Cost-Effective Point-Nonpoint Trading:

An Application to the Susquehanna River Basin

Technical Appendix

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Our SRB model is consistent with prior theoretical models of point-nonpoint pollution control (Malik et al., 1993; Shortle and Abler, 1997) in that it consists of: (a) an economic model of agricultural production and pollution control decisions, (b) point source pollution control costs, (c) a model of stochastic nutrient transport, and (d) a policy objective used to set trading ratios and permit levels and to gauge economic and environmental performance. These components are linked together so that we may investigate how alternative point-nonpoint trading program design decisions affect program costs and water quality.

The components of the model are calibrated using available data and parameters as described in Table A1. By calibration, we mean that some parameters are specified a priori while others are adjusted so that the model replicates available data for the non trading baseline scenario. For the most part, the specified parameters are drawn from a literature that reports a range of values. In consequence, many parameters of the model are not known with certainty. Many studies either ignore uncertainty by treating estimated parameters as though they were certain or deal with uncertainties by performing a simple sensitivity analysis (i.e., calculating the optimal solution under a few different parameter values). Following Abler and Shortle [1995], Davis and Espinoza [1998], and Claassen and Horan [2001], we deal with this parameter uncertainty through an ex post Monte Carlo analysis. The Monte Carlo analysis, which is described in greater detail below, is essentially a sophisticated sensitivity analysis that enables us to determine the robustness of model results for a range of parameter values.

**Modeling Nonpoint Sources**

**Economic model.** The vast majority of nonpoint loads are due to agriculture, with corn production
being one of the most important contributing agricultural activities. Corn production is modeled as a two-level, constant elasticity of scale (CES) technology that exhibits constant returns to scale at both levels [Sato 1967]. Following prior work based on this approach [Abler and Shortle 1992; Kawagoe et al. 1985; Thirtle 1985; Binswanger 1974], production in the $i$th region, denoted $y_i$, is a function of a composite biological input, $B_i$, and a composite mechanical input, $M_i$, i.e.,

$$y_i = A_i \left( \alpha_i B_i^{\rho_i} + (1 - \alpha_i) M_i^{\rho_i} \right)^{1/\rho_i} \tag{1}$$

where $A_i$ and $\alpha_i$ are parameters, and $\rho_i = (\sigma_i - 1)/\sigma_i$, where $\sigma_i$ is the elasticity of substitution between the biological and mechanical inputs. Similarly, $B_i$ is produced using land, $L_i$, and fertilizer, $N_i$:

$$B_i = K_i \left( \beta_i L_i^{u_i} + (1 - \beta_i) (u_i N_i)^{u_i} \right)^{1/\gamma_i} \tag{2}$$

where $K_i$ and $\beta_i$ are parameters, $u_i$ is the proportion of nitrogen taken up by the plant, and $K_i = (\sigma_{Bi} - 1)/\sigma_{Bi}$, where $\sigma_{Bi} = s_{Bi} \sigma_{i,L,N} + s_{Mi} \sigma_i, s_j (j = B, M)$ is the cost share of the $j$th input in production and $\sigma_{i,L,N}$ is the elasticity of substitution between $L_i$ and $N_i$. Nitrogen is more or less a fixed proportion of fertilizer, and so we denote $N_i$ as nitrogen. The mechanical input is produced using capital and labor. However, assuming the prices of these inputs remain fixed, there is no reason to further decompose $M_i$ into its constituent parts as capital and labor will be used in fixed proportions.

The price of corn, denoted $p$, is fixed and does not vary within the SRB. The same is true of the prices of nitrogen, $w_{N_i}$, and the mechanical input, $w_{M_i}$. Land supply takes a constant elasticity form, i.e., $L_i = b_i w_{L_i}^{\eta_i}$, where $b_i$ is a parameter, $w_{L_i}$ is the price of land, and $\eta_i$ is the elasticity of supply. Land supply is defined at the watershed level to reflect the opportunity cost of this input, which is likely to differ in each region in the SRB.

