Experimental Evidence on Policy Approaches That Link Agricultural Subsidies to Water Quality Outcomes

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Improving water quality in agricultural landscapes is an ongoing challenge, and most agri-environmental programs in the United States rely on voluntary adoption of conservation practices. Conservation-compliance initiatives require producers to meet specific conservation standards to qualify for payments from farm programs. However, these requirements do not require actual improvements in observed water quality. In this study, we introduce policies to reduce nonpoint source pollution that link eligibility for agricultural subsidies to compliance with water quality goals. We then use economic laboratory experiments to provide empirical evidence related to the performance of these policies. In the policy treatments, participants risk losing some or all of their subsidies if the ambient pollution level exceeds an announced target. A novel feature of our experiment is that we test a policy treatment that ensures that no subsidies are lost if a producer implements a verifiable conservation technology that reduces emissions. In these experiments, policies that link the receipt of subsidies to ambient water quality nearly achieve the socially optimal level of pollution. The results suggest that water quality policies that rely on the threat of subsidy reductions are a potentially viable option for reducing aggregate water pollution. Although a policy that allows polluters to avoid potential losses by implementing a verifiable conservation technology could increase political support for ambient-based policies, our results suggest that, depending upon the magnitudes of social damages from emissions and the cost of implementing a conservation technology, such policies may be less cost-effective for a comparable reduction in pollution.

Key words: Agri-environmental policy, ambient-pollution tax, conservation compliance, laboratory economics experiment, nonpoint source pollution, water quality.

JEL codes: Q25, Q53, Q58.

There is a growing consensus that nonpoint source (NPS) pollution generated as a byproduct of agricultural production is a major contributor to water quality problems such as eutrophication and algal blooms (Boesch, Brinsfield, and Magnien 2001; Ribaudo 2003; Rabotyagov et al. 2010). Despite this recognition, state and federal policies in the United States seldom tie financial incentives to the environmental performance of agricultural firms. There is, however, growing use of conservation-compliance policies that require agricultural firms to meet certain environmental standards to receive payments and subsidies associated with federal agricultural support programs, including subsidized crop insurance. Ribaudo, Key, and Sneeringer (2017) provide an excellent outline of the federal programs that are subject to compliance provisions under the 2014 Farm Bill (see table 1 on pg. 461 of their paper).

Farmer organizations and environmental groups have jointly supported the use of

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Amer. J. Agr. Econ. 101(1): 109–133; doi: 10.1093/ajae/aay057
Published online September 24, 2018

conservation compliance as a mechanism to improve environmental outcomes while continuing to support farmers through federal programs. In January of 2017, delegates for the American Farm Bureau Federation voted to continue supporting conservation compliance provisions tied to the U.S. federal crop insurance program (Hagstrom 2017). Currently, farmers who receive financial support from federal programs are required to reduce erosion by complying with a set of conservation standards on highly erodible cropland (HEL), and they are not permitted to drain wetlands. These compliance requirements have been shown to significantly reduce soil erosion (Claassen et al. 2017), and some argue that compliance requirements have the potential to achieve more improvements if they are expanded. Recent research suggests that including a set of nutrient management practices that improve water quality into the suite of compliance requirements could reduce excessive nitrogen fertilizer applications by up to 60% in the Mississippi River Basin, if enforcement mechanisms are adequate (Ribaudo, Key, and Sneeringer 2017). However, to our knowledge, no research has examined how conservation compliance and eligibility for farm program benefits could be tied directly to water quality outcomes.

Using an economic experiment, we test two such policy mechanisms that link receipt of subsidies to water quality goals, thereby reducing or eliminating producers' subsidies when water pollution exceeds a target level. Under both policies, the reduction in subsidies is determined by aggregate pollution emissions. In addition, one of the policies assures individual producers that they will not lose any of their subsidies if they adopt a costly conservation technology that reduces pollution. We compare the effect of these policy mechanisms with the effects of a linear ambient-pollution tax and a no-policy control.

