The Value of Ecological and Economic Information In Water Quality Management

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Beginning with Weitzman's [1974] article on the choice between price and quantity controls under uncertainty, it has been recognized that the ranking of environmental policy instruments under uncertainty generally differs from the ranking with perfect information, given asymmetric information about pollution abatement costs. However, there is surprisingly little empirical research on the merits of alternative instruments under uncertainty. This research empirically compares the performance of price and quantity instruments for reducing nitrogen pollution from agriculture under uncertainty. In addition, it explores the value of alterative types of information for improving the performance of nitrogen pollution control instruments.

Imperfect information about costs and benefits of water quality protection can greatly complicate policy decisions to protect and restore water resources. This has become very apparent to water quality managers in the U.S. in recent years, as they have struggled to comply with the U.S. Environmental Protection Agency's (EPA's) Total Maximum Daily Load (TMDL) regulations. The 1972 Clean Water Act is credited with reducing discharges from point sources and improving water quality. However, significant water quality problems remain in many regions of the nation, often because measures were not taken to reduce pollution loads from nonpoint sources (NPS), such as agriculture, urban developments and atmospheric deposition. The major initiative to remedy the nation's water quality problems is the EPA's TMDL program. TMDL regulations require states to list waters that are not meeting water quality criteria. For each listed water body, the states must identify the amount by which pollution loads from different sources must be reduced to meet the standards, and to develop and implement plans to achieve the load reductions [US EPA 2000]. The states were to accomplish this task in 8 to 13 years. However, in July 2001, the U.S. EPA announced a delayed in the implementation of the Total Maximum Daily Load final rulemaking for 18 months [Pianin 2001] because of the enormous problems states were encountering in meeting the mandate. The slow progress has been attributed in large degree to the fact that key information for assessing the conditions of streams, lakes, and estuaries, developing sensible plans to restore impaired waters was unavailable and costly to obtain [NRC 2000].

There is now great interest in more comprehensive watershed based approaches that address the diverse set of stressors on water quality that pursue water quality goals and balance costs and benefits [USDA and US EPA 1998, NRC 2000]. Achieving these ends requires a much broader set of information than traditional approaches have, and because much of the necessary information will be imperfect, decision-making under uncertainty will be unavoidable.

In this paper we examine how imperfect information of various types may influence the design and performance of instruments for water quality protection, and the value of investments to improve information for environmental policy design. This study is based on an empirical analysis of nitrogen pollution load management in the Pennsylvania portion of the Susquehanna River Basin (SRB). The 27.5 thousand square mile of SRB provides 50 percent of the water flows into one of the most valuable natural resources in the US - the Chesapeake Bay. The Bay's nutrient pollution problems are well documented [SRB Commission 1998, Abler *et al*., 2002, Chesapeake Bay Program 1999]. Agricultural nonpoint sources are major contributors to nitrogen loads in the SRB and Chesapeake Bay.

The following issues are investigated: (1) the performance of alternative policy instruments for nitrogen pollution control under alternative information structures; and (2) the value of different types of information for instrument performance. We analyze three aggregate types of uncertainty in watershed management: asymmetric information about pollution abatement costs, imperfect knowledge about pollution transport, and imperfect information about environmental damage costs. In developing numerical economic and biophysical model of the region and representing the uncertainties, we utilize data from readily available literature sources. That is, we reproduce the cheap (minimal) ex ante information on hand of the policy makers.

Methodology

The optimal economic design of a particular instrument maximizes the expected economic surpluses accruing to consumers, producers, and resource suppliers less environmental damage costs, subject to the distribution of farmers' responses to the policies being evaluated. Building on the model of Shortle *et. al.* [1998], assume a particular resource (e.g., a bay) is damaged by a single residual (e.g., nitrogen). Economic damages, D, are an increasing function of the ambient concentration of the residual, a, i.e. $D(a, \eta)$ with $D' > 0$, where η is a vector of imperfectly known environmental and economic parameters. Ambient pollution depends on loadings from agricultural nonpoint sources, g_i (i = 1, 2, …, n), i.e, $a = a(g_1, g_2, \ldots, g_n)$. Loadings depend on a vector of variable inputs, x_i, and imperfectly known site-specific characteristics influencing fate and transport of pollution (e.g., instream-loss parameters), ω_i. The relation for site i is $g_i = g_i(x_i, \omega_i)$.

