but with its diversified agricultural production conditions there is also a large share of farms which

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

[17] The MACS budget is large enough that eligible applicants are rarely denied funding (Norman Astle, MACS program administrator, personal communication 7/5/2012).

adopt conservation practices without cost share funding. Moreover, with the variable topography in the state, many farmers adopt multiple conservation practices, including vegetative cover, on a single farm, making it possible to study important behavioral responses to cost sharing such as slippage and indirect effects on other field practices.

The practices studied in this article are cover crops, conservation tillage, and vegetative cover. Cover crops are grown over the winter when many fields are left bare and vulnerable to soil erosion. From a water quality standpoint, cover crops are primarily geared to nitrogen reduction, by taking up the excess soluble nitrogen in the soil profile. 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. By reducing sediment movement from a field, conservation tillage is primarily effective for reducing phosphorus runoff to surface water bodies, a nutrient which tends to bind with soil particles. Cover crops and conservation tillage can be used in tandem, and they have complementary effects in improving soil quality and reducing soil erosion on cultivated land, as discussed in chapter 2 of this dissertation. However, incentive payments for either conservation practice potentially lead to the problem of slippage, because environmental subsidies for conservation practices can increase the profitability of cultivated land relative to vegetative cover (Lichtenberg and Smith-Ramirez, 2011). We consider the practice of vegetative cover, which includes pasture, hay, forest and other land that is not cultivated for annual crops.

The Chesapeake Bay Program (CBP) has developed a watershed model that links land use and farm management practices to the estimated loads 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, simulates the transport of pollution using 20-years of historical data.[18]

The CBP watershed model is calibrated based on historical water quality measurements from monitoring stations, but it makes certain simplifications of a complex process in developing the model parameters. While the historical measurements and calibrated model parameters utilized in the CBP watershed model are grounded in real-world processes, the model does not explicitly account for nonlinearities in NPS pollution generation, such as interactions between neighboring pollution sources (Rabotyagov, Valcu and Kling, 2013).[19] We use the CBP watershed model because, while simplified, it is the tool used by policymakers and government agencies in our study region. For our analysis, we use model parameters from the CBP watershed model on edge-of-stream agricultural pollution loads for nitrogen, phosphorus, and sediment, ratios of pollution reaching the Bay from the edge-of-stream in each segment ("delivery factors"), and percentage pollution reduction efficiencies for each conservation practice. The manner in which the CBP watershed model is utilized to estimate water quality impacts based on

[18] Data from the most recent Phase 5.3 CBP watershed model is publicly available: http://www.chesapeakebay.net/data . The model tracks water quality indicators at 296 monitoring stations.

[19] Watershed models such as the Soil and Water Assessment Tool (SWAT) explicitly account for nonlinearities in the NPS pollution production function (Wu and Tanaka, 2005; Rabotyagov, Valcu and Kling, 2013; Kling et al., 2014). The CBP watershed model uses delivery coefficients from edge-of-stream to the Bay, which is analogous to the linear approximation of the fate and transport of pollution model explored in Rabotyagov, Valcu and Kling (2013).

changes in farmer behavior will be described in more detail below in the Policy Simulation Methods section.

3. *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, 445 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 (see Lichtenberg, Parker and Lane (2012) for a more complete description).

Table 1 summarizes practice adoption, acreage share, and cost share enrollment for the two practice types for which cost sharing funds are available. 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 cost sharing than without funding—93 respondents adopted cover crops with cost sharing compared to 49 respondents who adopted cover crops without cost sharing. In contrast, conservation tillage is primarily self-funded when adopted, with 88 percent of those adopting doing so without cost share funding. Vegetative cover in the study region is primarily composed of pasture and hay, which are not normally part of cost share programs. However, some degree of vegetative cover on farms is common, with about 76 percent of the farms in the sample having some acreage in hay, pasture, or other vegetative cover. 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 rented minus any land rented to others. Among the respondents who adopted cover crops, those who adopted with cost sharing allocate a higher acreage share to the practice, with almost a third of a farm's operating acreage in cover crops among farmers who enrolled compared to 23.6% among farmers who adopted without enrollment. This is not the case for conservation tillage, where the average acreage share is approximately equal on farms that adopted with and without enrollment in a conservation tillage cost sharing program. Finally, among farms with vegetative cover, an average of about 31 percent of the farm's operating acreage is allocated to vegetative cover.

Table 2 summarizes the variables from the survey data collected on farm characteristics (e.g., farm type, topography, operating acreage, cattle, horses, sheep, distance to nearest surface water body), and farmer characteristics (e.g., education, income share from farming). Farm type indicates whether or not a farm has at least 50 acres in annual crops such as corn, soybeans and small grains. Topography variables include the proportion of operating acres by slope class: flat (0-2% grade), moderate (2-8% grade), and steep (>8% grade). 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 (e.g. streams, rivers, lakes, wetlands, bay).

In addition to the explanatory variables from the survey, we 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. Specifically, we calculate the cost per pound of erosion reduction using data from the CBP watershed model and per-acre practice costs. These benefits are calculated as the pounds of soil erosion reduced per acre due to practice adoption divided by the cost per acre of practice adoption.[20] 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 practice 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. The 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 input costs, it is expected that the acreage share in the conservation practice would be higher as the cost per unit of private benefit are lower.

4. Empirical Model of Cost Share Enrollment and Farmer Behavior

This section describes the estimation of the effect of cost sharing on farmer behavior. The practice adoption and cost share enrollment decisions may be jointly determined. There

[20] 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). 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.

may be correlation at several levels including in the adoption of conservation practices; in the enrollment decision for different cost sharing programs; and between cost share enrollment and conservation practice adoption, given the problem of self-selection into cost share programs. The econometric model is estimated as a two-stage simultaneous equation regression model, similar to the empirical specification in chapter 2 of this dissertation. In the first stage, cost sharing enrollment is simultaneously estimated for the two conservation practices for which cost share funding information is available, using a multivariate probit model. In the second stage, we estimate the share of farm operating acreage in 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, several 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.

4.1 First stage: Cost sharing enrollment

Consider first the cost sharing decision. In the model, each farmer j is assumed to be a profit-maximizing agent who chooses whether to enroll in program p, where $p = \{cc, ct\}$ refers to cover crops and conservation tillage, respectively. The farmer simultaneously decides whether or not to enroll in the cost sharing program for these two practices. (Since a large part of the vegetative cover on farms in Maryland is pasture and hay, cost sharing is not typically used for the adoption of this practice.) Note that enrollment in cost sharing for a given practice does not exclude the possibility of receiving cost sharing for the other practice. Let C_j^p be a binary indicator of farmer j's decision to enroll in program p.

Cost share enrollment depends on factors Z_j^p influencing the decision of farmer j to enroll in program p, including factors affecting the expected benefits of the conservation practice (e.g., distance to surface water bodies), transaction costs of application (e.g., income share from farming), erosion reduction costs of each practice, and other farm-level factors (e.g., topography, farm size). Assuming these variables enter the model linearly, a functional representation of the cost share decision is:

$$\begin{aligned} &C_j^p = 1 \quad if \quad Z_j^p \gamma^p + u_j^p \geq 0, \qquad p = \{cc, ct\} \\ &C_j^p = 0 \quad if \quad Z_j^p \gamma^p + u_j^p < 0, \qquad p = \{cc, ct\} \end{aligned} \tag{1}$$

where γ^p is a vector of parameters to be estimated for each cost share program; and u_j^p is an error term. It is expected that the same set of factors influences cost share enrollment for both practices.

Note that farmers who enroll in cost sharing for one conservation practice may be more likely to enroll in 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

$$\Omega_C = Var\begin{pmatrix} u^{cc} \\ u^{ct} \end{pmatrix} = \begin{pmatrix} \sigma_1^2 & \sigma_{21} \\ \sigma_{12} & \sigma_2^2 \end{pmatrix}. \tag{2}$$

Here, Ω_C is the 2x2 variance-covariance matrix of error terms of the cost-share equations. The error terms are assumed to be jointly normal, thus the system of equations represented in (1) and (2) is estimated using a bivariate probit model.

This two-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 $\hat{\rho}_{p,q} = \hat{\sigma}_{p,q}/\hat{\sigma}_p\hat{\sigma}_q$ is estimated as the correlation between enrollment in cost share programs for p and q. The simulated maximum likelihood (ML) estimation technique is described in more detail in chapter 2 of this dissertation.

4.2 Second stage: Farmer adoption decisions on conservation practices

Next, consider the farmer's adoption decisions for conservation practices. Self-selection is a well-known problem that complicates estimation of the treatment effect of program enrollment 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 explained by Wooldridge (2014), a standard method that corrects for self-selection in program evaluation is the control function approach, which uses generalized residuals as regressors in the outcome equations to control for potential correlation in the error terms, thereby allowing consistent though not efficient estimation of the effect program enrollment. The estimated coefficient associated with these regressors will be the covariance of error terms between the enrollment (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 $n = \{cc, ct, vc\}$

indicates the practice types of cover crops, conservation tillage, and vegetative cover, respectively. Cost share funding is very rare for vegetative cover, yet it is important to consider vegetative cover in the second-stage to account for the possibility of slippage. 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.[21]

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

(3) $${s^*}_{ji}^{n} = X_j^n \beta_i^n + \sum_{p=1}^{2} \hat{\lambda}_{ji}^{p} \delta_i^n + \tau^n C_j^{ct} + \varepsilon_j^n \,;$$

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

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

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

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 excluded from X_j^n. Following Lichtenberg and Smith-Ramirez (2011), we use distance to the nearest water body as an exclusion restriction such that it is included in Z_j^p but not X_j^n. We also use the share of family income from farming as an exclusion restriction, included in Z_j^p but not

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

X_j^n. Thus the outcome equations for acreage shares are identified by these exclusion restrictions as well as the nonlinearity of the program enrollment equations. Distance to nearest water body is a proxy for potential risk of water quality impairment that matters to the government funding agency but not necessarily to the farmer. Share of family income from farming is a proxy for the farmer's likelihood to enroll in government programs and have familiarity with the procedures involved in obtaining subsidies. Thus, a higher share of income from farming lowers transaction costs of enrollment, but should not influence the profit-maximizing allocation of practice acreage shares on a farm. Note that $\hat{\lambda}_{ji}^p$ are the estimated generalized residuals from each of the two cost share enrollment equations in (1), to allow for the potential correlation between the two cost share decisions and conservation practice acreage. The variable C_j^{ct} represents enrollment in the cost share program for conservation tillage.

Parameter estimates may switch based upon observed enrollment in a cover crop cost sharing program, C_j^{cc}, both for the generalized residuals as well as the erosion reduction cost and constant term in X_j^n shown in equation (3). Program enrollment for cover crops is used to indicate switching because the primary interest of this study is to evaluate the large cover crop cost sharing program in Maryland. Then $\theta_i^n = \{\beta, \delta\}, i = \{w, o\}$ are parameters estimated separately for each of the two regimes (with or without enrollment), which will be used to estimate the treatment effect of cover crop cost sharing. However, in many cases no statistically significant difference is observed between parameter estimates across cost-share regimes (i.e., $\hat{\theta}_w^n = \hat{\theta}_o^n$) 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, we restricted parameters to be equal across regimes when there is no prior theoretical reason to expect a difference between cost-share regimes.

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. Unlike Lichtenberg and Smith-Ramirez (2011), our study uses cost share enrollment for one specific practice—cover crops—to determine regime switching, while separately considering the effect of a cost share award for conservation tillage by including this as a right hand variable.

Errors of the system of equations (3) are assumed to be distributed jointly normal, but are not observed simultaneously across regimes $i = \{w, o\}$. The variance-covariance matrix of errors across acreage share equations, Ω_s, is of the following form:

$$\Omega_s = Var\begin{pmatrix} \varepsilon^{cc} \\ \varepsilon^{ct} \\ \varepsilon^{vc} \end{pmatrix} = \tag{4}$$

$$\begin{pmatrix} \sigma^2_{\varepsilon^{cc}} & \sigma_{\varepsilon^{ct}\varepsilon^{cc}} & \sigma_{\varepsilon^{vc}\varepsilon^{cc}} \\ \sigma_{\varepsilon^{cc}\varepsilon^{ct}} & \sigma^2_{\varepsilon^{ct}} & \sigma_{\varepsilon^{vc}\varepsilon^{ct}} \\ \sigma_{\varepsilon^{cc}\varepsilon^{vc}} & \sigma_{\varepsilon^{ct}\varepsilon^{vc}} & \sigma^2_{\varepsilon^{vc}} \end{pmatrix}$$

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

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. 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 vegetative cover. The simulated ML estimation technique with Halton sequences is described in more detail in chapter 2 of this dissertation.