By analyzing policy options that merge a conservation-compliance framework with a subsidy reduction that is based on observed ambient pollution, this study contributes to the literature on innovative NPS pollution policies in four ways. First, we develop a theoretical framework to show how subsidy reductions can be used to provide incentives designed to improve ambient water quality. In this framework, producer subsidies decrease if water pollution is excessive, but unlike an ambient tax, which can potentially increase indefinitely as pollution rises, the total subsidy reduction is capped at the original subsidy level. This introduces additional equilibria that could undermine incentives to reduce pollution at the margin. Second, we use an economic laboratory experiment to empirically analyze observed behavior and social welfare outcomes under the subsidy-reduction and traditional ambient-pollution tax policies. Such tax policies have generated positive social welfare outcomes in previous laboratory experiments (e.g., Spraggon 2004; Suter et al. 2008; Suter and Vossler 2014; Miao et al. 2016). It is an open empirical question whether the subsidy-reduction policy will generate similarly efficient outcomes, given the additional equilibrium and the change in framing (Tversky and Kahneman 1981). Thus, we are interested in determining whether this subsidy-reduction policy will generate similarly efficient outcomes. The third primary contribution of this study is the inclusion of a treatment in which participants can avoid the subsidy-reduction policy by making an individual investment in a conservation technology. This feature addresses concerns related to political influence and fairness often associated with policies to control ambient pollution that impose penalties on individual firms based on group-level outcomes. Finally, our experiment is designed such that firm-level emissions are determined both by a production decision and a technology decision. This feature of the experiment is in response to a recent review of economic experiments addressing mitigation of ambient pollution (Shortle and Horan 2013) that highlights the need for more realistic experimental designs in which participants make more than one abatement choice.

The results from this research provide several important insights. First, we find that the subsidy-reduction policy is as effective as the tax policy in motivating pollution abatement. In the experiment, both policies reduce pollution below levels achieved in the no-policy baseline and these policies nearly achieve the socially optimal level of pollution. Second, when participants receive individual assurances that they will not lose their subsidies if they invest in a conservation technology, we observe a significant increase in the number of participants who invest in the technology. This does not change the overall performance of the policy in reducing the ambient level of pollution; however, it results in a significant decrease in social welfare because individuals reduce pollution in ways that are more costly compared to what they would have done without the assurance option.

For policymakers, the results suggest that water quality policies that rely on the threat of subsidy reductions are a potentially viable option for reducing ambient water pollution in a cost-effective way. Additionally, allowing polluters to avoid penalties by making a conservation investment could increase political support for policies based on ambient pollution levels, but our results suggest that such policies could also cost more overall for a comparable reduction in pollution. Unlike a tax, which would penalize everyone in a specific watershed, a subsidy-reduction policy would only affect individuals who receive the subsidy. Our research assumes that each participant is a subsidy recipient. Future research that allows individuals to select into subsidy programs and accounts for heterogeneous incentives from such programs would provide additional insight into the effectiveness of the subsidy-reduction policy.

Background

The theory that underlies ambient-based pollution-control policies related to NPS water pollution was first introduced in the economics literature by Segerson (1988) and Xepapadeas (1991) and subsequently expanded by Hansen (1998) and Horan, Shortle, and Abler (1998). Given a lack of real-world opportunities to empirically test the performance of incentive-based policies based on ambient levels of pollution, economists have generally approached the problem using test-bed laboratory experiments designed to assess how human decision making in a controlled setting compares to theoretical predictions (Spraggon 2002, 2004, 2013; Alpízar et al. 2004; Poe et al. 2004; Cochard et al. 2005; Vossler et al. 2006; Suter et al. 2008, 2009, 2010; Spraggon and Oxoby 2010; Cason and Gangadharan 2013; Miao et al. 2016). Results from previous experiments illustrate some key tradeoffs in the design of policies based on ambient pollution levels; however, nearly all of the studies have shown that appropriately designed, ambient-based pollution-control policies can consistently incentivize groups to achieve pollution objectives even when individual behavior diverges from theoretical predictions. Recent research by Cason and Gangadharan (2013), for example, shows that formal penalties based on ambient pollution are significantly more effective in achieving pollution targets than informal peer-sanction mechanisms.

Despite the demonstrated positive performance of ambient-based policies in the laboratory, few policies implemented in the field have used overall water quality outcomes to determine penalties. Arguments against policies based on the ambient level of pollution have typically focused on the political feasibility (e.g., Cason and Gangadharan 2013) of imposing financial penalties on individuals based on a group outcome. As Shortle and Horan (2001) point out, with such a policy an individual firm that made a significant investment to improve its environmental performance could still be subjected to penalties if nearby firms did not similarly reduce their pollution or if stochastic changes in natural sources of pollution and/or weather caused the ambient pollution level in the waterbody to exceed the defined threshold.

Furthermore, agricultural firms traditionally have not been subjected to fees based on pollution outcomes. Shortle et al. (2012) noted that local, state, and federal initiatives in the United States aimed at improving water quality had typically followed a “pay the polluter” approach in which potential polluters are paid to take actions that seek to reduce their pollution, and that this approach had not led to the desired improvements in water quality in many watersheds. As previously noted, one exception to this reliance on paying agricultural producers for environmental stewardship is initiatives involving conservation compliance in which producers’ eligibility for subsidy programs is contingent on their implementation of specific environmental and conservation practices (Shortle et al. 2012).