Let $\pi_i(x_i, \delta_i)$ denote the economic returns to the ith farm, restricted on the vector of farm input use, x, and a vector of farm-specific characteristics, δ (e.g., the farmer's management ability). We assume that producers operate on competitive input and output markets, and take input and output prices as given. The vector of agricultural practice parameters, δ, is only private knowledge, i.e. management decision is made under asymmetric information. Given this specification, the expected social surplus is

$$ES = E\left[\sum_{i=1}^{n} \pi_i\left(x_i, \delta_i\right) - D\left(g_1(x_1, \omega_1), \ldots, g_n(x_n, \omega_n), \eta\right)\right] \tag{1}$$

where the expectation operator E utilizes the planner's distributions of the unknown parameters.

We analyze the performance of two environmental policy instruments, price and quantity controls, applied to agricultural input use. For nonpoint sources, input-based instruments are of particular interest because the monitoring the contributions of individual farms to nonpoint source loads is prohibitively costly [Shortle and Horan 2001; Ribaudo *et. al*. 1999]. The ex ante optimal *quantity controls* (x_i*) solves:

$$J^* = \max_{x_1, \ldots, x_n} ES = E\left[\sum_{i=1}^{n} \pi_i\left(x_i, \delta_i\right) - D\left(g_1(x_1, \omega_1), \ldots, g_n(x_n, \omega_n), \eta\right)\right] \tag{2}$$

An optimal *price control* (e.g., tax/subsidy scheme) (t_i*) maximizes the expected social surplus (1) contingent on polluters' responses to the policy given their privately held information. Specifically, let

$$x_i(t_i, \delta_i) = \arg\max_{x_i} \{\pi_i(x_i, t_i) - t_i x_i\} \text{ for all } i = 1, \ldots, n \tag{3}$$

where x_i is a vector of agricultural inputs in ith watershed, and t_i is a vector of taxes/subsidies applied to input subset which directly influences pollution runoff (e.g., land and fertilizer). The optimal tax/subsidy scheme maximizes (2) subject to (3).

Given asymmetric information about pollution abatement costs, the ranking of the policy mechanisms will generally differ, with the results depending on properties of the underlying profit and damage costs functions [e.g., Weitzman 1972, Wu 2000]. The difference in the expected social surplus between price and quantity controls is expressed as $\Delta_{tx} = J_t - J_x \gtreqless 0$, where the J_t refers to expected value of the price control, and J_x is the expected value of the quantity control. Δ_{tx} may be positive of negative.

Policy performance can be improved by collecting additional information to reduce or eliminate uncertainty about pollution control costs or benefits. The expected improvement in policy performance due to data gathering is the value of information. Since information collection is costly and the budget available for data collection is often limited, the value of information can help to target investment in research. For example, if the value of abatement cost information is higher than the value of other data types, and the costs are relatively low, collecting the control cost information can be the priority research direction. The data collection priorities are set before the actual data are gathered, and the *expected* effect of information on policy performance should be estimated. That is, the maximum social surplus should be calculated for every possible outcome of data collection, and then the results should be averaged given the probability of alternative findings. Hence, the value of information is the difference between the expected ex post and ex ante social surplus[1]. For example, the expected value of perfect information about δ under the quantity control is

$$VOI_{\delta}^{x} = E\left[\max_{x}\left(ES\left(x,\delta,\omega,\eta\right) \mid \delta\right)\right] - J_{x}^{*} \tag{4}$$

where the first term is the expected value of the optimal instrument contingent on realizations of δ, and the second term is the expected value of the decision without information (see (2)).

The value of information is contingent on the policy instrument. For example, given perfect information about pollution abatement costs, the optimized price and quantity mechanisms would perform the same: $\Delta_{tx} = 0$ if δ is known. Accordingly, the value of perfect

[1] We assume that *perfect* information about each of the imperfectly known parameter is expected to be collected. That is, there is the true value of the parameter is revealed.

information on producers will be greater for the instrument that provides the lesser expected social surplus value without that information.

SRB Model

The empirical analysis is conducted using a model that simulates pollution control costs, pollution transport, and pollution damage costs in 8 subwatersheds of the SRB. The subwatersheds are based on the classification used in the PA State Water Plan. The plan identifies 12 subwatersheds (see Figure 1 and Table 1). Of this twelve, watersheds 223, 404 and 410 are dropped from this work because their nonpoint source loadings are negligible (see Table 1). Watershed 401 is combined with watershed 301, since the watersheds individually have negligible loading but lie in the interior of the SRB.

We focus on nitrogen pollution loads from corn production. Corn production is the major source of nitrogen loading in the SRB, accounting for 30% of total nitrogen loadings delivered to surface water. This percentage rises even higher (approximately 67%) if atmospheric deposition is excluded [Abler *et. al.* 2002][2]. We model nitrogen loads as functions of nitrogen application and/or corn acreage in each subwatershed, and consider policy instruments that target these inputs.