Treatment effects for both enrolled and unenrolled farmers are then calculated based on estimated acreage shares from parameter estimates (Heckman and Vytlacil, 2007). We calculate the direct treatment effect on cover crop acreage share due to enrollment in the cover crop program as

(5) $$\widehat{TET}_j^n = \left\{\hat{s}_{wj}^n - \hat{s}_{oj}^n\right\} \text{ for enrolled farmer } j,$$

$$\widehat{TEU}_j^n = \left\{\hat{s}_{wj}^n - \hat{s}_{oj}^n\right\} \text{ for unenrolled farmer } j,$$

$$n = \{cc\}.$$

We also calculate the indirect treatment effect on conservation tillage due to enrollment in the cover crop program.

(6) $$\widehat{TET}_j^n = \left\{\hat{s}_{wj}^n - \hat{s}_{oj}^n\right\} \text{ for enrolled farmer } j,$$

$$\widehat{TEU}_j^n = \left\{\hat{s}_{wj}^n - \hat{s}_{oj}^n\right\} \text{ for unenrolled farmer } j,$$

$$n = \{ct\}.$$

A positive indirect effect indicates complementarity (crowding in) and a negative indirect effect indicates substitution (crowding out). Finally, we calculate the treatment effect on vegetative cover due to enrollment in the cover crop program.

(7) $$\widehat{TET}_j^n = \left\{\hat{s}_{wj}^n - \hat{s}_{oj}^n\right\} \text{ for enrolled farmer } j,$$

$$\widehat{TEU}_j^n = \left\{\hat{s}_{wj}^n - \hat{s}_{oj}^n\right\} \text{ for unenrolled farmer } j,$$

$$n = \{vc\}.$$

The slippage effect is expected to be negative, reflecting the loss of vegetative cover. For enrolled farmers, $\hat{s}_{oj}^{n}$ 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 the cover crop program. For unenrolled farmers, the counterfactual is $\hat{s}_{wj}^{n}$, representing the expected acreage share if these farmers had been enrolled in the cover crop program.

5. *Estimation results*

This section discusses the estimated treatment effects of cover crop enrollment, based on the two-stage econometric model of cost share enrollment and acreage share of conservation practices. Marginal effects 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.

In the multivariate probit model, a log-likelihood ratio test indicates that the explanatory variables are jointly significant at the 0.01% level, with a chi-squared test statistic of $\chi^2_{(28)}$ =192.1. The estimated correlation coefficient, $\hat{\rho}_{12}$, indicates positive correlation in the enrollment decisions for the cover crop and conservation tillage programs, which is statistically significant at the 5% level. The pseudo R-squared of this model is 0.301 (with a restricted log likelihood of negative 318.8 and an unrestricted log likelihood of negative 222.7). According to McFadden (1979), a pseudo R-squared value between 0.2 and 0.4 indicates very good model fit.

Figure 1 below compares predicted enrollment with actual enrollment in the survey. The columns show actual (observed) enrollment by practice type, and correspond to the descriptive statistics summarized in Table 1. The rows correspond to predictions. When making model predictions based upon the probability of enrollment for each practice type, the choice of a cutoff probability is decisive. The cutoff probability refers to the threshold above which the observation is considered “enrolled”, and below which the observation is considered “not enrolled”. It is known that when a sample has large imbalances between “successes” and “failures” (in this case, being enrolled or not), a default cutoff threshold of 0.5 is not practical.[22] Therefore, due to the heavily imbalanced nature of enrollment for conservation tillage in this survey—for which very few farmers are enrolled in cost sharing—cutoff probabilities had to be chosen in a different way. Figure 1 below shows predictions based on cutoff thresholds for both practices that jointly minimize Type I and Type II Errors. The figure shows that about 61 percent of the farmers enrolled in the cover crop program were correctly predicted to be enrolled (57 out of 93), and over 90 percent of the unenrolled (320 out of 352). A similar pattern is observed for conservation tillage enrollment, with a very high share of correct predictions among the unenrolled, and almost half among the enrolled.

Figure 1

[22]While a substantial share of surveyed farmers had an estimated probability to enroll in the cover crop program that was greater than 0.5, the range of predicted probabilities for conservation tillage enrollment were between approximately 0 and 0.35, given the small number of enrollees in cost sharing for this practice type.

	Observed enrollment by practice type			
	Cover crops		Conservation tillage	
	Unenrolled	Enrolled	Unenrolled	Enrolled
Predictions				
Unenrolled	320	36	352	14
Enrolled	32	57	67	12
Total	352	93	419	26

Cutoff point for predicted probability was chosen to jointly minimize both Type I and Type II Errors.

In the multivariate tobit model, a log-likelihood ratio test indicates that the explanatory variables are jointly significant at the 0.01% level, with a chi-squared test statistic of $\chi^2_{(54)} = 524.9$. A likelihood ratio test that the correlation coefficients are jointly equal to zero was rejected at the 0.01% level, with $\chi^2_{(3)} = 96.8$, indicating that the goodness-of-fit is significantly improved by allowing for correlation in the acreage share decisions for cover crops, conservation tillage, and vegetative cover. Not surprisingly, the correlation between cover crops and vegetative cover, as well as that between conservation tillage and vegetative cover, is negative.

Generalized residuals, as specified in equation (3), are included to correct for a farmer self-selection into cost share programs. A Wald test for joint significance of the generalized residuals shows they are not jointly significant, with with $\chi^2_{(12)} =$14.3 ($p =$0.2831). Nonetheless, given the strong theoretical reasons to account for nonrandom enrollment in cost sharing programs, it remains justified to use a Heckman selection model in order to remove potential selection bias, by allowing for correlation in the enrollment and acreage share decisions.

The pseudo R-squared of the multivariate tobit model is 0.315 (with a restricted log likelihood of negative 831.8 and an unrestricted log likelihood of negative 569.6). The estimated standard deviation in the tobit equation is comparable to the mean squared error in a linear regression. For cover crops, conservation tillage, and contour/strip acreage shares, the estimated standard deviations were 0.086, 0.227, and 0.121, respectively. This indicates that the model predictions were most accurate for cover crops, and least accurate for conservation tillage.These econometric estimates shown in Appendix Tables A1 and A2 are used to calculate average treatment effects for enrolled and unenrolled farmers, as shown in equations 5 to 7. 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.

It should be emphasized that the qualitative results of these treatment effects are more important than the precise estimates. The incorporation of additional layers of farmer behavioral response in the model leads to a substantial increase in the variability and uncertainty of estimates, and therefore lower precision in numerical predictions. This variability and uncertainty in estimated abatement stems from two primary sources. One is the randomness in measurement. Due to the relatively small sample size in the farmer survey, the precision of estimates falls as I attempt to capture a wider range of farmer behavior. The other source of variability is farmer heterogeneity itself, both observed and unobserved. Observed heterogeneity—based on farmer location, farm characteristics such as size or farm type, and farmer characteristics such as education—affects the abatement potential of a given farm, and can be distinguished from the randomness of measurement. However, *unobserved* heterogeneity is not distinguishable from randomness, absent a panel dataset, as both are contained in the error terms of the system of equations.

Keeping these caveats in mind, what is most important for the purposes of this dissertation is to demonstrate the potential cost of ignoring farmer behavioral response when analyzing the effectiveness of cost sharing programs. These known behavioral responses include not only nonrandom selection, but also indirect effects and slippage effects.

The ATT for the acreage share devoted to cover crops is 0.209 and significant at the 1% level. Considering that the acreage share with enrollment is 0.223 compared to only 0.014 without enrollment, this indicates that 94 percent of the average acreage share in cover crops is due to enrollment in the program. Hence, the MACS cover crop program had a large effect on enrolled farmers. There was also a positive indirect effect on conservation tillage, where 45 percent of the conservation tillage acreage share is estimated to be due to enrollment in the cover crop program. The estimation results indicate an increased acreage share of 0.191 out of the 0.425 acreage share with enrollment, suggesting substantial crowding-in of private investment in conservation tillage. As for the slippage effect, there was an estimated 21 percent loss of vegetative cover due to cost sharing for enrolled farmers. Specifically, there was a 0.05 acreage share in vegetative cover with enrollment compared to 0.239 acreage share without enrollment.

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 0.222 for acreage share in cover crops for unenrolled farmers, or 87 percent additionality. This is only slightly smaller than the percent additionality 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 are only 0.102, but this represents a projected 42 percent increase in conservation tillage among the unenrolled group. This suggests that the positive indirect effects for unenrolled farmers are similar in percentage terms to the corresponding indirect effects for enrolled farmers. In other words, while the absolute level of "crowding in" is likely greater for farmers already reached by the current program, there are similar percentage gains available for farmers who have not yet been enrolled. However, it is important to note that the estimated negative effect of slippage is quite large in the unenrolled group, at -0.140, representing a projected loss of one-third of a farm's vegetative cover due to the cover crop program. Not surprisingly, since the unenrolled group tends to be composed of smaller farms with a higher acreage share of vegetative cover, this suggests that there is a high risk that the conservation gains associated with expanding cover crops cost sharing to this group could be offset by slippage.

6. Policy simulation methodology

The policy simulation aims to examine how these various treatment effects on cover crops, conservation tillage, and vegetative cover may be expected to affect nutrient and sediment loads delivered to the Chesapeake Bay.

The individual farm-level treatment effects are integrated with the CBP watershed model to develop farm-level abatement and costs. We compare abatement costs from a baseline approach which assumes practice adoption for enrolled farmers is completely additional with a more realistic scenario that accounts for the behavioral response to cover crop enrollment including (i) for non-additional acreage shares on a given farm, (ii) indirect effects on conservation tillage, and (iii) slippage effects for vegetative cover. The farm-level abatement and cost estimates are relevant to gauge the relative importance of these various behavioral responses for water quality and cost effectiveness. We also use the survey's inverse sampling weights to translate the farm-level average water quality impacts to the population level for the entire state of Maryland. This allows us to make inferences about the role of the cover crop cost sharing program as a tool for achieving the Chesapeake Bay TMDL.

We begin with a description of the model parameters on pollution loads, practice 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, η_{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 $n = \{cc, ct\}$ indicate the practices of cover crops and conservation tillage, respectively. For vegetative cover, pollution reduction is achieved as a change in land use, rather than as a practice efficiency. Practice efficiency parameters, η_{kz}^{n}, for a given practice type n and pollutant k are constant in the study region, with the exception that η_{kz}^{cc} for cover crops varies spatially between the geographic regions of coastal plain and non-coastal plain when $k = nitrogen$. Finally, delivery factors, δ_{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.

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 scale of the 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.[23] 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 for each pollutant to the Chesapeake Bay due to cover crop cost sharing. The direct effect of cost sharing estimates abatement due only to the increased adoption of cover crops, not accounting for indirect effects or slippage. Let $\Delta q_{jk}^{i,D}$ represent the change in quantity abatement of pollutant k 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 is calculated as follows:

$$\Delta q_{jk}^{1,D} = A_j \cdot (\widehat{TET}_j^{cc} \cdot L_{kj}^{crop} \cdot \eta_{kj}^{cc}) \cdot \ \delta_{kj} \ \text{ for enrolled farmer } j \tag{8}$$

[23] 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").

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

Here, the quantities of abatement are expressed in pounds for nitrogen and phosphorus and in tons for sediment.

6.1 Indirect Effect

When multiple practice types are used on the same acre of land, the reduction efficiencies η_{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), but perform a robustness check in which we assume perfect positive correlation between cover crops and conservation tillage.

Let $\hat{s}_i^{cc}$ and $\hat{s}_i^{ct}$ be the estimated shares of operating acres in cover crops and conservation tillage, respectively, where $i = w$ and $i = o$, respectively, indicates with and without cost sharing. Since the two practices are not mutually exclusive, it is conceivable that they are used on the same fields. Moreover, if $\hat{s}_i^{cc} + \hat{s}_i^{ct} > 1$, there must be some overlap among practices. (Note that 2 of the 445 usable observations have combined acreage shares greater than one with cost sharing.) To calculate multiplicative reduction efficiencies, let $m = \{1, \ldots, 4\}$ be an index of mutually exclusive combinations of the practices, such that a single number, η_{kj}^{m}, refers to the reduction efficiency from a unique combination of practices on the same field:

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

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

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

$$m = 4 \leftrightarrow cc + ct, \text{ and } \eta_{kj}^{4} = \eta_{kj}^{cc} + \eta_{kj}^{ct} - \eta_{kj}^{cc} \cdot \eta_{kj}^{ct}$$

Similarly, acreage shares $\hat{s}_{i,j}^{m}$ are calculated for mutually exclusive combinations of the practices. When assuming independent placement of practices (i.e. no correlation in practice placement), the acreage shares can be calculated as follows:

$$m = 1 \leftrightarrow no\ BMPs, \text{ and } \hat{s}_{i}^{1} = (1 - \hat{s}_{i}^{cc}) \cdot (1 - \hat{s}_{i}^{ct}),$$

$$m = 2 \leftrightarrow cc, \text{ and } \hat{s}_{i}^{2} = \hat{s}_{i}^{cc} \cdot (1 - \hat{s}_{i}^{ct})$$

$$m = 3 \leftrightarrow ct, \text{ and } \hat{s}_{i}^{3} = (1 - \hat{s}_{i}^{cc}) \cdot \hat{s}_{i}^{ct}$$

$$m = 4 \leftrightarrow cc + ct, \text{ and } \hat{s}_{i}^{4} = \hat{s}_{i}^{cc} \cdot \hat{s}_{i}^{ct}$$

By definition, these acreage shares will sum to one, since one of these four combinations of practices must be present on all operating acreage on a farm. (Group m=1, in which neither practice is used, represents both cropland with neither practice in place as well as operating acreage that is not in crops.)