The Conservation Compliance Program was established by the 1985 Food Security Act to protect environmentally sensitive land by limiting soil erosion and protecting wetlands (Claassen et al. 2004, 2017). To receive payments from some federal programs, agricultural producers must use a specific set of soil conservation practices on HEL, and they are prohibited from draining wetlands for agricultural use. Conservation-compliance provisions have been credited with providing numerous nonmarket benefits for agricultural landscapes but have been criticized for their typically narrow focus on soil erosion and wetland conversion (Claassen et al. 2004;

Perez 2007; Arbuckle 2013). Expanding the scope of compliance programs could lead to cost-effective reductions in nutrient losses and improved water quality, and numerous agricultural and environmental groups have expressed support for such an expansion, including the American Farmland Trust (2011) and the Environmental Working Group (Perez 2007). A survey of Iowa producers found that the majority of them (69% of those surveyed) supported expanding the Conservation Compliance Program to include management of nutrients deposited in waterways (Arbuckle 2013).

The 2014 Farm Bill expanded the scope of conservation compliance by making producers' eligibility for federally subsidized crop insurance dependent on their compliance with the requirements for HEL and wetland conservation (Coppess 2014). Nearly 90% of the cropland in the United States is insured, and those producers rely on approximately $7 billion in annual federal subsidies of the premiums (O'Donoghue 2014; Farrin, Miranda, and O'Donoghue 2016). Other federal agricultural programs that now require conservation compliance include loan and disaster assistance programs managed by the Farm Service Agency (FSA) and conservation programs managed by FSA and the Natural Resources Conservation Service (NRCS). Several state-level conservation compliance policies have recently been implemented as well. The Wisconsin Farmland Preservation Program, for example, has tied eligibility for farmland tax credits to compliance with specific soil and water standards (Wisconsin Department of Agriculture, Trade, and Consumer Protection 2016). Although conservation-compliance policies currently are not connected directly to environmental performance outcomes, policymakers are increasingly interested in tying the benefits of agricultural support programs to agricultural management decisions that influence environmental quality.

Theoretical Framework and Experimental Design

Emissions of NPS pollution by multiple agricultural operations increase the ambient level of pollution in a waterbody and cannot be traced back to their sources. Inspired by the existing literature on ambient pollution policies and the growing interest in conservation compliance initiatives, this experiment tests two new policy mechanisms that link access to agricultural subsidies to ambient pollution levels. In this section, we describe the theoretical framework that underlies our experiments and our experimental design.

Individual producers can reduce their pollution emissions by adopting a conservation technology (e.g., planting cover crops) and/or reducing the quantity of inputs to crop production (e.g., applying fewer nutrients per acre). However, under any policy based on the ambient level of pollution, a producer that reduces its emissions could still be subjected to a tax or reduction in subsidy if other producers in the watershed do not adequately reduce their emissions. One way to promote environmentally-beneficial practices and address potential concerns about fairness associated with typical ambient-pollution-based policies is to protect agricultural producers who choose to adopt the conservation technology from the financial penalty regardless of whether the target pollution level is achieved.

Consider N identical agricultural firms indexed by i=1, 2, . . . , N that comprise a watershed. Each firm receives a government benefit, g, and earns net production income of $b(x_i)$, where x_i represents the quantity of inputs used in production. Net production income is assumed to be a function of input use, reaching a maximum at $x_i = \varphi$ (i.e., $\partial b_i \ / \ \partial x_i = 0$ if $x_i = \varphi$, $\partial b_i \ / \ \partial x_i > 0$ if $x_i < \varphi$, and $\partial b_i \ / \ \partial x_i < 0$ if $x_i > \varphi$). The intuition for why input use beyond φ reduces net production income is that excessive use of inputs (e.g., nutrient application) increases the costs of production faster than it increases production revenue. The quantity of emissions generated by a given firm, e_i , is positively related to input use, $\partial e_i \ / \ \partial x_i > 0$. In addition, firms face a binary choice related to their production technology, a_i. Specifically, they can choose between a conventional production technology ($a_i = 0$) and a conservation production technology ($a_i = 1$). The conservation technology reduces the emissions associated with a given level of input use: $e(x_i; a_i = 1) < e(x_i; a_i = 0) \ \forall \ x_\mathrm{i} > 0$. We assume that there is no additional cost of using the conventional technology. The cost of adopting the conservation technology is denoted by c so that the cost associated with the choice of technology is ca_i.