Pollution control costs

Corn production in each subwatershed is modeled as a single aggregate firm. To facilitate our focus on nitrogen and land use choices, consider the restricted profit function, where all agricultural inputs are contingent on fertilizer and land use:

$$\pi_i(n_i, l_i, p, w, \rho, r_i) = f(n_i, l_i, p, w) - \rho \cdot n_i - r_i \cdot l_i \qquad (5)$$

[2] Nonpoint sources are the leading cause of pollution in SRB and Chesapeake Bay [Chesapeake Bay Program 1999], and pollution from corn production is roughly 81% of all nonpoint nutrient loads [Carmichael and Evans 2000].

where n_i is nitrogen fertilizer applications to corn, l_i is land in corn, ρ is the fertilizer price, r_i is the land rental price, p is the corn price, w is the price vector for other inputs, and i indexes subwatersheds. Producers operate on competitive input and output markets, and all input prices except land are fixed. Land price is determined on a regional market.

The true functional form of profit $\pi_i(\cdot)$ is unknown by the regulator. For this analysis, we assume that the regulator approximates the function *f(.)* by a second-order Taylor series expansion about observed baseline values for fertilizer and land use:

$$\pi_i(\cdot) \cong \pi_{0i} + \beta_{1i}(n_i - n_{0i}) + 0.5\,\beta_{2i}(n_i - n_{0i})^2 + \theta_i(l_i - l_{0i}) + 0.5\,\theta_{2i} \\ (l_i - l_{0i})^2 + \Omega_i(n_i - n_{0i})(l_i - l_{0i}) - \rho n_i - r l_i \tag{6}$$

where π_{0j} is baseline profit from corn production in the *i*-th watershed, $\beta_i, \theta_i, \text{and}\, \Omega_i$ are Taylor expansion coefficients, and l_{oi} and n_{io} are the baseline levels of land and fertilizer use[3]. Assuming that the baseline values (l_{oi}, n_{oi}) are profit-maximizing choices (i.e. $\partial\pi_i/\partial n_i = 0$ and $\partial\pi_i/\partial l_i = 0$), the parameters of this expression are given by

$$\beta_i = \frac{\varepsilon_l \cdot l_{0i} \cdot r_0 \cdot \rho_o}{n_0\left(\varepsilon_l \cdot \varepsilon_n \cdot l_{oi} \cdot r_0 - \varepsilon_{nl}^2 \cdot \rho_o \cdot n_{oi}\right)} \tag{7}$$

$$\theta_i = \frac{\varepsilon_n \cdot r_0^2}{\varepsilon_l \cdot \varepsilon_n \cdot r_0 \cdot l_{0i} - \varepsilon_{nl}^2 \cdot \rho_0 \cdot n_{0i}} \tag{8}$$

$$\Omega_i = \frac{\varepsilon_{nl} \cdot r_o \cdot \rho_o}{\varepsilon_{nl}^2 n_{oi} \rho_o - \varepsilon_l \varepsilon_n r_o l_{oi}} \tag{9}$$

where ε_{li} is the elasticity of land demand, ε_{ni} is the elasticity of nitrogen demand, ε_{nli} is the cross-price elasticity, and the prices are set at their baseline values. To reflect regulator's

[3] For the baseline values we use a five year average

uncertainty about privately known production/abatement practices of polluters, the elasticity values are modeled as random variables. The coefficients β_i, θ_i, and Ω_i vary accordingly.

The opportunity costs of corn land in each subwatershed are increasing in the amount of land. The true form of the land supply function is unknown by the regulator. A first-order Taylor approximation is used to approximate land supply in the neighborhood of baseline land use:

$$l_i \cong l_{oi} + \gamma_i (r_i - r_{oi}) \tag{10}$$

where coefficient γ_i depends on the land supply elasticity (ε_{lsi}).

$$\gamma_i = \varepsilon_{lsi} \frac{l_{0i}}{r_{oi}} \tag{11}$$

Again, to reflect decision-maker's uncertainty, the privately-known land supply elasticity is modeled as a random variable, which determine actual slope of land supply γ_i in each subwatershed. The rent accrued by land suppliers can be computed as the difference between the revenues and the integral of the land marginal products:

$$R_i = r_i l_i - \int_a^{l_i} r_i(z, \gamma_i) \cdot dz \tag{12}$$

where the low limit of integration *a* is the level of land supply for which land rental price equals zero.