We then calculate abatement in the Bay in consideration of both direct and indirect effects of environmental incentive payments, which represents a more comprehensive measure of pounds of pollution load abated from cropland. Under this scenario, the change in the quantity of abatement is:

(9) $$\Delta q_{kj}^{D+I} = A_j \cdot \left\{\left[\sum_{m=2}^{4} \hat{s}_{w,j}^{m} \cdot L_{kj} \cdot \eta_{kj}^{m}\right] - \left[\sum_{m=2}^{4} \hat{s}_{o,j}^{m} \cdot L_{kj} \cdot \eta_{kj}^{m}\right]\right\} \cdot \delta_{kj}$$

Note that because there is no conservation practice abatement on land in which neither practice is in place (i.e. $\eta_{kj}^{1} = 0$, as shown above), the acreage share $\hat{s}_i^1$ is not included in equation (9).

6.2 Slippage Effect

The estimated reduction in vegetative cover due to cost sharing indicates that NPS pollution abatement may be partially offset by expanded cultivated acreage. Let $\hat{s}_i^{vc}$ be the estimated share of operating acreage in vegetative cover. Slippage occurs on a farm when $\hat{s}_{w,j}^{vc} < \hat{s}_{o,j}^{vc}$. In the context of slippage, the change in nutrient reduction to the Bay is not based on a nutrient reduction efficiency, but on the higher degree of runoff from cropland as opposed to vegetative cover. As noted, pollution runoff by land use, L_{kj}^{l}, is provided by the CBP model, where $l = \{crop, hay, pasture\}$. Since vegetative cover includes both hay and pasture in the econometric model, farm-specific runoff from vegetative cover is calculated as a weighted average of hay and pasture loads, with weights equal to each farmer's observed share of hay and pasture. Let s_j^{hay} be the observed share of vegetative cover that is in hay, and $s_j^{pasture} = 1 - s_j^{hay}$ be the observed share of vegetative cover in pasture. Then the nutrient load from vegetative cover for farmer j is simply $L_{kj}^{vc} = s_j^{hay} \cdot L_{kj}^{hay} + s_j^{pasture} \cdot L_{kj}^{pasture}$. For farms without any observed vegetative cover, a weighted average from the farmer's geographic region, z, is used: $L_{kj}^{vc} = s_z^{hay} \cdot L_{kj}^{hay} + s_z^{pasture} \cdot L_{kj}^{pasture}$.

The change in pounds of runoff due to lost vegetative cover is then calculated as Δq_{jk}^{S}, where the superscript S indicates slippage:

(10) $$\Delta q_{kj}^{S} = \left(\hat{s}_w^{vc} - \hat{s}_o^{vc}\right) \cdot \left(L_{kj}^{crop} - L_{kj}^{vc}\right) \cdot \delta_{kj}.$$

Note that Δq_{kj}^{S} will be negative when slippage occurs, indicating an increase in pollution, since $L_{kj}^{crop} > L_{kj}^{vc}$.

In sum, the overall abatement due to cover crop enrollment accounts for the abatement due to additional cover crop acreage (the direct effect), abatement due to additional acreage in conservation tillage (the indirect effect), and offset abatement due to the potential expansion of cropland into previously vegetative cover (slippage). For farmer j and pollutant k, let Δq_{kj}^{O} be the overall abatement due to cover crop cost sharing, where the superscript O indicates the overall effect:

$$\Delta q_{kj}^{O} = \Delta q_{kj}^{D+I} + \Delta q_{kj}^{S}. \tag{11}$$

6.3 Costs and population inferences

The direct, indirect, and overall quantities of abatement in the Chesapeake Bay are then translated to abatement costs using the base cover crop cost share rate of $45 per acre in the MACS program. The funding agency does not consider cover crop usage without cost sharing, and thus assumes complete additionality. Therefore the expenditure is simply based upon the acreage share with cost sharing.

$$e_j = 45 \cdot A_j \cdot \hat{s}_{w,j}^{cc}. \tag{12}$$

Letting $B = \{D, I, O\}$ indicate the behavioral response of direct effect, indirect effect, and overall effect, respectively, the abatement per dollar spent for each pollutant after considering the various behavioral responses is then calculated as:

$$a_{kj} = {}^{\Delta q_{kj}^{B}}\!\big/_{e_j} \tag{13}$$

These abatement amounts are then averaged across the surveyed farms to obtain average abatement per dollar spent on cover crop cost sharing, at the base payment rate of $45.

6.4 Comparison with a baseline least-cost scenario

For the sake of comparison, we also calculate abatement and costs for a baseline which assumes that all cover crop acreage paid for by a cost share award or adopted with given implementation costs are additional. In this scenario, the estimate of a farm's cover crop acreage with cost sharing is used in place of the treatment effect, thus abstracting from the issues of non-additional adoption, indirect effects, and slippage. Letting the superscript P indicate the baseline program-evaluation approach, the change in abatement is

$$\Delta q^{P}_{kj} = A_j \cdot (\hat{s}^{cc}_{w,j} \cdot L_{kj} \cdot \eta^{cc}_{kj}) \cdot \delta_{kj} \qquad (14)$$

Note that this scenario effectively assumes the acreage share in cover crops without enrollment ($\hat{s}^{cc}_{o,j}$) is zero, since the treatment effect is calculated as $\hat{s}^{cc}_{w,j} - \hat{s}^{cc}_{o,j}$. Abatement costs in this baseline least-cost scenario are calculated as before.

After scaling up to the population level, this provides two sets of abatement cost curves to compare: (i) a baseline 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 taken into account (non-additional adoption, indirect effects, and slippage). Much of the economic literature simulating the effects of agricultural cost sharing on water quality has focused on (i), thus abstracting from farmer behavioral response to environmental incentive payments. Other studies that have incorporated behavioral response in models that link land use decisions to water quality, such as Wu and Tanaka

(2005), do not account for changes in acreage decisions on a given farm, nor potential indirect effects or slippage.

7. <u>*Policy simulation results*</u>

This section describes the policy simulation results in which the estimated treatment effects are combined with the CBP watershed model to obtain farm-level abatement and costs due to enrollment in the cover crop program. We compare abatement and costs for the baseline least-cost scenario with the scenario using the behavioral model that estimates additionality for the direct effect of enrollment on cover crops, indirect effects on conservation tillage, and slippage effects on vegetative cover. We emphasize the qualitative impacts of farmer behavioral response on NPS pollution, rather than the precise abatement estimates. These policy simulation scenarios demonstrate the cost of ignoring nonrandom enrollment, indirect effects, and slippage effects in the context of water quality models that evaluate the effectiveness of voluntary NPS pollution abatement policies.

7.1 Farm-level abatement and costs

Table 4 shows average abatement per acre in the survey sample, weighted based on the inverse survey 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 per acre and average abatement per dollar spent (equation 13) for enrolled farms.

For comparison purposes, row [a] shows the baseline scenario in which all incentive payments are additional and there are neither indirect effects nor slippage effects, calculated based on equation (14). Row [b] 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 (8). Row [c] shows the indirect effect on abatement, which is calculated as equation (9) minus equation (8). Since the nutrient reduction efficiencies for multiple practices are multiplicative, not additive, it is impossible to calculate the additional benefit of conservation tillage acreage separately from the direct effect of cover crop acreage. Rather, the additional benefit of the conservation tillage acreage is simply the difference between the combined effect (equation 9) and the direct effect (equation 8). Row [d] shows the effect of slippage, or the additional pounds of runoff due to reduced vegetative cover, shown in equation (10). Finally, row [e] shows the overall abatement after considering self-selection, indirect effects, and slippage, as shown in equation (11). This can be derived from the table by taking the sum rows [b], [c], and [d].

For enrolled farmers, we find that the baseline approach overestimates the reductions in all three pollutants. For example, nitrogen abatement is reduced from 1.58 pounds per acre to 1.45 pounds per acre after accounting for all behavioral responses. Hence, the overall effect of the behavioral model suggests that the overall effect is 92 percent of the baseline scenario. We find that the decline in additional nutrient abatement is almost entirely due to self-selection, because the beneficial indirect effect on conservation tillage compensates for the lost abatement due to slippage. Similar patterns are observed for phosphorus and sediment abatement, though the beneficial indirect effect on abatement is greater for these pollutants, since conservation tillage is better-suited for reducing the loss of phosphorus and sediment from fields rather than nitrogen. Moreover, when cover crops are used on a field treated with conservation tillage, the additional phosphorus and sediment benefits of the cover crop are very small. In these cases, the primary benefit of the cover crop is through taking up excess soluble nitrogen, preventing the nitrogen from moving through the soil profile into the groundwater.

Column [2] displays the abatement achieved per dollar spent on cover crop cost sharing, and similar patterns are observed. There is approximately an 8 percent reduction in abatement achieved per dollar spent after accounting for behavioral responses. In short, the baseline approach is optimistic in its abatement and cost estimates, but among enrolled farmers the lost abatement and additional costs due to the consideration of behavioral responses does not completely undermine the effectiveness of the program. This is due in both to the high estimates of additionality for the enrolled group, and offsetting effects of the environmentally-beneficial crowding-in of conservation tillage and the environmentally-harmful loss of vegetative cover.

Columns [3] and [4] of table 4 show the same abatement and cost estimates among the currently unenrolled farmers. Among the unenrolled, the baseline approach gives highly optimistic estimates of the benefits of extending cost sharing to this group of farmers. We find that average nitrogen abatement per acre decreases by almost 60 percent, and abatement per dollar spent decreases by two-thirds, after considering all behavioral responses. This larger loss of environmental benefits is due to a combination of factors. First, we estimate that additionality is lower among this group, resulting in a 14 percent loss of abatement in comparison to the baseline approach. Second, we find that the beneficial crowding-in of conservation tillage is smaller among the unenrolled. Most importantly, we estimate the potential for slippage to be particularly large among the currently unenrolled farms, as this group tends to have greater acreage shares to in hay and pasture compared to the enrolled group. We find that slippage offsets 56 percent of the abatement contained in the baseline approach, reducing the abatement per dollar spent by almost two-thirds. This has large implications for the cost-effectiveness of extending the cost sharing program in Maryland in order to meet TMDL goals. In particular, program administrators should analyze previous acreage in vegetative cover before extending cost sharing payments to previously unenrolled farms. While this may increase program administrative costs, it would be essential to reduce the possibility of slippage and increase the cost-effectiveness of incentive payments.

Admittedly, there is uncertainty around the averages that we have estimated, as shown in the bootstrapped 95% confidence intervals. To some degree this was expected, given our relatively small sample size and the heterogeneity of farmers in our study region. Rather than placing a high stake in the specific estimates for the direct effect, indirect, and slippage, we emphasize the overall importance of considering farmer behavioral response in water quality models that seek to estimate the effects of cost sharing policies. Among unenrolled farmers, we generally find a large reduction in water quality benefits and cost effectiveness due to non-additional adoption and slippage. It is imperative to consider these behavioral factors when evaluating the possibility of extending the cost sharing program to new groups of farmers. In comparison, the cost share funding allocated to enrolled farmers has relatively smaller differences between the baseline and behavioral scenarios. While the overall behavioral abatement per acre is still generally lower than what would be calculated in the baseline scenario, additional cover crop adoption is high and substantial environmental benefits exist. Of course, behavioral considerations are still important for the enrolled group, but the potential for crowding-in of conservation tillage helps to offset the loss of vegetative cover, resulting in substantially higher abatement per acre and abatement per dollar in this group of farmers. Nonetheless, we find the qualitative result to be the same for both groups—namely, that behavioral considerations are necessary to more accurately evaluate the water quality impact of cost sharing policies.

7.2 Policy simulation results at regional watershed level

In this section, we discuss the policy simulation results that translate the econometric analysis from the survey sample to the population level for the state of Maryland. The inverse sampling weights provided 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,

(15) $$Q_k^g = \sum_j^{J_g} \Delta q_{kj}^B \cdot w_j \text{ for farmer } j \text{ in group } g$$

As before, $B = \{D, I, S, O\}$ indicates the behavioral response of direct effect, indirect effect, slippage effect and overall effect, respectively. To find the cost associated with obtaining this total quantity of abatement, we utilize the abatement per dollar spent calculated for each farm from equation (13), a_{kj}. The estimated total cost, T_k^g, for achieving the total quantity of abatement of pollutant k in the state of Maryland is then calculated as:

(16) $$T_k^g = \sum_j^{J_g} \left(\left(\frac{1}{a_{kj}} \right) \cdot \left(\Delta q_{kj}^B \cdot w_j \right) \right) \text{ for farmer } j \text{ in group } g,$$

which, after combining with equation (13), simplifies to

$$T_k^g = \sum_j^{J_g} \left(e_j \cdot w_j \right).$$

(17)

These results are shown in Table 5. Columns [1] and [2] show the total quantity of abatement for the population of enrolled and unenrolled farms, respectively. The total cost share funding required to achieve these levels for each group, T_k^g, is shown in the column heading.