An individual firm's profit is a function of the subsidy it receives, net production income, and the cost associated with the production technology chosen. The level of emissions generated by the firms in the watershed is assumed to have no direct impact on agricultural profits. Formally, the firm's profit-maximization problem is given by

$$(1)\qquad \max_{x_i, a_i} \pi(x_i,\ a_i) =\ g + b(x_i) - ca_i.$$

Since adoption of the conservation technology imposes a cost without increasing net income from production, a profit-maximizing firm is predicted to use the conventional production technology ($a_i = 0$) and input quantity φ that satisfies $\partial b_i \ / \ \partial x_i = 0$.

Total ambient pollution in the watershed is a function of the emissions from all N firms: $z(e_1, e_2,\ \ldots,\ e_N)$. The total economic damage from ambient pollution is represented by $D(z)$, and we assume that this damage affects downstream water users such as municipalities (as a loss of water quality) but does not directly affect the profits of the agricultural firms. We further assume that emissions are additive so that the ambient level of pollution, z, is $\sum_{i=1}^{N} e_i$ and that the amount of damage increases linearly with ambient pollution.

The social planner's objective is to maximize social net benefit (SNB)—total profit for the group of producers minus the cost of damage from their emissions, by choosing the optimal input quantity (x_i) and technology choice (a_i) for each firm,

$$(2)\qquad \max_{x_i, a_i}\ \sum_{i=1}^{N} (g + b(x_i) - ca_i) - D(z).$$

In equation (2), $D(z)$ can be replaced with, $d\sum_{i=1}^{N} e_i(x_i; a_i)$ where d is the marginal cost of damages.[1]

Since economic damages from emissions do not enter the firm's profit function but have a negative impact on social welfare, emissions are predicted to exceed the efficient level, z^*, when there is no regulatory policy in place. Because the amount of damage is assumed to increase linearly with total emissions, imposing a constant tax rate of $\tau = D'(z)$ per unit of ambient pollution on each firm theoretically provides an appropriate incentive for profit-maximizing producers to reduce the amount of pollution they emit to the socially optimal level. Setting τ equal to $D'(z)$ aligns the social planner's problem with the firm's profit-maximization problem. A tax threshold of $\bar{z}\ \leq\ z^*$ can also be implemented to reduce the tax burden on individual firms. With the threshold, all of the firms in the watershed pay tax rate τ on each unit of ambient pollution exceeding $\bar{z}$,

$$(3)\qquad T(z) = \begin{cases} \tau(z - \bar{z}) & \textit{if}\ \ z > \bar{z} \\ 0 & \textit{if}\ \ z\ \leq\ \bar{z}. \end{cases}$$

As previously noted, the feasibility of implementing a tax on ambient pollution is questionable. The alternative policy approach analyzed in this study links agricultural subsidies currently received by a producer, from programs such as federal crop insurance, to the level of ambient pollution in the waterbody. When the overall level of pollution exceeds the threshold, $\bar{z}$, the producer's subsidy is reduced by $R(z)$. This reduction in the subsidy can be structured the same way as the pollution tax but cannot exceed the amount of the original subsidy, g,

$$(4)\qquad R(z) = \begin{cases} g & \textit{if}\ \ z \geq \bar{z} + \dfrac{g}{r} \\ r(z - \bar{z}) & \textit{if}\ \ \bar{z}\ <\ z\ <\ \bar{z} + \dfrac{g}{r}, \\ 0 & \textit{if}\ \ z\ \leq\ \bar{z} \end{cases}$$

where r is the marginal rate of the subsidy reduction. With $r\ =\ \tau$, the theoretical incentives generated by the subsidy reduction are identical to the incentives under the tax when $z\ <\ \bar{z} + \frac{g}{r}$. In equation (4), $\frac{g}{r}$ represents the units of excess pollution (i.e., pollution above the threshold, $\bar{z}$) that results in the complete removal of the subsidy. In other words, when $z \geq \bar{z} + \frac{g}{r}$, the financial penalty equals g and the subsidy is completely dissipated. The feasibility of the subsidy reduction policy therefore critically depends on the magnitude of the subsidy received by a producer being large relative to r (which itself is equal to the marginal damage of pollution). There is undoubtedly considerable spatial and temporal

[1] We assume that there are no additional monitoring or enforcement costs that would affect social welfare. In reality, there would be a variety of administrative costs involved with these policies. We simplify the policy setting to focus on analyzing the behavioral change generated by the policies and leave it to future research to investigate monitoring and enforcement.