Pollution transport

The mean annual nitrogen load from corn land to the mouth of watershed *i* is modeled as a function of nitrogen concentration in runoff, agricultural land area, and mean annual precipitation[4]:

$$g_i = A_i\left(\varphi_{1i} z_i^2 N_c l_i + \varphi_{2i}\left(z_i^2 N_c\right)^2 l_i + \varphi_{3i} z_i\right) \tag{13}$$

where g_i is the expected annual load to the mouth of the watershed *i*; z_i is mean annual precipitation; φ_{1i}, φ_{2i}, and φ_{3i} are regression coefficients; A_i is scaling (calibration) coefficient; N_c is nitrogen concentration in the agricultural runoff. Nitrogen concentration N_c is estimated as the ration of nitrogen runoff mass ($(1-u)\ n_i$) and water volume ($z_i\ l_i$):

$$N_c = \mu_i \frac{(1-u)(n_i / l_i)}{z_i} \tag{14}$$

here μ_i is a calibration coefficient.

Only a portion of deliveries to surface waters in each subwatershed ultimately reaches the Chesapeake Bay, which is chief area of concern for policy purposes. The portions of deliveries in the *i*-th watershed that ultimately reach the Bay are modeled with constant delivery coefficients ω_i, so that total delivered nitrogen loads from corn production to the Bay are:

$$s = \sum_i \omega_i g_i . \tag{15}$$

To reflect imperfect knowledge about pollution transport processes, transport coefficients ω_i are random variables. Their means and variances are based on U.S. Geological Survey's SPAtially Referenced Regressions On Watershed attributes (SPARROW) model [US Geological Survey 2000].

[4] For details see [Abler *et. al.* 2002]

Damage costs

The mean annual damage from SRB nitrogen loads to the Chesapeake Bay is modeled as a convex increasing function of the total nitrogen load:

$$D = \psi \cdot s^{\tau} \tag{16}$$

where D is economic damage, ψ is a coefficient, τ is elasticity of damage function, and $\partial D/\partial s > 0, \partial^2 D/\partial s^2 > 0$. The function integrates the biophysical responses of the water system to nitrogen load and economic valuations of the changes in water system services due to pollution. Both biophysical processes in water system and social factors affecting ecosystem valuation are complex and not perfectly understood. To reflect the regulator's imperfect knowledge about environmental damage, both parameters ψ and τ are random variables.

To estimate the effect of information collection on the policy performances and the value of information, we model five information scenarios. For the first scenario (scenario a)), we compare policies designed with the baseline information. For the next four scenarios, we analyze the expected improvements in the performances of the policies designed with information about producers' profits/control costs (β, θ, Ω, and γ) (scenario b)); pollution transport processes (ω) (scenario c)); environmental damage (ψ and τ) (scenario d)); and all the above (scenario e)).

Modeling uncertainty

There has been little research on the structure of agricultural production and agricultural land markets in SRB, and the region does differ substantially from other regions of the US. Accordingly, beyond the restrictions imposed by economic theory, there is substantial ignorance about the corn production and land parameters. We utilize uniform distributions for these parameters. The range of possible realizations is based on the literature for other regions [Hertel 1996, Abebe *et. al*. 1989, Roberts and Heady 1982, Vroomen and Larson 1991] (see Table A2). We also use a uniform distribution for the damage cost parameters. The studies of damages from nitrogen load in the Chesapeake Bay mostly concentrate on ecological effects of pollution without considering economic consequences [Sims and Coale 2002]. Limited economic studies focus on specific well-defined services of the water system (e.g., angling) or pursue site-specific case-studies [e.g., Kirkley *et al* 1999, Bockstael *et al* 1995]. For this analysis, the range of the possible values for the damage cost parameters is selected in such a way that the model solutions reproduce the optimal loads defined in the Chesapeake Bay agreement and by USGS (40% – 20% load reduction from the baseline values; Belval and Sprague 1999, Chesapeake Bay Program 2000). The range of marginal damage elasticity (i.e., exponent of the damage function) τ is selected to reflect both elastic and inelastic marginal damages.

In contrast to the lack information for assessing abatement costs and damage costs, there has been substantial research on the transport of nitrogen in the SRB. We use pollution transport coefficients based on the USGS SPARROW model [Abler *et. al.* 2002, Carmichael and Evans 2000]. The coefficients are normally distributed.

The model is computed using the constrained optimization procedure (CO) in GAUSS 3.22 (Advanced Mathematical and Statistical System; Aptech 2003). The terms in the expression for the expected social surplus (1) are highly nonlinear with respect to the uncertain parameters, which makes it difficult to compute the expected value of the social surplus analytically. A Monte Carlo procedure was used to calculate the expected value as a sample mean of the function [Rubinstein 1981]. We compute the expected social surplus (1) as a sum of the social surplus values for randomly drawn values of the uncertain parameters divided by the total number of draws M:

$$ES(x_1,\ldots x_8) \approx \frac{1}{M}\sum_{m=1}^{M}\left[\sum_{i=1}^{8}\pi_i(x_i,\beta_{im},\theta_{im},\Omega_{im}) - D(g_1(x_1,\omega_{1m}),\ldots,g_8(x_8,\omega_{8m}),\psi_m,\tau_m)\right] \tag{17}$$