The total abatement of nitrogen obtained due to enrollment in cover crop cost sharing is estimated to have been approximately 1.33 million pounds after accounting for non-additionality, indirect effect and slippage effect. This is in contrast to an estimate of about 1.5 million pounds when behavioral response is not considered. As expected, the baseline program evaluation scenario overstates the abatement obtained, by approximately 12 percent—but perhaps more interestingly the indirect effect and slippage effect more or less cancel each other out among enrolled farms. That is, the beneficial effect of crowding-in of conservation tillage for nitrogen abatement is erased due to lost vegetative cover. In contrast, crowding-in of conservation tillage has relatively larger effects on abatement of phosphorus and sediment, given the effectiveness of this tillage method at reducing erosion. Surprisingly, we find that the overall behavioral scenario for statewide abatement is *larger* than the baseline abatement—by 88 percent and 72 percent, respectively for phosphorus and sediment. Intuitively, this result arises not only from the fact that conservation tillage is particularly effective at phosphorus and sediment abatement, but also from the fact that cover crops primarily target nitrogen abatement. Thus, the baseline scenario will tend to understate the potential phosphorus and sediment benefits of the program, by ignoring the crowding in of private investment in other practices.

The total cost of achieving this level of abatement at the base cover crop payment of $45 per acre is estimated to have been about $10.2 million[24], which is the same for all pollutants. Dividing total cost by total abatement, T_k^g/Q_k^g, leads to an implied average costs of abatement for each pollutant in the state through the cover crop cost sharing program. Average statewide costs for nitrogen abatement obtained through enrolled farmers increased by about 12% after accounting for nonadditional adoption, indirect effects and slippage (from $6.80 per pound to $7.64 per pound). In contrast, given the results described above the cost of phosphorus and sediment abatement *decreased* by 47% and 42%, respectively, following consideration of behavioral responses, particularly crowding-in of conservation tillage. The reduction in average statewide costs for phosphorus and sediment is due to the relatively larger effect that the conservation tillage practice has on phosphorus and sediment runoff in comparison to nitrogen.

Turning to the currently unenrolled farmers, the statewide level results should be interpreted as the potential abatement obtainable from expanding the cover crop program to include farmers who do not yet participate. The estimated total statewide cost of $18.8 million assumes that these farmers can be incentivized to join the program at current cost share rates. However, estimated abatement levels account for differential levels of additionality and varying indirect and slippage effects among the unenrolled group. Results for this group are shown in column [2] of Table 5.

[24] This estimate is smaller than the actual MACS budget in 2009 and 2010 (approx. $19 million in 2009, and $17 million in 2010) partly because MACS offers additional incentives over and above the $45 per acre base payment for early planting and the use of certain types of cover crops.

Despite the smaller average size of the unenrolled farms, the potential abatement obtainable from this group is higher than the abatement obtained from enrolled farms. This is due to the greater number of unenrolled farms in the state. Nonetheless, the percent of additional abatement is lower for unenrolled farms in comparison to the enrolled group. For example only about 81 percent of nitrogen abatement is additional (2.32 million pounds out of 2.87 million pounds in the baseline scenario). This is partly due to the fact that many unenrolled farms already use cover crops without incentive payments. More importantly, after considering the slippage effect, total overall nitrogen abatement obtainable is a further 38% lower than in the direct scenario that does not consider the possibility of other behavioral responses, and full 50% lower than in the baseline scenario (1.43 million pounds out of 2.37 million pounds without considering behavioral response). While indirect effects still play a positive role among the unenrolled, the potential negative effect of slippage is substantially larger among this group. For this reason, statewide abatement of all three pollutants declines after considering all behavioral responses, but the negative effects caused by lost vegetative cover and non-additional adoption turn out to be largest for nitrogen.

After considering the total cost of achieving these gains at $45 per acre ($18.8 million), the average cost of additional nutrient abatement in the state from extending the cover crop cost sharing program is found once again by dividing total cost by total abatement, T_k^g/Q_k^g. Average statewide costs of abatement for each pollutant substantially increase when accounting for expected farmer behavioral responses to cost sharing among the unenrolled group. For example, the average cost of nitrogen abatement increases by over 100%, from $6.56 per pound to $13.16. Similar cost increases are observed for phosphorus and sediment, however it is important to note that the cover crop program does not primarily target these pollutants.

The statewide estimates suggest that efforts to expand the cover crop program to currently unenrolled farmers will be less cost effective, since it would likely require enrolling non-additional acres and unintentionally reducing acreage that is currently in vegetative cover such as hay or pasture. The targeting of unenrolled farmers to meet stricter water quality standards and TMDL goals for Maryland will be much costlier than standard models based on implementation costs imply.

Once again, it is important to acknowledge the uncertainty around these estimates, due to the heterogeneity in Maryland farms and reflected in the bootstrapped 95% confidence intervals. For this reason, we do not emphasize the specific abatement cost numbers, but rather the overall trend toward higher statewide costs after considering the behavioral response of farmers to cost sharing incentive payments, particularly for the unenrolled group. This is particularly policy relevant given that higher cost share payments may be needed to incentivize this group to enroll, and such higher payments would only increase the potential for slippage and non-additional enrollment.

As a robustness check, we estimate the econometric model and subsequent water quality effects for a more subset of the sample that is more homogeneous, in which farms without annual crops are excluded. In practice this excludes farms with only hay and pasture, and no corn, soybeans, or small grains. This results in a sample of 331 farmers, with a smaller number of farmers in the unenrolled group. Results are shown in tables A3 and A4 of the appendix. The patterns of abatement in the various policy scenarios are qualitatively the same, but two differences in the magnitude of results are notable. First, while the additionality of the cover crop program is still quite large, self-selection plays a larger role among this sub-sample of farmers, particularly among enrolled farmers. The implied marginal cost of nitrogen abatement at the statewide level increases by 25 and 36 percent for the enrolled and unenrolled group, respectively, after considering non-additional enrollment (in comparison to 8 and 23 percent in the full sample). Second, slippage is substantially larger in the enrolled group for this sub-sample in comparison to the full sample. This is because the counterfactual estimates of what vegetative cover would have been on these farms in the absence of cost sharing is substantially larger when using a more homogeneous group of farms. While it is not clear that the smaller sample size is preferred—since farms with only hay and pasture make up a non-negligible share of farms in the study region—this clearly suggests that the potential problem of slippage, and its effects on water quality, should not be ignored among both the enrolled and unenrolled groups of farmers.

8. 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 baseline assumption of perfect additionality used in the existing literature with a more realistic scenario in which behavioral responses to cost share payments are considered. These behavioral responses include the non-additionality of incentive payments due to endogenous enrollment, indirect effects of crowding in or out of other conservation practices, and slippage effects.

We find that the baseline scenario is highly optimistic, especially when considering the possibility of expanding the cost sharing program to farmers currently not enrolled. Our results are consistent with previous estimates (Mezzatesta, Newburn and Woodward, 2013; Claassen and Duquette 2013) showing that the additionality for the cover crop program is high—with 81 to 93 percent of statewide nitrogen abatement attributable to the direct effect of enrollment. At the state level, this translates to an increase of average marginal abatement costs of 8 percent and 23 percent among the enrolled and unenrolled groups, respectively. However, we find that the potential water quality impacts of the indirect effect on conservation tillage and the slippage effect are very large. Among enrolled farmers, the beneficial effect of crowding in of conservation tillage due to the incentive payment is mostly negated by the loss of vegetative cover due to payments for working land practices. The positive indirect effects on abatement are particularly large in magnitude for phosphorus and sediment, for which conservation tillage plays a more decisive role than cover crops. Among unenrolled farmers the estimated loss of vegetative cover due to cost share payments is larger than it is in the enrolled group, and has the potential to negate the nearly half of water quality gains from extending cost sharing to this group.

There is considerable heterogeneity in the water quality impacts of cost share payments, and the characteristics of the unenrolled group make them particularly susceptible to losses of environmental benefits through slippage. We find these qualitative results to be consistent across different samples of our data, including a smaller and more homogeneous group of farmers that have planted at least some acreage in annual crops such corn and soybeans. The uncertainty and variability around the abatement estimates due to indirect effects and slippage effects indicates that these estimates should not be interpreted as precise predictions. However, they demonstrate the large potential cost of ignoring these known behavioral effects when evaluating cost sharing policies.

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.

Figures

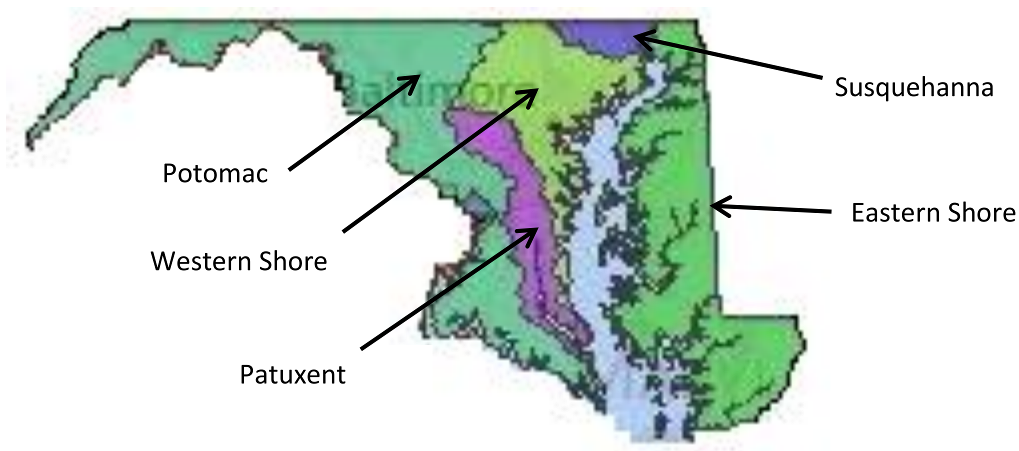


Figure 1. Major river basins in Chesapeake Bay watershed in Maryland

Tables

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	303	49	93	24.0%	32.2%
Conservation tillage	228	191	26	55.7%	54.9%

N=445

Table 2. Descriptive Statistics for Farmer Survey Data

Variable	Mean	Std. Dev.	Min	Max
Distance to the nearest water body (miles)	0.45	1.4	0	11
Proportion income from farming	0.55	0.4	0	1
Missing data for "Proportion income from farming" (1=missing)	0.04	0.2	0	1
50 or more acres in corn, soybeans, or small grains (1 = yes)	0.51	0.5	0	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
Log operating acres	5.15	1.6	0.69	9.19
Highest level of education attained Did not graduate high school	0.15	0.4	0	1
High school grad or some college	0.60	0.5	0	1
Completed college or graduate school	0.25	0.4	0	1
Log cattle (dairy or beef)[a]	1.69	2.2	0	7.90
No cattle (1 = no cattle)	0.58	0.5	0	1
Log horses or sheep[a]	0.53	1.1	0	5.33
No horses or sheep (1 = no horses or sheep)	0.75	0.4	0	1
Erosion reduction cost ($ / pound reduced) Cover crops	0.020	0.013	0.004	0.054
Conservation tillage	0.009	0.006	0.002	0.024

N=445

[a] When observations have no livestock, the undefined log values are coded to zero.