Net benefits from corn production in a competitive equilibrium (without trading), denoted $NB_{NPS}^C$, equal profits plus the infra-marginal rents that accrue to landowners, i.e.,
\[NB_i^c = p y_i^c - w_N N_i^c - w_M M_i^c - \int_0^{L_i} (v/b_i)^{1/\eta_i} dv,\]

where \(v\) is a dummy of integration and the superscript \(c\) denotes all values are evaluated at competitive levels. The benefits from production in a trading equilibrium, denoted \(NB_i^T\), are

\[NB_i^T = p y_i^T - w_N N_i^T - w_M M_i^T - p_x \left[ x_i^T - \hat{x}_{i0} \right] - \int_0^{L_i} (v/b_i)^{1/\eta_i} dv,\]

where \(\hat{x}_{i0}\) is the vector of the initial allocation of nonpoint permits (denominated in terms of expected loadings or inputs) to the \(i\)th region, \(x_i^T\) is a vector of final permit holdings after trades occur, \(p_x\) is the equilibrium vector of permit prices, and the superscript \(T\) denotes that all values are evaluated at levels that occur in the trading equilibrium. Thus, region \(i\)'s costs of nonpoint controls under a trading equilibrium are defined as the reduction in net benefits that result from trading,

\[c_i(N_i, L_i, M_i) = NB_i^c - NB_i^T \quad (3)\]

The economic model for nonpoint sources is calibrated for each region using cost shares and production shares developed from USDA [2000] and Pennsylvania data [PASS 1998]. For the elasticities \(\sigma_i\), \(\sigma_{iL,N}\), and \(\eta_i\), we adopt existing estimates provided in the literature (Table A1).

**Nutrient loadings model.** Nonpoint loads from a region are defined as the amount of nitrogen entering the Susquehanna River or its tributaries from that region. We derived nonpoint loadings functions from the results of a study by Carmichael and Evans [2000], which was based on the simulation model Generalized Watershed Loadings Function (GWLF) [Haith et al., 1992]. These researchers used the GWLF model under contract to Pennsylvania’s Department of Environmental Quality to develop Total Maximum Daily Load (TMDL) recommendations for Pennsylvania. Because models such as GWLF are too complex to easily link with economic models for the purposes of optimization and economic analysis, Carmichael and Evans [2000] used Monte Carlo simulation techniques to generate data sets that could be used to statistically parameterize the loadings functions.
This is not an unusual procedure for simplifying complex process models. The use of a large number of random samples means that we should not have any biases related to sample selection. We used their data to parameterize GWLF according to the form

\[ r_i = r_{1i} P_i^2 N_{Ci} L_i + r_{2i} (P_i^2 N_{Ci})^2 L_i + r_{3i} P_i \]  

(4)

where \( P_i \) is precipitation, \( N_{Ci} \) is the per acre concentration of nitrogen leaving fields, and \( r_{qi} \) (\( q=1,2,3 \)) are parameters. The parameters \( r_{qi} \) (\( q=1,2,3 \)) were obtained by applying OLS to equation (4) (plus an error term) using data supplied by Carmichael and Evans. The results of those regressions are not presented here but they are available from the authors upon request. In most cases, each parameter was positive and significant at the 1% level.

The variable \( N_{Ci} \) is related to nitrogen according to the relation

\[ N_{Ci} = \psi_i (1 - u_i) N_i / (P_i L_i) \]  

(5)

where \( \psi_i \) is a parameter. Thus, the loadings function can be written as

\[ r_i = r_{1i} P_i \psi_i (1 - u_i) N_i + r_{2i} (P_i \psi_i (1 - u_i) N_i)^2 / L_i + r_{3i} P_i \]  

(6)

The variable \( P_i \) is taken to be stochastic in our simulation model. Thus there are two forms of uncertainty in the model: parameter uncertainty, which is dealt with by performing a Monte Carlo analysis (as mentioned above and explained in greater detail below), and uncertainty due to stochastic weather events, which is dealt with for each of the Monte Carlo simulations (also elaborated on below). \( P_i \) is taken to be gamma distributed with a mean and variance based on precipitation data for the regions (Table A1). Finally, we scale each of our loadings functions so that the expected loadings that result from nitrogen and land use inputs defined by our base case data equal the nonpoint loadings defined by our base case data in Table 1 in the main text.