For the baseline information scenario (a), the policy performance is computed by maximizing the ES (17) with respect to the policy choices x^* or t^* subject to the farmers' responses to the policies (3):

$$J^* = \max_{x_1,\ldots,x_8} ES \tag{18}$$

For the other information scenarios (b – e), we calculate the expected social surplus as an average of the optimal performances of the policies designed with information. For example, the expected policy performance for the scenario with abatement cost, transport, and damage cost information is:

$$J^{**} = \frac{1}{M}\sum_{m=1}^{M}\max_{x_{1m},\ldots,x_{8m}}\left[\sum_{i=1}^{8}\pi_i(x_i,\beta_{im},\theta_{im},\Omega_{im}) - D(g_1(x_1,\omega_{1m}),\ldots,g_8(x_8,\omega_{8m}),\psi_m,\tau_m)\right] \tag{19}$$

where j indexes randomly drawn values of abatement cost parameters.

We select the sample size M based on two criteria: 1) to produce the results which do not depend on the sample size, and 2) to guarantee that the differences among results for alternative policy instruments and information scenarios are statistically significant. For the baseline information scenario (a), six sample sizes were analyzed: M = 100, 200, 500, 1000, 1500, and 3000. The discrepancy between the results for M = 1500 and M = 3000 was less than 1%. We choose the sample size M = 1500 for all scenarios. Then, for the scenarios (b) through (d), we calculate the 95% confidence intervals as the mean of the optimal ES values plus/minus the product of the estimated standard deviation s_M and the t-value [Lane 2001]:

$J^{**} - t \cdot s_M \leq J^{**} \leq J^{**} + t \cdot s_M$. We find no overlaps in the confidence intervals, and hence, the obtained differences in *ES* for alternative information scenarios and instruments are statistically significant.

Results

The simulation results are summarized in Tables 1 and 2. Table 1 reports the expected net benefits, i.e. the expected increase in social surplus from imposing regulation in comparison with the no-regulation case. Table 2 summarizes the value of information for alternative policies. Both tables present results for various information sets that might be held by the policy maker. The baseline information column means that the policy maker is unsure about the values of fate and transport variables, cost variables, and damage variables (scenario a)). The results in the second column are for the case in which the regulator has information on pollution transport, but the rest of the variables are still uncertain as in column 1 (scenario b)). The third column is for the case in which the regulator has perfect information about all abatement cost parameters (while other parameters remain uncertain), meaning that there is no longer any asymmetric information between firms and the regulator. Prices and quantity controls perform equivalently in this scenario (scenario c)). The fourth column is for the case in which the regulator has perfect information about damage cost parameters (while other parameters remain uncertain, so that asymmetric information again persists in this case) (scenario d)). Finally, the last column represents the case in which the regulator has perfect information about all parameters in the model. Again, there is no asymmetric information in this case and the two policies produce equivalent outcomes (scenario e)).

Given the baseline information, input taxes outperform the input quantity control by \$3.4

million (22.9%) (see Table 1). The difference between the instruments decreases for other information scenarios; however, for all information scenarios, price regulation performs no worse than the quantity control. Under a quantity control policy, firms are unable to make adjustments in their production and pollution control choices. In contrast, firms are able to adjust their choices to their own benefit under a price policy. Also, damages could be increased or decreased due to this adjustment. So the firms' adjustments could cause either an ex ante gain or loss relative to the quantity control policy, in either case creating ex ante differences in net benefits under the two policies. Weitzman's results indicate that whether or not the regulator expects the adjustments to produce a net gain or loss depends on the variance of impacts to damages and firm profits. Building on this intuition, the price controls are expected to produce greater social surplus in our model because the benefits of increased variability, in terms of expected producer profits, outweigh the costs of increased variability, in terms of expected damages[5].

Information collection improves the expected performance of both policies. However, the improvement depends on the type of information collected and on the policy mechanism used. First, consider the issue of the type of information being collected. The first two rows of table 2 report the value of information for each of the indicated scenarios relative to the baseline scenario. Table entries are simply the difference in expected net benefits between the given scenario and the baseline scenario. The benefits of obtaining different types of information depend on how the information is used to improve policy. Essentially, information can be used to improve the allocation of controls across producers and/or to alter the overall level of control.

[5] In our model the regulator has the ability to perfectly target all firm choices that influence emissions, which is the same as choosing emissions directly in the case of deterministic emissions. Our model differs from Weitzman's in terms of the functional forms used as he had quadratic cost and benefit functions while ours are more nonlinear

For instance, information on fate and transport processes is primarily important for setting the correct allocation of controls: with better information comes improved targeting. However, the benefits of improved targeting will generally only be large if there is a significant amount of heterogeneity in transport coefficients across firms. In our model there is not much heterogeneity in transport and so we find a relatively small value of obtaining more information about the fate and transport process.