Table 3. Estimated Acreage Share in Practice Type With and Without Enrollment in Cover Crop Cost Sharing Program

	Enrolled (N=93)	Unenrolled (N=352)
	[1]	[2]
Cover crop		
Without Enrollment	0.014	0.034
With Enrollment	0.223	0.255
Direct Effect	0.209***	0.222*
	(0.072)	(0.146)
Conservation tillage		
Without Enrollment	0.234	0.141
With Enrollment	0.425	0.244
Indirect Effect	0.191	0.102
	(0.161)	(0.167)
Vegetative cover		
Without Enrollment	0.239	0.430
With Enrollment	0.190	0.290
Slippage Effect	-0.050	-0.140*
	(0.136)	(0.094)

Significant at *** 1% level, ** 5% level, * 10% level.
Standard errors in parentheses calculated by the Delta Method

Table 4. Average Abatement per Acre and Abatement per Dollar Spent Due to Enrollment in Cover Crop Cost Sharing Program

		Enrolled		Unenrolled	
		Abatement per operating acre	Abatement per thousand dollars ($45 award)	Abatement per operating acre	Abatement per thousand dollars ($45 award)
		[1]	[2]	[3]	[4]
Nitrogen (pounds)					
Baseline effect [a]	[a]	1.58 [0.98 , 2.54]	156.5 [143.8 , 170.4]	1.65 [0.23 , 3.99]	144.7 [136.6 , 153.6]
Direct effect	[b]	1.47 [0.11 , 2.05]	146.4 [14.7 , 161.6]	1.42 [0.01 , 3.79]	126.1 [4.5 , 141.3]
Indirect effect	[c]	0.35 [-0.55 , 0.76]	35.5 [-62.7 , 93.6]	0.18 [-0.14 , 0.82]	16.6 [-131.9 , 264.6]
Slippage effect	[d]	-0.37 [-2.26 , 0.9]	-38.5 [-284.9 , 106.9]	-0.92 [-2.06 , 0.82]	-94.0 [-3914.1 , 278.7]
Overall effect	[e]	1.45 [-1.38 , 2.82]	143.5 [-161.5 , 284]	0.68 [-1.57 , 3.81]	48.8 [-4957.6 , 366.7]
Phosphorus (pounds)					
Baseline effect [a]	[a]	0.03 [0.02 , 0.05]	3.00 [2.77 , 3.27]	0.04 [0 , 0.09]	3.13 [2.97 , 3.32]
Direct effect	[b]	0.03 [0 , 0.04]	2.81 [0.27 , 3.1]	0.03 [0 , 0.08]	2.74 [0.1 , 3.06]
Indirect effect	[c]	0.04 [-0.07 , 0.09]	4.28 [-8.77 , 11.69]	0.02 [-0.02 , 0.11]	2.23 [-22.29 , 41.8]
Slippage effect	[d]	-0.02 [-0.11 , 0.05]	-1.51 [-12.95 , 5.68]	-0.06 [-0.12 , 0.05]	-5.52 [-287.29 , 15.8]
Overall effect	[e]	0.06 [-0.12 , 0.13]	5.59 [-12.55 , 14.36]	0.00 [-0.11 , 0.15]	-0.55 [-293.59 , 30.22]
Sediment (tons)					
Baseline effect [a]	[a]	0.02 [0.01 , 0.03]	2.06 [1.72 , 2.41]	0.03 [0 , 0.07]	2.62 [2.46 , 2.8]
Direct effect	[b]	0.02 [0 , 0.03]	1.93 [0.21 , 2.26]	0.03 [0 , 0.07]	2.30 [0.07 , 2.58]
Indirect effect	[c]	0.03 [-0.05 , 0.07]	3.07 [-6.42 , 8.2]	0.02 [-0.02 , 0.09]	1.96 [-22.05 , 40.08]
Slippage effect	[d]	-0.01 [-0.09 , 0.04]	-1.39 [-11.11 , 5.19]	-0.05 [-0.11 , 0.05]	-5.21 [-269.84 , 16.66]
Overall effect	[e]	0.03 [-0.09 , 0.1]	3.61 [-11.24 , 11.99]	0.00 [-0.1 , 0.12]	-0.95 [-429.07 , 29.77]

Bootstrapped 95% confidence intervals in brackets based on 500 bootstrap iterations.

[a] The baseline effect assumes complete additionality, no indirect effect, and no slippage effect.

Table 5. Statewide Total Abatement and Costs Due to Enrollment in Cover Crop Cost Sharing Program

		Enrolled	**Unenrolled**
		[1]	[2]
Total cost of achieving abatement levels ($ millions)		10.2	18.8
Nitrogen (thousands of pounds)			
Baseline effect [a]	[a]	1,498 [802 , 2575]	2,873 [603 , 7592]
Direct effect	[b]	1,393 [96 , 2148]	2,329 [23 , 6765]
Indirect effect	[c]	360 [-499 , 812]	392 [-467 , 1688]
Slippage effect	[d]	-420 [-2224 , 765]	-1,288 [-2659 , 869]
Overall effect	[e]	1,333 [-1133 , 2847]	1,432 [-1767 , 7201]
Phosphorus (thousands of pounds)			
Baseline effect [a]	[a]	28.0 [15.1 , 46.8]	59.9 [12.4 , 160.4]
Direct effect	[b]	26.0 [1.8 , 39.5]	48.7 [0.6 , 142.1]
Indirect effect	[c]	43.3 [-68.2 , 97.1]	50.9 [-72.2 , 230]
Slippage effect	[d]	-16.6 [-96.5 , 32.2]	-80.9 [-167.9 , 55.6]
Overall effect	[e]	52.7 [-103.9 , 125.7]	18.8 [-156 , 296]
Sediment (thousands of tons)			
Baseline effect [a]	[a]	17.9 [9.4 , 29.5]	42.3 [8.5 , 114.4]
Direct effect	[b]	16.6 [1 , 26]	34.6 [0.3 , 104.2]
Indirect effect	[c]	29.7 [-42.1 , 70.9]	36.8 [-49.4 , 178.2]
Slippage effect	[d]	-15.4 [-77.2 , 28.6]	-67.0 [-145 , 41.7]
Overall effect	[e]	30.8 [-75.3 , 86.7]	4.4 [-128 , 207]

Bootstrapped 95% confidence intervals in brackets based on 500 bootstrap iterations.

[a] The baseline effect assumes complete additionality, no indirect effect, and no slippage effect.

Chapter 4: Conclusion

1. Lessons learned

The United States has thus far made limited policy efforts to reduce NPS pollution in its rivers, streams, and coastal waters. Over time, emphasis has shifted from voluntary programs that seek to encourage land retirement (e.g. CRP, then CREP) to voluntary programs that encourage the adoption of working-land conservation practices (e.g. EQIP, MACS), including the expanded use of cover crops. However, in the Chesapeake Bay and many other U.S. waterways, voluntary conservation programs in agriculture coupled with regulation of point sources through the Clean Water Act have simply not been sufficient to achieve water quality goals.

For this reason, the EPA has implemented the Chesapeake Bay TMDL in order to incorporate agriculture, storm water runoff, septic systems, and other nonpoint sources in a watershed-scale effort to reach water quality standards by 2025. The enactment of this TMDL turns a new page in U.S. policy efforts to reduce NPS water pollution, and will likely have wide-reaching consequences for NPS pollution from agriculture in the United States. In this context, my research in this dissertation speaks to several larger policy questions, including: (i) How well does conservation cost sharing work as a policy instrument for addressing NPS water pollution, and can it therefore be used to help meet the TMDL? (ii) Are there ways in which the effectiveness of conservation cost sharing can be improved and, if so, how could this be implemented? (iii) Finally, what lessons can Maryland's experience with conservation cost sharing provide when considering alternative policy approaches to achieving the TMDL for NPS pollution from agriculture, most notably water quality trading? I will treat each of these in turn, and conclude with a reflection on the applicability of these results to other regions.

1.1 Voluntary cost sharing and the TMDL

To what degree can voluntary cost sharing programs help achieve the goals set forth Chesapeake Bay TMDL? Will voluntary programs be sufficient to achieve these goals? Since the EPA provides subsidies to publicly-owned treatment works (POTWs), it is conceivable that expanded agricultural cost sharing could be used as a primary policy instrument to work toward the TMDL. But what would expanding voluntary cost sharing for conservation practices such as cover crops actually accomplish? My dissertation research speaks directly to these questions.

(i) Effect of cost sharing on farmer behavior

In Chapter 2 of this dissertation, I have shown that the additionality of cover crop incentive payments is generally quite high. This is consistent with previous research on additionality of cover crop cost sharing programs, including Mezzatesta, Newburn and Woodward (2013), Claassen and Duquette (2013), and Lichtenberg & Smith-Ramirez (2011). When considering only the direct effects on cover crops, I find approximately 92% additionality among Maryland farmers who have enrolled in this program. Most relevant for the TMDL, my research expands on the previous literature by estimating the expected additionality of extending the cover crop program to farmers who are not yet enrolled. Additionality is expected to be similar for these unenrolled farmers, at approximately 91%. Therefore, when considering only the direct effect on cover crop adoption among the unenrolled, incentive payments result in substantial reductions of nitrogen, phosphorus and sediment downstream, in comparison to the status quo in which these farmers remain unenrolled in the program.

More importantly, Chapter 2 of this dissertation establishes the importance of a further behavioral consideration in the analysis of cost sharing programs: namely, the indirect effects of payments for one practice on other complementary or substitute practices. Previous economic literature has shown that correlation in conservation practice adoption exists, and agronomic literature has provided certain theoretical reasons to expect patterns of substitution or complementarity in working-land practices. My research indicates that payments for cover crops results in crowding-in of private conservation investment in the practice of conservation tillage, leading to increases in this tillage method of approximately 69 and 54 percent among enrolled and unenrolled farmers, respectively. Because conservation tillage substantially reduces soil erosion in comparison to conventional tillage methods, this indirect effect substantially improves the phosphorus- and sediment-abatement effectiveness of the cover crop program, providing a further benefit toward meeting TMDL goals. However, because conservation tillage also relies heavily upon herbicides to burn down weed growth prior to planting, the overall effect on environmental health is not clearly answered by this dissertation. In cost sharing programs, as in economics in general, there is no such thing as a free lunch.

Chapter 3 of this dissertation directly turns to the question of the water quality impacts of cost sharing programs. This research incorporates insights from the first part of the dissertation by focusing on the practice for which indirect effects are statistically significant (i.e. conservation tillage), and then broadens the scope of behavioral responses to include slippage. The possibility of slippage in cost sharing programs—or the reduction of vegetative cover in response to cropland incentive payments—had been demonstrated both theoretically (Khanna et al. 2002; Lichtenberg 2004a) and empirically (Lichtenberg and Smith-Ramirez, 2011) in previous literature. However, the water-quality effect of slippage in cost sharing programs had not been empirically studied. In addition, the overall impact of cost sharing programs on water quality is not well understood, nor has there been an exploration of the relative importance of non-additional enrollment, indirect effects, and slippage effects in terms of the common currency of pollutant abatement.

My research indicates a substantial loss of vegetative cover as a result of the cost sharing program, corroborating the empirical results of Lichtenberg & Smith-Ramirez (2011). Most relevant for the TMDL, it shows that the potential for slippage is particularly high among currently unenrolled farms. When estimating the impact of the cover crop program on nitrogen, phosphorus and sediment abatement, this research shows that accounting for behavioral responses leads to higher abatement costs in comparison to baseline policy evaluation scenarios which assume perfect additionality. However, the difference in costs is relatively small: with an 8 and 23 percent increase in abatement costs for the enrolled and unenrolled group, respectively, in comparison to a baseline program evaluation approach.

Thus, the additionality achieved by cost sharing programs is affected by three factors: self-selection itself, indirect effects on other practices due to complementarity or substitution, and slippage. My research shows that the indirect effects of the cover crop program are beneficial, but these benefits are either cancelled out by slippage (among enrolled farms) or completely overshadowed by slippage (among currently unenrolled farms).

(ii) Effect of cost sharing on NPS pollution abatement

More importantly, Chapter 3 of this dissertation goes further than previous studies by estimating water quality impacts. That is, I express the magnitude of self-selection, indirect effects, and slippage effects in terms of nitrogen, phosphorus, and sediment abatement in the Chesapeake Bay, rather than limiting the analysis to behavioral changes on the farm.

Each of these three behavioral responses have important effects on abatement and expected costs. Since the additionality (direct effect) of the cover crop program is relatively high, self-selection has only a small impact on the abatement and cost effectiveness of the program. Thus, analyses that only consider the effect of nonrandom enrollment will tend to be optimistic in their assessments of the cover crop program. However, as shown above, indirect effects and slippage effects play a large role. In terms of indirect effects, the crowding-in of private investment in conservation tillage is larger among already-enrolled farms. Throughout Maryland, nitrogen abatement from the cover crop program increases by approximately 26 and 17 percent among enrolled and unenrolled farmers, respectively, due to the crowding-in of conservation tillage. Even higher gains from crowding-in are expected for phosphorus and sediment abatement, given that conservation tillage is more effective at reducing runoff of these pollutants in comparison to nitrogen.

In contrast, the loss of vegetative cover is expected to be more substantial among unenrolled farmers. Nitrogen abatement is expected to decrease by approximately 30 and 55 percent among enrolled and unenrolled farmers, respectively, due to slippage, in comparison to a scenario that only considers self-selection in enrollment. When combining the slippage effect with the crowding-in effect, among enrolled farmers, the nitrogen benefits of crowding-in (of conservation tillage) are cancelled out by slippage; but among unenrolled farmers, the negative effects of slippage on nitrogen abatement are three times the magnitude of the beneficial effect of crowding-in.

(iii) To what degree would expanding cost sharing help achieve the TMDL goals?

The water quality simulation results in this dissertation point to both the advantages and limitations of voluntary conservation policy to date. When focusing only on the direct effect of cover crop cost sharing on cover crops, there are substantial gains from expanding the program to currently unenrolled farms. By using the inverse sampling weights to scale up to the population level, approximately 2.3 million pounds of additional nitrogen abatement, and about 48 thousand pounds of additional phosphorus abatement are attainable across the state of Maryland. However, when considering indirect effects on other practices and the slippage effect, the expansion of cover crop cost sharing becomes a less favorable prospect—only 1.4 million pounds of additional nitrogen abatement and 19 thousand pounds of phosphorus abatement are expected by expanding the program to unenrolled farms, at an average abatement cost of $13.16 and about $1000 per pound, respectively.