*Modeling Point Sources*
Point source abatement cost functions are derived using data from a Susquehanna River Basin Commission (SRBC) report [Edwards and Stoe, 1998]. The report provides base level emissions (abatement) for the most important point sources of nitrogen in the SRB, as well as costs for adopting various nutrient control technologies and the emissions levels for each source under these technologies. For most sources, there was data on at least two technologies: three stage annual treatment and five stage annual treatment. Data for these technologies was aggregated to the regional level from individual sources and used to calibrate an abatement cost function. Following Horan et al. [2001], we model abatement costs for simplicity as a decreasing, convex function of emissions

$$c(e_k) = z_k e_k^{\zeta_k} + F_k$$

where $z_k > 0$ is a parameter, $\zeta_k < 0$ is the elasticity of costs with respect to emissions, and $F_k$ is a fixed cost. There are three parameters in (7) to be calibrated, and so we also use information provided by Camacho [1992] and Malik et al. [1994] to relate the marginal costs of abatement by nonpoint sources with point source marginal abatement costs. Specifically, we calculate the marginal costs of reducing nitrogen use by 10% (since abatement is not well-defined for stochastic pollution), denoted $\lambda_k$, and assume point source marginal abatement costs are some multiple $\delta$ of this value, i.e.,

$$\zeta_k z_k e_k^{\zeta_k - 1} = \delta \lambda_k$$

(Table A1). This procedure enables us to calibrate point source costs in a manner that avoids scaling differences between point and nonpoint source costs. When evaluating a particular trading program, however, the restriction that $\zeta_k z_k e_k^{\zeta_k - 1} = \delta \lambda_k$ is no longer maintained; marginal costs from each source are allowed to vary independently. Finally, loadings from point sources into a region are given by aggregate emissions within the region.

Nutrient Delivery
Nonpoint source loadings and point source emissions are measured as loadings into the watershed in which they originate. However, only a fraction of the loadings or emissions generated from each watershed is delivered to become part of the ambient pollution concentration in the Chesapeake Bay, which is the chief area of concern for policy purposes. The proportion of the load that is delivered is modeled as a constant delivery coefficient, $\alpha_i$, so that total delivered loads are

$$a = \sum_{i=1}^{n} \alpha_i r_i + \sum_{k=1}^{s} \alpha_k e_k$$  \hspace{1cm} (8)

This relation represents a first-order approximation to the actual transport process, which is thought to be reasonable in many cases [Roth and Jury 1993]. The delivery coefficients are taken to be stochastic and gamma distributed with a mean and variance as reported by Carmichael and Evans [2000], as derived from the USGS SPARROW model [Smith et al. 1997] (Table A1).

**Monte Carlo Simulation**

For a particular trading scenario (these are described below), model results are obtained as the quantity of permits and the trading ratio are jointly chosen to minimize the costs of pollution control, subject to the expected loadings constraint and also subject to the restriction of a uniform trading ratio (also described below). Mathematically, the cost-effective outcome is the solution to

$$\text{Min } TC = \Sigma c_r + \Sigma z_i \text{ s.t. } E\{a\} \leq 0.6E\{a_b\} \text{ and also subject to the restriction of 1:1 within group trading, where } E\{a_b\} \text{ represents baseline expected delivered loads.}$$

The Monte Carlo analysis proceeds by solving the model $K$ times to produce $K$ simulations or samples. For each sample, we randomly draw a set of values for the specified parameters and then calibrate and solve the model. Note that, in each sample, stochastic variables such as precipitation and delivery coefficients remain stochastic during the optimization procedure and are
accounted for by the expected loadings term \(E\{a\}\). Each sample essentially represents a different possible state of the SRB – and hence a distinct watershed in terms of economic and environmental conditions. The \(K\) samples therefore produce a distribution of results. For instance, sample expected total costs are \(\sum_{k=1}^{K} TC_k / K\), where the subscript \(k\) denotes the \(k\)th sample.