Abatement cost information is used to improve both the allocation of controls and the overall level of control. But the benefits of improved targeting based on cost information will generally only be large if there is significant heterogeneity in abatement costs across firms. There is more heterogeneity in costs than there is in transport coefficients, yet the overall level of heterogeneity in the Susquehanna River Basin is relatively small. The result is that, relative to transport information, there is a larger value associated with obtaining abatement cost information but the value is still not large.

Finally, damage cost information is used primarily to set the overall level of control. This is important information because the presence of damages is the only reason to have controls. As might be expected, the value of obtaining damage cost information is much greater than the value of other types of information, and this information is expected to yield 89 percent (under quantity controls) to 93 percent (under a price policy) of the expected net benefits that might arise if the government was able to obtain perfect information about all uncertain variables.

Now consider the issue of how the policy mechanism affects the value of information collected. This is presented in the final row (labeled *Difference*) in Table 2. Information has higher value for the quantity control than for the price control. For information structures with abatement costs, this result can be explained by the differences in baseline policy performances: with compliance costs information, price and quantity mechanisms perform the same; however, price mechanism outperforms the quantity one for baseline information scenario. Hence, information collection has smaller effect on the performance of price control.

Table 1. Expected Net Benefit Values for Alternative Policies and Information Structures

	Baseline information (10^6)	Pollution fate and transport information (10^6)	Abatement cost information (10^6)	Damage information (10^6)	Pollution fate, abatement costs, and damage information (10^6)
Quantity (J_x^*)	14.82	15.03	19.27	23.33	25.75
Price (J_t^*)	18.22	18.36	19.27	24.18	25.75
Δ_{tx}	*3.40*	*3.33*	*0.00*	*0.85*	*0.00*

Table 2. Value of Alternative Information Structures for Alternative Policy Mechanisms

	Fate and Transport information (10^6)	Abatement cost information (10^6)	Damage information (10^6)	Pollution fate, abatement costs, and damage information (10^6)
Quantity	0.21	4.45	8.51	10.93
Price	0.14	1.05	5.96	7.53
Difference	*0.07*	*3.40*	*2.55*	*3.40*

Conclusions and perspectives for future research

We examined how imperfect information of various types may influence the performance of tax and quantity instruments for water quality protection, and the value of investments to improve information for environmental policy design in the Pennsylvania portion of SRB. The analysis shows that for all information structures considered, the input price regulation performs better than the input quantity controls. For both mechanisms, information collection improves policy performance, with damage information having the greatest impact. Information collection is crucial when quantity control is used, since the price mechanism performs relatively well even with minimal available information.

Our results are contingent on the assumptions about the functional forms and probability distributions used. These assumptions might have significant effect on expected policy performances and value of information. For example, [Adams and Crocker 1984] has shown that the knowledge about function specifications can have bigger value than the information about parameters in the function. Sensitivity of our results to alternative functional forms and distributions will be conducted in future.

Finally, we did not explicitly model the process of information collection, instead we analyzed just extreme cases with “minimal” (baseline) or complete data for each uncertain factor. However, in reality, it might be infinitely costly to collect perfect information of any kind, and partial information can be more preferable. Information theory suggests [Lawrence 1998], that data should be collected up to the point when marginal cost of information collection equals the marginal benefits of information.

Unfortunately, modeling information collection processes and costs requires much more complicated models. We consider our research as a useful starting point in empirical analysis of the link between information collection and environmental policy design, and much more researches on the topic should be done in future.

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Appendix A. Graphs and Data Tables