To put these abatement quantities in perspective, Table 1 shows the Chesapeake Bay Program's estimates of nitrogen and phosphorus runoff arising from nonpoint agricultural sources in Maryland as of 2013, as well as the levels of runoff targeted to meet TMDL goals by 2025. Comparing the 2013 estimates with the 2025 targets reveals the additional abatement required from nonpoint agricultural sources. The additional N abatement required is about 1.97 million pounds; the additional P abatement is about 112 thousand pounds. In the context of these TMDL goals—and after considering self-selection, indirect effects, and slippage effects—expanding cost sharing to *all* currently unenrolled Maryland farmers would achieve 73% of the TMDL N target for unregulated agricultural sources, and only 17% of the TMDL goal for phosphorus.

On the one hand, this shows the beneficial potential of expanding the cover crop program in Maryland, particularly for nitrogen. If nearly three-quarters of the TMDL goal for unregulated agricultural sources can be achieved by expanding the cover crop program, at an average cost of $13.16, this seems like a wise policy decision. However, the cost estimate assumes that *all* unenrolled farmers can be incentivized to enroll at the current base cost sharing rate of $45 per acre, a potentially heroic assumption. To the extent that higher subsidy levels are required, the average abatement costs will increase. Moreover, the TMDL goal for phosphorus is far from being achieved by expansion of the cover crop program. And even assuming complete enrollment at $45 per acre, the average abatement cost is relatively high, at about $1000 per acre, after considering slippage effects. This suggests to policymakers that great caution is due when expanding the cover crop program to unenrolled farms, especially those with large existing stands of vegetative cover such as hay or pasture. Wider adoption of cover crops in Maryland will likely not achieve the state's TMDL agricultural NPS goals for nitrogen, and will not come close to achieving TMDL goals for phosphorus.

(iv) Variability and uncertainty in cost sharing programs

Finally, it is noteworthy that the policy simulation results showed that the incorporation of farmer behavioral response in the model led to a substantial increase in the variability and uncertainty of water quality benefits. The bootstrapped 95% confidence interval around the baseline program evaluation approach is 0.8 to 2.58 million pounds of nitrogen abatement in Maryland achieved by cover crop cost sharing. However, after considering nonrandom enrollment, estimated abatement not only falls but the potential range of outcomes also widens: the bootstrapped 95% confidence interval is .096 to 2.148 million pounds of abatement. This of course translates to a wide range of possible costs of additional abatement. Moreover, after considering both indirect effects and slippage, the 95% confidence intervals widen even further and indeed encompass zero, reflecting a great deal of uncertainty in the water quality gains from cost share payments.

This variability and uncertainty in estimated abatement stems from two primary sources. One is the randomness in measurement. Due to the relatively small sample size in the farmer survey, the precision of estimates falls as I attempt to capture a wider range of farmer behavior. The other source of variability is farmer heterogeneity itself, both observed and unobserved. Observed heterogeneity—based on farmer location, farm characteristics such as size or farm type, and farmer characteristics such as education—affects the abatement potential of a given farm, and can be distinguished from the randomness of measurement. However, *unobserved* heterogeneity is not distinguishable from randomness, absent a panel dataset, as both are contained in the error terms of the system of equations.

However, the policy implications of this variability are twofold, depending on the variability's source. Variation due purely to randomness represents uncertainty in the effectiveness of cost sharing, sounding a note of caution regarding voluntary cost sharing programs. If the gains from expansion of conservation cost sharing are highly uncertain, other avenues should be pursued by a risk-averse policymaker and public. In contrast, variation due to farmer heterogeneity represents both a challenge and an opportunity. To the extent that heterogeneity can be observed, policymakers may improve cost sharing programs by targeting additional funds where they will have the largest behavioral and water quality impact. Moreover, heterogeneity implies the existence of gains from trade in potential water quality trading programs, and this occurs whether the source of heterogeneity is observed or unobserved (to the policymaker). That is, trading is only feasible when there is heterogeneity since gains from trade are present only when agents have different marginal abatement costs. Cost sharing program administrators do not observe the hidden information relating to the heterogeneous marginal costs of abatement, and therefore are unable to take advantage of unobserved heterogeneity. But water quality trading programs can elicit this hidden cost information through farmers' willingness-to-accept in the market. To these two potential opportunities—targeting of cost sharing, and water quality trading—I now turn.

1.2 Improving voluntary cost sharing programs

One method of improving the effectiveness of cost sharing programs is through better targeting of funds to where they will have the largest water quality impact. When considering the targeting of voluntary incentive payments, the range of behavioral responses identified in this dissertation certainly presents a challenge. Behavioral variation—including non-additional adoption, indirect effects, and slippage—combines with other sources of farm-level heterogeneity to produce a range or distribution of marginal abatement costs achievable through cost sharing programs.

The identification of common features distinguishing the low-cost from high-cost farmers is necessary for targeting of cost sharing programs. These distinguishing features must be observable for targeting to be implemented in practice, and include geographic location (river basin or sub-basin), farm size, farm topography, farm type, as well as differences in cover crop planting and implementation that influence abatement. The MACS program already targets cost share payments to some extent by providing additional bonuses to farmers for various reasons. In 2016, these factors include rewarding those who plant early, plant in fields where manure was applied in the spring, plant rye, and/or plant in a field that was previously corn or tobacco. Together, these bonuses can increase the incentive payment to a maximum of $90 per acre.

Targeting could be potentially be expanded to include other observable characteristics that have been identified to influence abatement and cost effectiveness. For example, farmers in certain geographic regions could be incentivized to enroll through bonuses similar to those already provided by MACS.[25] If farm topography is shown to influence effectiveness, target bonuses could also be awarded for cover crops planted on fields with steep or moderate slopes. Other target bonuses are conceivable as well, for example for farms with a certain quantity of animals, or at a certain proximity from surface water bodies.

Behavioral sources of variation are, in principle, not immediately observable to the policymaker. However, to the extent that additionality, indirect effects, and slippage effects are correlated with observable farm and farmer characteristics, targeting could also take advantage of the behavioral responses to cost sharing identified in this dissertation. For some farmers—those who exhibit high additionality, a crowding-in of conservation tillage, and low amounts of slippage—the marginal abatement costs associated with cost sharing are very low indeed. For other farmers, who exhibit the opposite characteristics, marginal abatement costs can be very high. By combining behavioral characteristics with observable farm- and farmer-level characteristics, substantial gains from targeting cost sharing funds are likely available.

Using the econometric model in this dissertation, an efficient allocation of cost sharing resources can be modeled by ranking the marginal costs of abatement from least- to highest-cost, and proceeding with cost share incentive payments until a given budget is exhausted. Such a ranking would consider not only geographic information and observable farm characteristics that affects pollution abatement costs, but also farmer characteristics that influence the behavioral response to environmental incentive

[25] Note that in previous years MACS did provide an enrollment bonus to farmers in certain “priority watersheds”. However, in 2016 this bonus is not available.

payments. Even within identifiable groups—such as the river basin in which a farm is located—the abatement levels and costs vary. Identifying the distribution of abatement costs for enrolled and unenrolled farms within these river basins will be useful to policymakers seeking to target limited cost share funds. While the sampling weights provided by MASS are intended to scale up to the state-level (as opposed to the river basin level), comparisons between the survey and the 2012 Census of Agriculture suggest that the survey is representative of Maryland agriculture at the level of the major river basins of the Eastern Shore, the Potomac, and a combination of the Western Shore, Susquehanna, and Patuxent basins. This suggests that estimating gains from better targeting represents a potentially fruitful avenue of future research using the econometric model presented in this dissertation.

1.3 Implications for water quality trading

Due to the hidden nature of a farmer's individual marginal cost information, targeting of cost share funds based on unobserved heterogeneity is not feasible. However, substantial efficiencies may be gained from taking advantage of such differences in abatement cost. Certain mechanism designs have the feature of eliciting the hidden cost information from agents through their willingness-to-accept in a market. Water quality trading programs are one such mechanism that is being considered as either a supplement or a substitute for cost sharing in the context of the Chesapeake Bay TMDL.

Heterogeneity itself is important in determining the feasibility and potential gains from water quality trading. Indeed, trading only occurs when heterogeneity exists, since gains from trade are present only when participants in the market have different valuations—in this case, different marginal abatement costs. However, most empirical studies evaluating the possibility of water quality trading have not been able to consider farm-level marginal abatement costs. For example, Hanson and McConnell (2008) use statewide incentive payments of $20 and $30 per acre, along with flat 15% and 30% nitrogen reduction efficiencies (thus resulting in four scenarios). They also assume a 20% charge for administering the program. Thus, they are able to account for some variation in program costs, but no variation in farmer response.

The econometric model developed in this dissertation can be used to simulate the gains from trade available between farmers with different marginal abatement costs, as well as between, for example, high-abatement-cost property developers and low-abatement-cost farmers in Maryland. Unlike previous literature, this would account for farm-level heterogeneity in the cost of abatement by cover crops, estimating the hidden information of abatement costs through econometric analysis of the existing cost sharing program.

Several trading scenarios can be analyzed, to better understand the tradeoffs associated with different water-quality trading policy choices. For example, gains from trade could be estimated *within* river basins (Eastern Shore, Potomac, and Patux./Susque./Western), in comparison to gains from trade across *all* river basins in Maryland. What are the costs of restricting trade to certain geographic areas? Similarly, tradeoffs exist between expected water quality benefits and expected trading activity under different baseline requirements (Just and Horowitz, 2013; Ribaudo and Savage, 2014). If trading is limited only to farms who are not enrolled in MACS—or even farms without cover crops—the additional water quality benefits may be more certain, but trading activity may be decreased due to limiting the population of eligible market participants. In contrast, trading activity may increase if all Maryland farmers can participate, but additional water quality benefits would likely decrease as many of these farms have already adopted cover crops, along with other conservation practices. Moreover, water quality trading programs—like voluntary cost sharing programs—are also subject to the problem of slippage, i.e. some farmers that did not have crop acreage may plant crops in order to be able to participate in trading markets. What are the associated reductions in water quality benefits? Future work using the econometric model presented in this dissertation can help answer these questions.

2. Applicability of results to other regions

This dissertation has relied on data from farmers in Maryland, a state which is characterized by variability in both its production conditions and farm types. To what extent are these results generalizable to different regions of the United States? Since the Chesapeake Bay TMDL may serve as a model for other watersheds, this is an important question for researchers and policymakers alike.

Given the voluntary nature of cost share incentive payments, the issue of non-additional adoption cannot, in theory, be assumed away in any region of the country. However, in regions with fewer private benefits of cover crop adoption, the problem of non-additionality will likely be smaller in magnitude. This is because in these regions, unlike Maryland, very few farmers adopt cover crops *without* incentive payments. In the Mississippi River basin, for example, the private returns of cover crop adoption are quite different from Maryland, and self-funded cover crop adoption is extremely rare.[26] Similarly, the prevalence of slippage will also vary in different regions of the country that have production conditions that differ from those in the mid-Atlantic. Maryland's varied terrain causes many farms to maintain a substantial acreage share in vegetative cover, in order to prevent erosion on highly sloped land. In more homogeneous flat terrain, such as in the Midwest region, the potential for slippage is lower simply because almost all farming acres are already cultivated for annual crops.

The prevalence of indirect effects in other regions of the United States will depend on the specific patterns of complementarity or substitution between practices. The variable production conditions in the mid-Atlantic certainly increase the combinations of practices observed on a given farm. While this seems to imply that indirect effects will be less applicable in regions with less variability in production conditions, it is important to consider the specific conservation practices for an indirect effect is hypothesized. For the two practices with substantial correlation observed in this dissertation—cover crops and conservation tillage—the agronomic and economic complementarities do not depend on variable topography or erosion-reduction benefits. Rather, the complementarities depend upon soil fertility, suppression of weed emergence, and increased efficiency of planting in the fall (Reeves, 1994; Blum et al., 1997; SARE, 2012). For these reasons, the possibility of positive correlation in the adoption of conservation tillage and cover crops should not be ruled out in other regions of the United States.

[26] Personal correspondence with Cathy Kling, June 15, 2015.

Finally, Maryland is not alone in the United States in having a landscape characterized by varied topography, and a heterogeneous agricultural community. Moreover, the jurisdiction of the Chesapeake Bay watershed most similar to Maryland in its production conditions and variability—Pennsylvania—is also the jurisdiction that is furthest from meeting its TMDL goals for the agricultural sector. While the enforcement mechanisms of the Chesapeake Bay TMDL are still perhaps unclear, the policy response to jurisdictions that are *not* meeting water quality targets will be critically important policy question that needs to be faced, for the viability of watershed-scale NPS pollution in the future. This research can help inform policy design not only in Maryland, but also many other regions going forward.