Table 1. Functional Forms and Parameters Used in the Experiment

Description	Functional Form	Parameter Values
Net production income	$b_i = \alpha - \gamma(\varphi - x_i)^2$	$\alpha = 400;\ \gamma = 10;\ \varphi = 6$
Subsidy (general earnings)	g	$g = 400$
Emissions function	$e_i = \left(1 - \frac{a_i}{\delta}\right)x_i$	$\delta = 2; x_i \in [0,\ 9]; a_i \in \{0,\ 1\}$
Cost of conservation technology	c	$c = 150$
Pollution function	$z = \sum_{i=1}^{N} e_i$	$N = 6$
Damage function	$D(X) = dX$	$d = 52$

variation in agricultural subsidies and marginal pollution damages across the United States. In 2013, it is estimated that annual crop insurance subsidies alone amounted to approximately \$19,000 for the average producer with crop insurance (Shields 2015). Despite recent changes in the crop insurance program, with over 90% of cropland acreage insured in the United States (Farrin, Miranda, and O'Donoghue 2016), it seems likely that the subsidies received by many producers would provide sufficient incentives for the subsidy reduction policy to be viable.

Under both the tax and the subsidy reduction, an individual firm's profit-maximization problem involves choosing the optimal input quantity, x_i, and technology, a_i,

$$(5) \qquad \max_{x_i, a_i}\ g + b(x_i) - ca_i - E[P(z)]$$

where $E[P(z)]$ is the expected financial penalty when $P(z)$ is either $T(z)$, the tax intervention, or $R(z)$, the subsidy-reduction intervention.

Next, consider a policy that assures a firm that its subsidy will not be reduced or eliminated if it adopts a verifiable conservation technology. A profit-maximizing firm will choose to adopt the conservation technology if its total expected profit (including subsidies) when using the technology is greater than its expected profit with the conventional technology,

$$(6) \qquad (g - c + b(x_i)) \geq (g - E[R(z)] + b(x_i)).$$

Thus, the producer's technology choice depends on the expected reduction in subsidy, which itself depends on the expected level of total pollution. The firm's profit maximizing input choice, x_i, also depends on whether it is subject to the subsidy reduction policy.

Incorporating the potential for assurance from the penalty in the ambient-pollution policy introduces two important behavioral considerations. First, the firm's input decision becomes a function of the number of firms in the watershed that are likely to adopt the conservation technology and receive assurance. Firms receiving assurance from the policy are expected to use inputs until $\partial b_i \ / \ \partial x_i = 0$, since they are not at risk of being penalized for their emissions and are therefore expected to choose the input level resulting in the highest net production income, φ. Firms that do not adopt the conservation technology and therefore do not receive assurance from potential penalties must consider how emissions from the "unregulated" firms affect the probability that the ambient pollution level will exceed the threshold and trigger the tax or reduction in subsidies.

The second behavioral consideration is that the risk preferences of individual firms could play a role in their input use and technology decisions and consequently in the overall outcome of the policy. Risk-averse firms should be relatively more likely to adopt the conservation technology and thus reduce uncertainty regarding the imposition of penalties. Our experiment therefore incorporates a risk-preference test (Holt and Laury 2002) to empirically examine the relationship between participants' decisions in the experiment and their risk preferences.

Our theoretical framework informs the specific functional forms and parameters used in the experiment. Those functions and parameter values are presented in table 1. Firm profit is a function of the subsidy it receives, net production income, its technology decision, and any penalty that it receives related to ambient pollution levels. In the experiment, the level of the subsidy, g, is 400 experimental dollars. Net production income (b_i) is generated as a quadratic function of input use, such that $b(x_i) = \alpha - \gamma(\varphi - x_i)^2$ where x_i is the firm's input decision. The values for parameters α, γ, and φ are equal to 400, 10, and 6, respectively. In the experiment, the input choice is determined directly by the participant's choice of one of ten "management decisions" labeled A through J (see table 2). A participant maximizes net production income by choosing management decision G, which involves 6 units of input use. The relationship between input use, x_i, the choice of technology, a_i, and the quantity of emissions generated by an individual firm, e_i, is given by $e_i = \left(1 - \frac{a_i}{2}\right)x_i$. Therefore, with the conventional technology, $a_i = 0$, and the emissions generated by a given firm is equal to its input use. With the conservation technology in place, emissions are equal to one half of the inputs used. The cost, c, of using the conservation technology in the experiment is 150 experimental dollars. Aggregate pollution, z, is the linear summation of the individual firms' emissions. Social damage increases linearly with pollution so that each unit of pollution generates an additional 52 experimental dollars of damage. When these parameters are used to solve the social planner's problem (equation (2)), one finds that the socially optimal level of pollution is 20.4 units. Unlike our theoretical framework, which relies on continuous functions, we used discrete management and technology options to simplify the decision space in the experiment. In the discrete decision space used for the experiment and shown in table 2, the socially optimal level of pollution is 18 units, achieved by each firm choosing management decision D and the conventional technology, $a_i = 0$. This outcome generates 3 units of emissions per firm and achieves a social net benefit of 3,324, which is the highest possible social net benefit given the decision environment in the experiment.