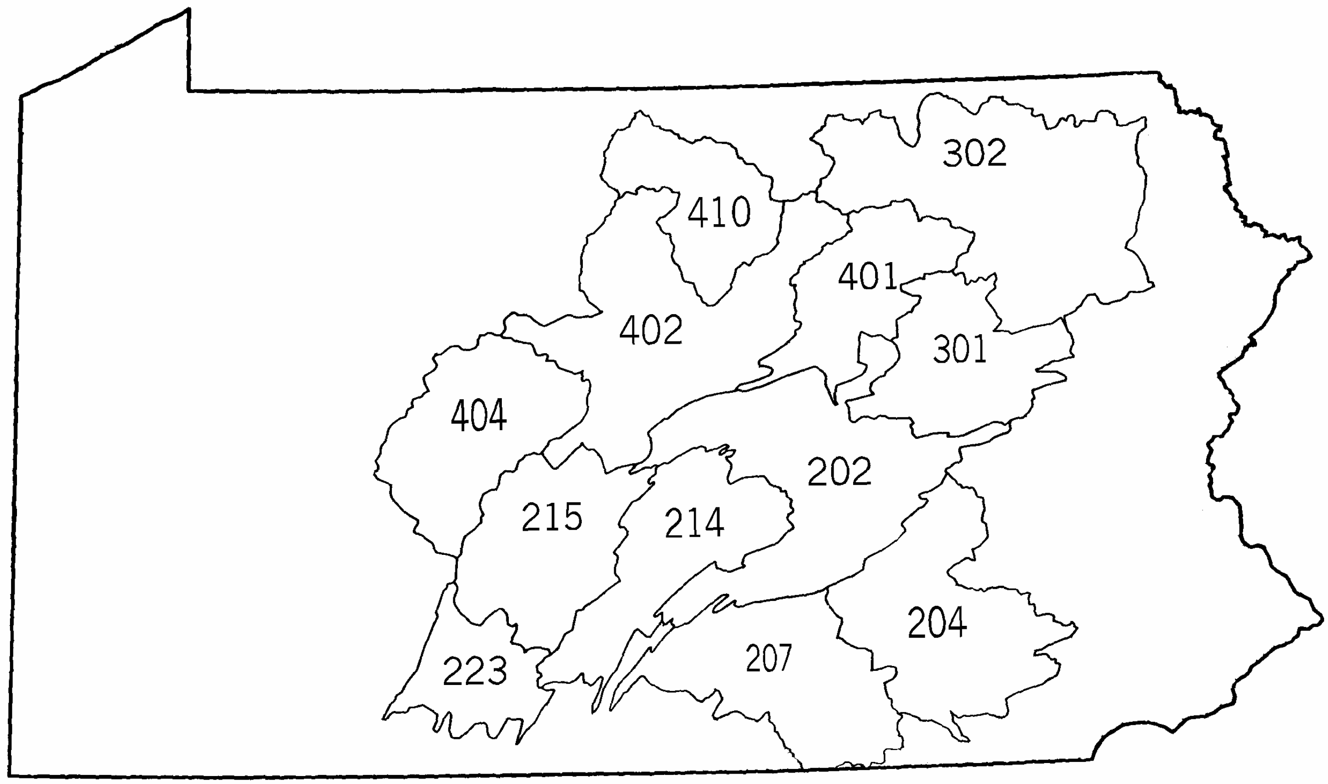

Figure 1. Watersheds in the Susquehanna River Basin in Pennsylvania

Source: Horan *et. al*. 2002a.

Table A1. Average Annual Nitrogen Load to the Mouth of Subwatersheds

Watershed	NPS load (MT)	PS load (MT)	Total load (MT)	Rank based on total load
202	3,499.8	167.1	3,666.9	3
204	5,694.2	3,231.5	8,925.6	1
207	4,314.1	1,142.0	5,456.1	2
214	1,499.1	71.8	1,571.0	7
215	1,980.6	76.5	2,057.1	6
*223**	*1,492.3*	*28.6*	*1,520.9*	*8*
301**	1,367.2	147.9	1,515.1	9
302	1,607.0	726.4	2,333.3	4
401**	1,230.6	74.3	1,304.9	11
402	1,987.1	210.9	2,198.1	5
*404**	*1,270.9*	*94.5*	*1,365.5*	*10*
*410**	*459.0*	*68.5*	*527.4*	*12*

Source: Evans [personal communications]
* watersheds in *italic* are dropped from the analysis
** these two watersheds are combined and modeled as a single watershed

Table A2. Watershed Data used in the analysis

Watershed/ Characteristics	202	204	207	214	215	302	301 and 401	402	Source
Crop Land (ha) (l_{i0})	32719.5	43955.6	30550.6	11927.3	7187.0	5781.8	18542.7	9450.2	County crop land from PA Agricultural Statistics [USDA and PADA 2003] and watershed area in each county from [Abler *et al* 2002]
Nitrogen use (Metric ton) (n_{i0})	5918.1	9047.	5694.8	2239.2	1413.2	960.7	3275.5	1666.0	County corn production from PA Agricultural Statistics [USDA and PADA 2003]; watershed area in each county, nitrogen content per bushel of corn and nitrogen uptake rate from [Abler *et al* 2002]
Load regression coefficient φ_1 (10^{-5})	646.0	486.9	205.2	552.2	386.5	646.0	92.4	429.5	Horan *et al* 2002b
Load regression coefficient φ_2 (10^{-11})	8601.8	820.9	921.2	5464.9	742.5	8601.8	54.9	690.5	Horan *et al* 2002b
Load regression coefficient φ_3 (10^{4})	136.2	523.1	174.8	92.2	110.7	136.2	46.4	121.7	Horan *et al* 2002b
Calibration coefficient A (10^{-8})	3.4	20.1	35.9	2.3	29.3	8.5	310.7	56.4	Model calibration procedure
Calibration coefficient μ (10^{5})	1.4	1.4	1.3	1.7	1.6	1.5	1.4	1.4	Model calibration procedure
Precipitation, millimeters (z_i)	817.5	929.7	818.6	1052.7	1052.7	811.6	811.6	811.7	Abler *et al* 2002 and Teigen and Singer 1992
NPS load to the mouth of watershed (Metric ton)	3499.8	5694.2	4314.1	1499.2	1980.6	1607.0	2597.8	1987.1	Evans, personal communications