2.1 Multiple pollutants

A related point is that different pollutants present problems in different regions of the United States. For example, phosphorus is the major contaminant of inland lakes, ponds and reservoirs, while nitrogen is seen as the primary driver of the hypoxic zone in the Gulf of Mexico (Goolsby et al., 2001).

The Chesapeake Bay TMDL targets reductions of all three different major co-pollutants by 2025: nitrogen, phosphorus, and sediment. Discharge and abatement of these pollutants is correlated, but distinct. For example, among the practices examined in this dissertation, cover crops are most efficient at reducing nitrogen runoff by preventing the leaching of nitrogen through the soil profile. However, conservation tillage and contour/strip are relatively more efficient at reducing phosphorus and sediment runoff, by limiting soil erosion throughout the growing season. For these reasons, efficiency in the abatement of one pollutant may be lost when policymakers target another pollutant alone. The econometric model developed in this dissertation can be used to explore and quantify the dollar value of these lost efficiencies.

3. <u>Review</u>

In this dissertation, I began by outlining the importance of nonpoint source (NPS) pollution on water quality in the United States, and in particular the role of agriculture. In describing the trajectory of U.S. policy on NPS pollution from agriculture, the policy emphasis shifted from voluntary land retirement programs, to voluntary working-land conservation programs, and finally to the new stage of TMDL regulation at the watershed-scale, which is still in its infancy. My research seeks to shed light on this shifting policy background—by providing a comprehensive evaluation of farmer behavioral response to voluntary incentive payments, and connecting this with a policy simulation of NPS water quality impacts.

In Chapter 2 of this dissertation, I identified the indirect effects of cost sharing policies on other non-subsidized practices, estimating the effect of crowding-in (due to practice complementarity) or crowding-out (due to practice substitution) for three working-land practices. In Chapter 3, I integrated the econometric model of cost sharing with a biophysical water quality model to show the relative importance of farmer behavioral responses in terms of NPS pollution abatement and marginal abatement costs. The policy simulation model incorporated not only self-selection and indirect effects (as shown in Chapter 2), but also was expanded to consider the potential loss of vegetative cover (i.e. slippage effects). This allowed for measurement of the dollar-value impact of each potential layer of behavioral response to cost sharing.

Chapter 4 concluded with a discussion of the implications of this research for TMDL regulations in the Chesapeake Bay watershed. Larger policy questions included the extent to which voluntary programs could help to achieve TMDL goals, whether cost sharing programs can be substantially improved through better targeting of funds, and the lessons available for water quality trading from this analysis of the cost sharing program. Ultimately, my estimates imply that voluntary cost sharing of cover crops will not be sufficient to meet Maryland's agricultural water quality goals for nitrogen, and only achieve a small fraction of the further reductions that are required for phosphorus, even if all farmers in Maryland can be incentivized to enroll. Other policy measures, such as improved targeting and water quality trading, will be needed. Farmers are a diverse group, and each farmer responds to cost sharing incentive payments differently. Behind the average results presented here, there is a distribution of behavioral responses to incentive payments. A wise policy approach will seek to benefit from this diversity in farmer NPS pollution abatement costs, as well as the heterogeneity in abatement costs among other nonpoint sources.

Tables

Table 1. TMDL Progress and Targets for NPS Agricultural Pollution in Maryland, by Major River Basin

	Nitrogen			Phosphorus		
	2013 Progress (lbs / yr)	2025 Target (lbs / yr)	% Difference	2013 Progress (lbs / yr)	2025 Target (lbs / yr)	% Difference
Eastern shore	8,824,999	7,435,245	16%	860,423	783,008	9%
Patuxent	471,930	428,599	9%	69,779	63,415	9%
Potomac	6,145,943	5,740,933	7%	475,304	456,349	4%
Susquehanna	716,585	651,043	9%	41,936	37,403	11%
Western shore	661,246	594,104	10%	59,154	54,460	8%
Total	**16,820,703**	**14,849,924**	**12%**	**1,506,596**	**1,394,636**	**7%**

Source: Chesapeake Bay Program, U.S. EPA

Appendix

Table A1. Marginal Effects for Multivariate Probit Model of Enrollment in Cost Share Programs by Practice Type

	Cost share enrollment	
	Cover crops	Conservation tillage
Distance to the nearest water body	-0.0107	-0.0161
(miles)	(0.008)	(0.010)
Proportion income from farming	0.062	0.049*
	(0.038)	(0.026)
Missing data for "Proportion income	-0.5102***	-0.2847***
from farming" (1=missing)	(0.042)	(0.026)
50 or more acres in corn, soybeans, or	0.1694***	0.034
small grains (1 = yes)	(0.037)	(0.028)
Proportion acres in slope class		
Moderate (2-8% grade)	0.0646***	0.0171
	(0.025)	(0.021)
Steep (> 8% grade)	-0.0177	-0.0968
	(0.078)	(0.071)
Log operating acres	0.03**	-0.0024
	(0.012)	(0.008)
Highest level of education completed		
High school or some college	0.0912***	0.0707**
	(0.032)	(0.031)
Completed college or graduate school	0.1565***	0.0791**
	(0.039)	(0.034)
Log cattle (dairy or beef)	0.0146	0
	(0.011)	(0.009)
No cattle (1 = no cattle)	0.0457	-0.0032
	(0.055)	(0.044)
Log horses or sheep	-0.0608***	-0.0227*
	(0.016)	(0.013)
No horses or sheep (1 = no horses or	-0.1318***	-0.0285
sheep)	(0.038)	(0.030)
Erosion reduction cost ($ / lb. reduced)		
Cover crops	0.0717	-
	(0.803)	-
Conservation tillage	-	-0.1052
	-	(1.412)
Observations	445	445

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

Table A2. Marginal Effects for Multivariate Tobit Model of Acreage Shares With and Without Enrollment in Cover Crop Cost Sharing Program by Practice Type

	Acreage share					
	Cover crops		Conservation tillage		Vegetative cover	
	With Enrollment	Without Enrollment	With Enrollment	Without Enrollment	With Enrollment	Without Enrollment
Conservation tillage cost share (1 = enrolled)	-0.0819		0.0865		-0.1097	
	(0.121)		(0.229)		(0.330)	
50 or more acres in corn, soybeans, or small grains (1 = yes)	0.0275		0.2213***		-0.2261***	
	(0.026)		(0.047)		(0.048)	
Proportion acres in slope class						
Moderate (2-8% grade)	-0.0026		0.0636*		0.0206	
	(0.015)		(0.032)		(0.038)	
Steep (> 8% grade)	-0.1058**		0.0407		-0.0542	
	(0.040)		(0.072)		(0.068)	
Log operating acres	-0.0045		-0.007		-0.031*	
	(0.008)		(0.014)		(0.019)	
Highest level of education completed						
High school or some college	-0.0341		0.0093		0.076*	
	(0.023)		(0.040)		(0.043)	
Completed college or graduate school	-0.0269		-0.0097		0.1676***	
	(0.028)		(0.049)		(0.051)	
Log cattle (dairy or beef)	-0.0001		-0.0158		0.039***	
	(0.005)		(0.013)		(0.012)	
No cattle (1 = no cattle)	-0.0022		-0.0537		-0.1248**	
	(0.025)		(0.054)		(0.056)	
Log horses or sheep	-0.001		0.0181		0.0317	
	(0.010)		(0.022)		(0.020)	
No horses or sheep (1 = no horses or sheep)	-0.0109		0.0739		-0.1018*	
	(0.023)		(0.052)		(0.055)	
Erosion reduction cost ($ / lb. reduced)						
Cover crops	0.0268	-0.0052	-	-	0.0086	-0.0226
	(0.017)	(0.007)			(0.012)	(0.016)
Conservation tillage	-	-	0.0303	0.0126	-	-
			(0.057)	(0.025)		
Lambda (covariance w/ cover crop cost share)	-0.0257	-0.0257	-0.0599	-0.0566	0.0448	-0.0133
	(0.091)	(0.034)	(0.133)	(0.071)	(0.061)	(0.103)
Lambda (covariance w/ conservation tillage cost share)	0.1108	-0.0197	-0.0713	0.0275	0.0435	0.0524
	(0.176)	(0.052)	(0.224)	(0.095)	(0.122)	(0.188)
Observations	445		445		445	

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

Table A3. Average Abatement per Acre and Abatement per Dollar Spent Due to Enrollment in Cover Crop Cost Sharing Program – Reduced Sample Using Only Farms with Annual Crops (Corn, Soybeans, and Small Grains)

		Enrolled		Unenrolled	
		Abatement per operating acre	Abatement per thousand dollars ($45 award)	Abatement per operating acre	Abatement per thousand dollars ($45 award)
		[1]	[2]	[3]	[4]
Nitrogen (pounds)					
Baseline effect [a]	[a]	1.52 [1.02 , 3.07]	158.4 [144.4 , 173.2]	1.60 [0.28 , 5.03]	145.1 [136.6 , 154.1]
Direct effect	[b]	1.21 [0.02 , 2.2]	126.8 [4.5 , 163]	1.20 [0 , 4.46]	109.9 [3.4 , 136.9]
Indirect effect	[c]	0.38 [-0.61 , 0.76]	41.7 [-68.3 , 79.7]	0.27 [-0.22 , 1.09]	26.0 [-110.2 , 168.6]
Slippage effect	[d]	-1.14 [-3.34 , 0.61]	-126.6 [-383.1 , 75.4]	-1.25 [-1.69 , 0.1]	-120.6 [-957.9 , 11.4]
Overall effect	[e]	0.45 [-2.65 , 2.52]	42.0 [-337.3 , 247.8]	0.22 [-1.53 , 4.32]	15.2 [-998.9 , 161.2]
Phosphorus (pounds)					
Baseline effect [a]	[a]	0.03 [0.02 , 0.06]	2.97 [2.73 , 3.24]	0.04 [0.01 , 0.11]	3.23 [3.07 , 3.36]
Direct effect	[b]	0.02 [0 , 0.04]	2.38 [0.09 , 3.06]	0.03 [0 , 0.1]	2.46 [0.08 , 3.03]
Indirect effect	[c]	0.05 [-0.08 , 0.09]	4.98 [-8.41 , 10.31]	0.04 [-0.03 , 0.15]	3.74 [-20.71 , 27.45]
Slippage effect	[d]	-0.05 [-0.14 , 0.03]	-5.31 [-17.75 , 3.3]	-0.08 [-0.11 , 0.01]	-7.75 [-67.37 , 0.73]
Overall effect	[e]	0.02 [-0.15 , 0.12]	2.05 [-19.92 , 12.79]	-0.01 [-0.11 , 0.18]	-1.56 [-80.56 , 12.01]
Sediment (tons)					
Baseline effect [a]	[a]	0.02 [0.01 , 0.04]	2.04 [1.65 , 2.39]	0.03 [0 , 0.09]	2.53 [2.31 , 2.74]
Direct effect	[b]	0.02 [0 , 0.03]	1.64 [0.06 , 2.18]	0.02 [0 , 0.08]	1.92 [0.04 , 2.45]
Indirect effect	[c]	0.03 [-0.06 , 0.07]	3.64 [-6.68 , 7.53]	0.03 [-0.03 , 0.13]	3.00 [-13.92 , 21.87]
Slippage effect	[d]	-0.04 [-0.12 , 0.02]	-4.74 [-14.63 , 2.75]	-0.07 [-0.09 , 0.01]	-6.46 [-48.89 , 0.56]
Overall effect	[e]	0.01 [-0.13 , 0.08]	0.54 [-15.39 , 9.62]	-0.01 [-0.09 , 0.14]	-1.54 [-58.36 , 9.42]

Bootstrapped 95% confidence intervals in brackets based on 500 bootstrap iterations.

Sub-sample using only farms with annual crops (N = 331)

[a] The baseline effect assumes complete additionality, no indirect effect, and no slippage effect.

Table A4. Statewide Total Abatement and Costs Due to Enrollment in Cover Crop Cost Sharing Program – Reduced Sample Using Only Farms with Annual Crops (Corn, Soybeans, and Small Grains)

		Total Abatement in Maryland	
		Enrolled	**Unenrolled**
		[1]	[2]
Total cost of achieving abatement levels		**$9.6 M**	**$13.8 M**
Nitrogen (thousands of pounds)			
Baseline effect [a]	[a]	1,404 [860 , 2840]	2,079 [419 , 7115]
Direct effect	[b]	1,118 [21 , 2108]	1,531 [5 , 6406]
Indirect effect	[c]	376 [-548 , 810]	385 [-461 , 1581]
Slippage effect	[d]	-1,236 [-3366 , 483]	-1,694 [-2506 , -42]
Overall effect	[e]	287 [-2821 , 2349]	280 [-2061 , 6403]
Phosphorus (thousands of pounds)			
Baseline effect [a]	[a]	26.3 [16.3 , 53.6]	43.7 [8.8 , 150.2]
Direct effect	[b]	20.9 [0.4 , 39.8]	32.4 [0.1 , 136]
Indirect effect	[c]	46.7 [-77.9 , 94.7]	60.6 [-70.9 , 205]
Slippage effect	[d]	-50.0 [-139.4 , 20.7]	-111.7 [-169.7 , -2.9]
Overall effect	[e]	17.7 [-149.3 , 117.7]	-18.7 [-176.6 , 249.8]
Sediment (thousands of tons)			
Baseline effect [a]	[a]	16.9 [10.1 , 33.4]	30.1 [6.3 , 101.9]
Direct effect	[b]	13.4 [0.2 , 25]	22.2 [0 , 92.5]
Indirect effect	[c]	32.3 [-49.9 , 69.4]	41.9 [-48.5 , 149.3]
Slippage effect	[d]	-43.2 [-120.6 , 17.3]	-87.0 [-131.6 , 0]
Overall effect	[e]	2.5 [-123 , 83.6]	-22.9 [-127.7 , 172.2]

Bootstrapped 95% confidence intervals in brackets based on 500 bootstrap iterations.