The sample size \(K\) is chosen according to the procedure described by Abler, Rodríguez, and Shortle (1999). If \(y\) is a welfare measure to be estimated by the Monte Carlo procedure, then \(K\) can be chosen such that, with 95% probability, the margin of error is no greater than \(\varepsilon = \delta \hat{y}\), where \(\hat{y}\) is the estimate of \(y\) and \(\delta\) is the percentage deviation from the mean. The appropriate sample size is then computed as \(K^* = (1.96/\delta \hat{y})^2 \sigma^2\), where \(\sigma^2\) is the variance of the estimate. In choosing \(K\), we specified a 95% probability that expected net benefits be estimated with a deviation of \(\delta \leq 0.015\). Our initial guess of \(K=1000\) was more than adequate, and so this is our sample size.
References


Table A1. Factor Cost Shares, Production Shares, and Distributions of Uncertain Parameters

<table>
<thead>
<tr>
<th>Region</th>
<th>Production Shares</th>
<th>Point and Nonpoint Transport Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Distribution</td>
</tr>
<tr>
<td>202</td>
<td>0.149</td>
<td>Gamma</td>
</tr>
<tr>
<td>204</td>
<td>0.364</td>
<td>Gamma</td>
</tr>
<tr>
<td>207</td>
<td>0.135</td>
<td>Gamma</td>
</tr>
<tr>
<td>214</td>
<td>0.076</td>
<td>Gamma</td>
</tr>
<tr>
<td>215</td>
<td>0.068</td>
<td>Gamma</td>
</tr>
<tr>
<td>302</td>
<td>0.064</td>
<td>Gamma</td>
</tr>
<tr>
<td>301-401</td>
<td>0.086</td>
<td>Gamma</td>
</tr>
<tr>
<td>402</td>
<td>0.058</td>
<td>Gamma</td>
</tr>
</tbody>
</table>

Deterministic and Uncertain Parameters That Do Not Vary by Region a

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Distribution</th>
<th>Mean</th>
<th>Variance</th>
<th>Sources and/or Justification for Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land Cost Share</td>
<td>None (deterministic)</td>
<td>0.1561</td>
<td>----</td>
<td>USDA [2000]</td>
</tr>
<tr>
<td>Fertilizer Cost Share</td>
<td>None (deterministic)</td>
<td>0.2561</td>
<td>----</td>
<td>USDA [2000]</td>
</tr>
<tr>
<td>Mechanical Cost Share</td>
<td>None (deterministic)</td>
<td>0.5878</td>
<td>----</td>
<td>USDA [2000]</td>
</tr>
<tr>
<td>Elasticity of substitution between composite inputs</td>
<td>Uniform</td>
<td>0.5</td>
<td>0.0533</td>
<td>Binswanger, [1974]; Chambers and Vasavada, [1983]; Fernandez-Cornejo, [1992]; Hertel, [1989]; Kawagoe et al., [1985]; Ray, [1982]; Thirtle, [1985]</td>
</tr>
<tr>
<td>Elasticity of substitution between land and fertilizer</td>
<td>Uniform</td>
<td>1.25</td>
<td>0.025</td>
<td>Same as for the elasticity of substitution between composite inputs.</td>
</tr>
<tr>
<td>Elasticity of land supply</td>
<td>Uniform</td>
<td>0.3</td>
<td>0.0075</td>
<td>Chavas and Holt [1990]; Holt [1990]; Lee and Helmberger [1985]; Tegene et al. [1988]</td>
</tr>
<tr>
<td>Uptake</td>
<td>Uniform</td>
<td>0.7</td>
<td>0.0033</td>
<td>Keeney [1982]; Peterson and Frye [1989], NRC [1993]</td>
</tr>
<tr>
<td>Ratio of PS marginal abatement costs to NPS marginal abatement costs</td>
<td>Uniform</td>
<td>6</td>
<td>5.333</td>
<td>Malik et al. [1994]</td>
</tr>
<tr>
<td>Precipitation</td>
<td>Gamma</td>
<td>40.19</td>
<td>7.943</td>
<td>Carmichael and Evans [2000]</td>
</tr>
</tbody>
</table>

aThe distributions of uncertain parameters do not vary by region, but the values of these parameters do vary across regions for each Monte Carlo simulation as each uncertain parameter is drawn independently for each region.
Notes

1. This research was funded in part by Cooperative Agreement number 43-3AEL-8-80058 with the U.S. Department of Agriculture, Economic Research Service, Resource Economics Division. We are grateful to Barry Evans and Bob Edwards for access to their data. All remaining errors are our own. The views expressed here are the authors’ and do not necessarily reflect those of ERS or the USDA.

2. According to the SRBC data, three stage annual treatment provided the same reduction as five stage seasonal treatment, but at a lower cost. Similarly, five stage annual treatment provided the same reduction as the limit of technology, but at a lower cost.