Table A2. Descriptions of random variables

Variable	Notation	Distribution	Characteristics	Source
Own price elasticity of nitrogen demand	ε_N	Uniform	Mean = - 0.157 Variance = 0.008 SD = 0.087	Hertel 1996, Abebe *et. al*. 1989, Roberts and Heady 1982, Vroomen and Larson 1991

			Coeff. of Var. = -0.551 Interval = [-0.307,-0.007]	
Own price elasticity of land demand	ε_L	Uniform	Mean = - 0.253 Variance = 0.021 SD = 0.144 Coeff. of Var. = -0.569 Interval = [-0.503,-0.003]	Hertel 1996, Abebe *et. al*. 1989, Roberts and Heady 1982, Vroomen and Larson 1991
Cross-price elasticity of nitrogen demand	ε_{NL}	Uniform	Mean = 0.147 Variance = 0.007 SD = 0.081 Coeff. of Var. = 0.552 Interval = [0.007,0.287]	Hertel 1996, Abebe *et. al*. 1989, Roberts and Heady 1982, Vroomen and Larson 1991
Price elasticity of land supply	ε_{LS}	Uniform	Mean = 0.500 Variance = 0.080 SD = 0.283 Coeff. of Var. = 0.566 Interval = [0.010,0.990]	Abler *et al* 2002
Transport coefficient for watershed 202	ω_1	Normal	Mean = 0.710 Variance = 0.110 SD = 0.332 Coeff. of Var. = 0.467 Interval = [0, 1]	Horan *et al* 2002b
Transport coefficient for watershed 204	ω_2	Normal	Mean = 0.730 Variance = 0.110 SD = 0.338 Coeff. of Var. = 0.462 Interval = [0, 1]	Horan *et al* 2002b
Transport coefficient for watershed 207	ω_3	Normal	Mean = 0.580 Variance = 0.160 SD = 0.400 Coeff. of Var. = 0.688 Interval = [0, 1]	Horan *et al* 2002b
Transport coefficient for watershed 214	ω_4	Normal	Mean = 0.680 Variance = 0.130 SD = 0.355 Coeff. of Var. = 0.519 Interval = [0, 1]	Horan *et al* 2002b
Transport coefficient for watershed 215	ω_5	Normal	Mean = 0.630 Variance = 0.070 SD = 0.261	Horan *et al* 2002b

			Coeff. of Var. = 0.417 Interval = [0, 1]	
Transport coefficient for watershed 302	ω_6	Normal	Mean = 0.610 Variance = 0.070 SD = 0.265 Coeff. of Var. = 0.433 Interval = [0, 1]	Horan *et al* 2002b
Transport coefficient for combined watershed 301 and 401	ω_7	Normal	Mean = 0.660 Variance = 0.070 SD = 0.265 Coeff. of Var. = 0.401 Interval = [0, 1]	Horan *et al* 2002b
Transport coefficient for watershed 402	ω_8	Normal	Mean = 0.560 Variance = 0.140 SD = 0.370 Coeff. of Var. = 0.661 Interval = [0, 1]	Horan *et al* 2002b
Damage coefficient	ψ	Uniform	Mean = $1.895\ 10^{-4}$ Variance = $5.334\ 10^{-9}$ SD = $7.303\ 10^{-5}$ Coeff. of Var. = 0.385 Interval = [$0.063\ 10^{-3}$, $0.316\ 10^{-3}$]	The range of the possible values for the damage coefficient is selected in such a way that the model solutions reproduce the optimal loads defined in the Chesapeake Bay agreement and by USGS (40% – 20% load reduction from the baseline values; Belval and Sprague 1999, Chesapeake Bay Program 2000)
Damage exponent	τ	Uniform	Mean = 2.005 Variance = 0.330 SD = 0.574 Coeff. of Var. = 0.287 Interval = [1.01, 3]	The range for the damage exponent is selected to represent convex environmental damage function.