Sub-sample using only farms with annual crops (N = 331)

[a] The baseline effect assumes complete additionality, no indirect effect, and no slippage effect.

Bibliography

Albers, H., Ando, A., and Chen, X., 2008. Spatial-econometric analysis of attraction and repulsion of private conservation by public reserves. *Journal of Environmental Economics and Management* 56, 33-49.

Alexander, R., Smith, R., and Schwartz, G., 2000. Effect of stream channel size on the delivery of nitrogen to the Gulf of Mexico. *Nature* 403, 758-761.

Belmont, P., Gran, K., Schottler, S., Wilcock, P., Day, S., Jennings, C., Lauer, J.W., Viparelli, E., Willenbring, J., Engstrom, D., and Parker, G., 2011. Large shift in source of fine sediment in the Upper Mississippi River. *Environmental Science & Technology* 45, 8804-8810.

Blum, U., King, L., Gerig, T., Lehmann, M., and Worsham, A., 1997. Effects of clover and small grain cover crops and tillage techniques on seedling emergence of some dicotyledonous weed species. *American Journal of Alternative Agriculture* 12, 146-161.

Cappellari, L., and Jenkins, S., 2003. Multivariate probit regression using simulated maximum likelihood. *The Stata Journal* 3, 278-294.

Chabé-Ferret, S., and Subervie, J., 2013. How much green for the buck? Estimating additional and windfall effects of French agro-environmental schemes by DID-matching. *Journal of Environmental Economics and Management* 65, 12-27.

Claassen, R., Cattaneo, A., and Johannson, R., 2008. Cost-effective design of agri-environmental payment programs: U.S. experience in theory and practice. *Ecological Economics* 65(4) 737-752.

Claassen, R., and Duquette, E., 2013. Additionality in agricultural conservation payment programs. *Journal of Soil and Water Conservation* 68, 74A-78A.

Cooper, J., 2003. A joint framework for analysis of agri-environmental payment programs. *American Journal of Agricultural Economics* 85, 976-987.

Diaz, R., and Rosenberg, R., 2008. Spreading dead zones and consequences for marine ecosystems. *Science* 321, 926-929.

Dorfman, J., 1996. Modeling multiple adoption decisions in a joint framework. *American Journal of Agricultural Economics* 78, 547-557.

Greene, W., 2003. *Econometric Analysis (5th ed.).* Prentice Hall.

Goolsby, D., Battaglin, W., Aulenbach, B., and Hooper, R., 2001. Nitrogen input to the Gulf of Mexico. *Journal of Environmental Quality* 30(2), 329-336.

Hanson, J., and McConnell K.E., 2008. Simulated trading for Maryland's nitrogen loadings in the Chesapeake Bay. *Agricultural and Resource Economics Review* 37(2), 211-226.

Heckman, J., 1979. Sample selection bias as a specification error. *Econometrica* 153-161.

Heckman, J., and Vytlacil, E., 2007. Econometric evaluation of social programs, Part I: Causal models, structural models and econometric policy evaluation. *Handbook of Econometrics*, Volume 6B, 4779-4874.

Horowitz, J., and Just, R., 2013. Economics of additionality for environmental services. *Journal of Environmental Economics and Management* 66(1), 105-122.

Howarth, R., 2002. Sources of nutrient pollution to coastal waters in the United States: Implications for achieving coastal water quality goals. *Estuaries* 25(4), 656-676.

Khanna, M., 2001. Sequential adoption of site-specific technologies and its implications for nitrogen productivity: A double selectivity model. *American Journal of Agricultural Economics* 83, 35-51.

Khanna M., Isik, M., and Zilberman, D., 2002. Cost-effectiveness of alternative green payment policies for conservation technology adoption with heterogeneous land quality. *Agricultural Economics* 27, 157-174.

Khanna M., Yang, W., Farnsworth, R., and Önal, H., 2003. Cost-effectiveness targeting of land retirement to improve water quality with endogenous sediment deposition coefficients. *American Journal of Agricultural Economics* 85(3), 538-553.

Kling, C., Panagopoulos, Y., Rabotyagov, S., Valcu, A., Gassman, P., Campbell, T., White, M., Arnold, J., Srinivasan, R., Jha, M., Richardson, J., Moskal, L.M., Turner, R.E., and Rabalais, N., 2014. LUMINATE: linking agricultural land use, local water quality and Gulf of Mexico hypoxia. *European Review of Agricultural Economics* 41(3), 431-459.

Lacroix, A., and Thomas, A., 2011. Estimating the environmental impact of land and production decisions with multivariate selection rules and panel data. *American Journal of Agricultural Economics* 93(3), 784-802.

Lankoski, J., Lichtenberg, E., and Ollikainen, M., 2008. Point/nonpoint effluent trading with spatial heterogeneity. *American Journal of Agricultural Economics* 90(4), 1044-1058.

Lankoski, J., Lichtenberg, E., and Ollikainen, M., 2010. Agri-environmental program compliance in a heterogeneous landscape. *Environmental Resource Economics* 47, 1-22.

Laukkanen, M., and Nauges, C., 2014. Evaluating greening farm policies: A structural model for assessing agri-environmental subsidies. *Land Economics* 90(3), 458-481.

Lichtenberg, E., 2004a. Cost-responsiveness of conservation practice adoption: A revealed preference approach. *Journal of Agricultural and Resource Economics* 29, 420-435.

Lichtenberg, E., 2004b. Are green payments good for the environment? *Agricultural and Resource Economics Review* 33, 138-147.

Lichtenberg, E., and Smith-Ramirez, R., 2011. Slippage in conservation cost-sharing. *American Journal of Agricultural Economics* 93, 113-129.

Lichtenberg, E., Parker, D., and Lane S., 2012. "Best management practice use and nutrient management in Maryland: A 2010 snapshot." Center for Agricultural and Natural Resource Policy, Department of Agricultural and Resource Economics, University of Maryland, College Park, February 2012.

Lubowski, R., Plantinga, A., and Stavins, R., 2003. Determinants of land-use change in the United States 1982-1997. *Discussion Paper 03-47, Resources for the Future*, 48pp.

Lynch, L., Hardie, I., and Parker, D., 2002. "Analyzing agricultural landowners' willingness to install streamside buffers." *Working Paper, 02-01, Department of Agricultural and Resource Economics, University of Maryland, College Park.*

McFadden, D., 1979. Quantitative Methods for Analyzing Travel Behavior of Individuals: Some Recent Developments, in: D. Hensher and P. Stopher, eds., *Behavioral Travel Modelling*, Chapter 15.

Mezzatesta, M., Newburn, D., and Woodward, R., 2013. Additionality and the adoption of farm conservation practices. *Land Economics* 89, 722-742.

Rabotyagov, S., Campbell, T., Jha, M., Gassman, P., Arnold, J., Kukalova, L., Secchi, S., Feng, H., and Kling, C., 2010. Least-cost control of agricultural nutrient contributions to the Gulf of Mexico hypoxic zone. *Ecological Applications* 20(6), 1542-1555.

Rabotyagov, S., Valcu, A., and Kling, C., 2013. Reversing property rights: Practice-based approaches for controlling agricultural nonpoint-source water pollution when emissions aggregate nonlinearly. *American Journal of Agricultural Economics* 96(2), 397-419.

Rabotyagov, S., Kling, C., Gassman, P., Rabalais, N., and Turner, R., 2014. The economics of dead zones: Causes, impacts, policy challenges, and a model of the Gulf of Mexico hypoxic zone. *Review of Environmental Economics and Policy* 8(1), 58-79.

Reeves, D., 1994. Cover crops and rotations, pp. 125-172. In J. Hatfield and B. Stewart (eds.) Crops Residue Management: Advances in Soil Science. Lewis Publishers, Boca Raton, FL.

Revised Universal Soil Loss Equation 2, 2014. United States Department of Agriculture, Agricultural Research Service.

Roberts, M., and Bucholtz, S., 2005. Slippage in the Conservation Reserve Program or Spurious Correlation? A Comment. *American Journal of Agricultural Economics* 87(1), 244-250.

Roberts, M., and Lubowski, R., 2007. The enduring impacts of land retirement policies: Evidence from the Conservation Reserve Program. *Land Economics* 83(4), 516-538.

Smith-Ramirez, R., 2005. On the evaluation of conservation cost-sharing programs: An application of a Monte Carlo EM algorithm. *Doctoral dissertation, Department of Agricultural and Resource Economics, University of Maryland, College Park*.

Shortle, J., and Horan, R., 2013. Policy instruments for water quality protection. *Annual Review of Resource Economics* 5(1), 111-138.

Sullivan, P., Hellerstein, D., Hansen, L., Johannson, R., Koenig, S., Lubowski, R., McBride, W., McGrannahan, D., Roberts, M., Vogel, S., and Bucholtz, S., 2004. The Conservation Reserve Program: Economic implications for rural America. *Agricultural Economic Report, vol. 834, U.S. Department of Agriculture, Economic Research Service,* 55 pp.

Sustainable Agriculture Research and Education, 2012. *Managing Cover Crops in Conservation Tillage Systems*. Balkcom, K., Schomberg, H., Reeves, W., and Clark, A.

Train, K., 2009. *Discrete Choice Methods with Simulation (2nd ed.).* Cambridge University Press.

US Environmental Protection Agency, 2002. *National Water Quality Inventory: Report to Congress for the 2002 Reporting Cycle*. Washington, DC: Environmental Protection Agency.

US Environmental Protection Agency, 2009. *National Water Quality Inventory: Report to Congress*, 2004 Reporting Cycle. Washington, DC: Environmental Protection Agency.

US Environmental Protection Agency, 2016. Assessment and Total Maximum Daily Load Tracking and Implementation System (ATTAINS).

https://www.epa.gov/waterdata/assessment-and-total-maximum-daily-load-tracking-and-implementation-system-attains

US Forest Service, 1993. *Continued Strengthening of the Clean Water Act Reflects the Public's Concern for Clean Water*. http://www.na.fs.fed.us/spfo/pubs/n_resource/buffer/part3.htm

US Geological Survey, 2003. *Residence Times and Nitrate Transport in Ground Water Discharging to Streams in the Chesapeake Bay Watershed*. Water Resources Investigations Report 03-4035.

US Geological Survey, 2011. *Sources, Fate and Transport of Nitrogen and Phosphorus in the Chesapeake Bay Watershed: An Empirical Model.* Scientific Investigations Report 2011-5167.

Wainger, L, Van Houtven, G., Loomis, R., Messer, J., Beach, R., and Deerhake, M., 2013. Tradeoffs among ecosystem services, performance certainty, and cost-efficiency in implementation of the Chesapeake Bay Total Maximum Daily Load. *Agricultural and Resource Economics Review* 42(1), 196-224.

Wieland, R., Parker, D., Gans, W., and Martin, A., 2009. *Costs and cost efficiencies for some nutrient reduction practices in Maryland*. NOAA Chesapeake Bay Office and Maryland Department of Natural Resources, Annapolis, MD.

Wooldridge, J., 2014. Quasi-maximum likelihood estimation and testing for nonlinear models with endogenous explanatory variables. *Journal of Econometrics* 182, 226-234.

Wu, J., and Babcock, B., 1998. The choice of tillage, rotation, and soil testing practices: Economic and environmental implications. *American Journal of Agricultural Economics* 80, 494-511.

Wu, J., 2000. Slippage effects of the Conservation Reserve Program. *American Journal of Agricultural Economics* 82, 979-992.

Wu, J., Adams, R., Kling, C., and Tanaka, K., 2004. From microlevel decisions to landscape changes: An assessment of agricultural conservation policies. *American Journal of Agricultural Economics* 86(1), 26-41.

Wu, J., and Tanaka, K., 2005. Reducing nitrogen runoff from the Upper Mississippi River Basin to control hypoxia in the Gulf of Mexico: Easements or taxes? *Marine Resource Economics* 20, 121-144.

Wu, J., 2005. Slippage effects of the Conservation Reserve Program: Reply. *American Journal of Agricultural Economics* 87(1), 251-254.