Experimental Procedures and Treatments

We analyze the effect of decisions that determine the ambient level of pollution in a waterbody using an economic laboratory experiment involving 156 undergraduate student participants in sessions conducted in the Spring of 2016 at the University of Delaware in the Center for Experimental & Applied Economics in the United States. Each experiment session involved 18 or 24 students to allow for groups with six participants each. Participants were recruited via email using lists managed by the university's economics department. The emails stated that participants in the research would be paid an average of \$30 to participate in a 90-minute experiment about decision making; no other information about the experiment was provided prior to the session. The average, maximum, and minimum take home earnings were \$31.67, \$72.75, and \$21.50, respectively. The average earnings are roughly equivalent to earning \$20 per hour, which is nearly twice what most on-campus jobs pay undergraduate students and is in line with the payments of other recent experiments (such as Suter et al. 2010; Arnold et al 2013; Messer, Duke, and Lynch 2014; Fooks et al. 2016; Banerjee 2017).

Each experiment session consisted of five phases: instruction, practice rounds, the experiment, an adapted Holt-Laury lottery, and a short survey. The practice rounds and experiment session were programmed using Willow software (Weel 2016), and students were randomly assigned a tablet computer to use during the session. Students were seated at desks equipped with privacy barriers that prevented participants from viewing the computer screens of other participants.

First, participants were given the experiment instructions as a paper handout (see online supplementary material, appendix II) and time to read them independently. The instructions were then reviewed audibly via a prerecorded PowerPoint presentation. After reviewing the instructions, participants completed a short activity to make sure that they understood how the experiment worked and then participated in five unpaid practice rounds[2] to ensure that they were comfortable making decisions on the tablet before beginning the experiment.

Participants were told that they were managers of firms and that they were randomly assigned to a six-person watershed group, but they were not able to identify the other members of their group. Participants were further informed that they would make decisions in a series of rounds that would determine how much they earned and the amount of pollution emitted to a water source common to their watershed group. They were also told that all of the firms in their group were

[2] Spraggon (2004) found that participants in an experiment required a minimum of five rounds to adequately understand how the experiment worked.

Table 2. Emissions and Profits Related to the Two Decisions Made by Firms in Each Round of the Experiment, 1) Firm *i*'s Management (Input) Decision and 2) Firm *i*'s Technology Decision

Management Decision (corresponding input level, x_i)	General Earnings (g)	Net Production Income (b_i)	Technology 1 (Conventional; $a_i = 0$) Profit (π_i)	Technology 1 (Conventional; $a_i = 0$) Emissions (e_i)	Technology 2 (Conservation; $a_i = 1$) Profit (π_i)	Technology 2 (Conservation; $a_i = 1$) Emissions (e_i)
A ($x_i = 0$)	400	40	440	0.0	290	0.0
B ($x_i = 1$)	400	150	550	1.0	400	0.5
C ($x_i = 2$)	400	240	640	2.0	490	1.0
D ($x_i = 3$)	400	310	710	3.0	560	1.5
E ($x_i = 4$)	400	360	760	4.0	610	2.0
F ($x_i = 5$)	400	390	790	5.0	640	2.5
G ($x_i = 6$)	400	400	800	6.0	650	3.0
H ($x_i = 7$)	400	390	790	7.0	640	3.5
I ($x_i = 8$)	400	360	760	8.0	610	4.0
J ($x_i = 9$)	400	310	710	9.0	560	4.5

identical in terms of potential net production income, profits, and pollution relationships. Participants were encouraged to ask administrators points of clarification about the experiment procedures. Otherwise, communication was not permitted.

Each experiment session involved four treatments in a within-subject design, and each treatment involved five decision rounds, resulting in twenty total rounds. In each round, participants simultaneously chose the technology to use (the conventional technology or the costly conservation technology) and one of the ten management decisions (A–J) shown in table 2. The list of management options and the corresponding levels of net production income were shown on each participant's screen. The options were identical for all participants and were constant in all rounds of the experiment. The 150 experimental dollar cost of the conservation technology was also shown.

In addition to the net production income, participants received 400 experimental dollars as "general earnings" in each round. No additional information was provided about that money, which represented a subsidy paid to the firm. The participant's profit in each round consisted of the general earnings plus net production income minus the cost of the conservation technology if adopted. The relationship between the management decisions and resulting profits and emissions for each technology are shown in table 2.

The four treatments included a no-policy control (C1), a linear tax (T2), a linear subsidy reduction (T3), and a linear subsidy reduction with an assurance of no penalty for participants who adopted the conservation technology (T4). In the control treatment, there were no penalties for the resulting emissions. In the policy treatments, participants were subject to a pollution threshold of 18 units per group and treatment-specific penalties when the group emissions exceeded that amount in a given round.

Under the linear tax treatment (T2), all firms in a watershed group paid a tax of 52 experimental dollars, which is equivalent to the marginal damage of pollution, for each unit of pollution over the threshold. Under the policy treatments T3 and T4, participants lost some or all of their general earnings (the subsidy) when the pollution from their group exceeded the threshold. As with the tax, the amount of the subsidy reduction increased linearly by 52 experimental dollars with each unit of pollution over the threshold. Unlike the tax, the subsidy reduction could not exceed the full amount of the subsidy (400 experimental dollars). Treatments T3 and T4 both used the subsidy-reduction mechanism, but T4 gave the participants the option to avoid the risk of a subsidy reduction by adopting the conservation technology. The intuition for T4 is that whereas input choices can be difficult to observe, the use of a visible conservation technology can be verified more easily (for example by using remote sensing technology), which would reduce the cost of monitoring for program administrators (Rees and Stephenson 2014).

Prior to the first round of each treatment, the watershed groups were randomly re-assigned (imperfect stranger matching) and specific instructions related to the

Table 3. Adapted Holt-Laury Risk-Elicitation Task

Decision Row	Option A	Option B
1	\$20 if the die is 1 \$16 if the die is 2–10	\$39 if the die is 1 \$1 if the die is 2–10
2	\$20 if the die is 1–2 \$16 if the die is 3–10	\$39 if the die is 1–2 \$1 if the die is 3–10
3	\$20 if the die is 1–3 \$16 if the die is 4–10	\$39 if the die is 1–3 \$1 if the die is 4–10
4	\$20 if the die is 1–4 \$16 if the die is 5–10	\$39 if the die is 1–4 \$1 if the die is 5–10
5	\$20 if the die is 1–5 \$16 if the die is 6–10	\$39 if the die is 1–5 \$1 if the die is 6–10
6	\$20 if the die is 1–6 \$16 if the die is 7–10	\$39 if the die is 1–6 \$1 if the die is 7–10
7	\$20 if the die is 1–7 \$16 if the die is 8–10	\$39 if the die is 1–7 \$1 if the die is 8–10
8	\$20 if the die is 1–8 \$16 if the die is 9–10	\$39 if the die is 1–8 \$1 if the die is 9–10
9	\$20 if the die is 1–9 \$16 if the die is 10	\$39 if the die is 1–9 \$1 if the die is 10
10	\$20 if the die is 1–10	\$39 if the die is 1–10

Note: Participants chose either option A or option B in each decision row.

treatment were handed out to the participants, who first read them and then observed a prerecorded PowerPoint review. A Latin-square orthogonal design was used to determine the order in which the four treatments were presented in each experiment session to control for potential order effects, resulting in four treatment orders: [C1, T2, T3, T4], [T2, T3, T4, C1], [T3, T4, C1, T2], and [T4, C1, T2, T3].

It should be noted that although the theory that we use to describe behavior is based on one-shot game-theoretic predictions, the actual experiment involved many consecutive decision rounds. We believe that the one-shot game predictions are a reasonable behavioral benchmark for two reasons. First, participants knew that there would be a finite number of rounds in each treatment. The finitely repeated nature of the game implies that cooperative outcomes are unlikely to occur given that backward induction can be used to unravel strategies that are not Nash equilibria (NEs) in the one-shot game (Normann and Wallace 2012). Second, as mentioned, imperfect stranger matching was used at the beginning of each new treatment, which reduces concerns regarding reputation effects over the course of the experiment. To account for any changes in behavior across rounds, our econometric models presented in the results section explicitly account for potential round and order effects.

Once the initial experiment phase was complete, participants undertook an adapted Holt and Laury (2002) risk-elicitation task (see table 3) that provided a measure of their risk preferences. Participants chose option A or option B in each of ten decision rows, and the payout for each option was one of two amounts—\$20 or \$16 in option A and \$39 or \$1 in option B. The likelihood of earning the higher amount was low (P(high earnings) = 1/10) in the first decision row and increased by 1/10 in each consecutive row. By the tenth decision row, the higher payout was certain (P(high earnings) = 1) so it was always rational to choose option B and earn \$39. In the other rows, option B was considered the riskier decision because of the large difference between the low and high payouts. Due to the large payments offered, one-sixth of the participants were randomly selected to receive a payout for one randomly selected decision row. Each decision was equally likely to be chosen to determine their payout, giving them an incentive to

Table 4. Mean Group Outcomes for Control and Three Policy Treatments

Treatment	NE Prediction and Resulting Pollution	Proportion using Conservation Technology	Group Pollution	Social Net Benefit	Social Efficiency
C1: No policy	$\boldsymbol{a}=0,\ \boldsymbol{x}=6,\ z=36$	0.027 (0.068)	34.20 (2.40)	2,952 (53.54)	0.061 (0.135)
T2: Tax	$\boldsymbol{a}=0,\ \boldsymbol{x}=3,\ z=18$	0.085 (0.104)	19.48 (2.58)	3,226 (77.05)	0.754 (0.195)
T3: Subsidy reduction	$\boldsymbol{a}=0,\ \boldsymbol{x}=3,\ z=18$; $\boldsymbol{a}=0,\ \boldsymbol{x}=6,\ z=36$	0.068 (0.109)	19.66 (2.90)	3,233 (88.59)	0.769 (0.224)
T4: Subsidy reduction with assurance	$\boldsymbol{a}=0,\ \boldsymbol{x}=3,\ z=18$	0.504 (0.269)	20.03 (2.26)	3,078 (121.76)	0.380 (0.307)
All treatments pooled ($n=520$)	– –	0.171 (0.249)	23.34 (6.77)	3122 (146.00)	0.491 (0.369)

Note: Standard deviations are presented in parentheses; 26 groups and 5 rounds generate 130 observations for each treatment cell.

treat each decision seriously. As we describe in our analytical methods section, risk averse individuals were identified based on the choices they made during the Holt-Laury risk-elicitation task.

Each participant's final take-home earnings consisted of their firm's total profits from the experiment, with 600 experimental dollars equal to \$1, and their payouts from the risk-elicitation exercise. The final task for each participant was to complete a short survey that collected demographic data, such as their gender, age, race, academic major, home state or country, and the number of economic courses they had taken.

Theoretical Predictions

To frame the analysis of results, we develop theoretical predictions of behavior in the four treatments based on the parametrization of the experiment described in the previous section. These predictions are summarized in table 4. Additionally, we present a payoff matrix for each treatment in the online supplementary material, appendix I. In the experiment, firms are homogeneous in terms of the functions that determine their profits and emissions and are explicitly informed of this. This symmetry implies that they have complete information related to the incentives faced by other firms in their group, which is necessary for them to form equilibrium expectations. Applying the parameters to equation (5), the profit function for an individual participant in each round of the "no-policy control" (C1) is

$$\pi_{C1}(a_i, x_i) = 800 - 10(6 - x_i)^2 - 150a_i \quad (7) \quad s.t.\ a_i \in \{0,\ 1\},\quad x_i \in \{0,1,2,3,4,5,6,7,8,9\}.$$

Pollution does not influence profits and therefore profit maximization requires $a_i = 0$ and $x_i = 6$. Choosing the conservation technology ($a_i = 1$) involves a cost of 150 and provides no financial benefit. Input use greater or less than $x_i = 6$ implies that the second term on the right-hand side of equation (7) is positive and therefore reduces profits.[3]

In the tax treatment (T2), an individual firm's profit equation can be written as

$$\begin{aligned} \pi_{T2}(a_i, x_i) = {} & 800 - 10(6 - x_i)^2 \\ & - max[0,\ 52(z_{-i} + (1 - a_i/2)x_i - 18)] \\ & - 150a_i \quad (8) \\ s.t.\ & a_i \in \{0,\ 1\},\ x_i \in \{0,\ 1,\ 2,\ 3,\ 4,\ 5,\ 6,\ 7,\ 8,\ 9\}, \end{aligned}$$

where z_{-i} represents the cumulative emissions from the other five firms in the group. In this treatment, $\boldsymbol{a} = 0,\ \boldsymbol{x} = 3$, is a unique NE. To show this, first note that a profit maximizing firm will never choose $x_i < 3$ or

[3] We create a decision space in which the predicted management decision is not a corner solution to allow for a possible distribution of behavior around a predicted outcome. Although theory predicts that no one would choose input levels higher than 6, human decision makers sometimes exhibit behavior that is difficult to explain with standard theory.

$x_i > 6$. Input use below 3 reduces net production income by at least 70 compared to $x_i = 3$, which is more than the marginal reduction in tax liability of 52. Increasing input use above 6 reduces net production income and can only increase the firm's tax liability and therefore always reduces profits.

We now show that choosing the conservation technology, which reduces the emissions associated with any input choice by half, at a cost of 150, is a strictly dominated strategy. If $z_{-i} \leq 12$, aggregate emissions would not exceed the tax threshold of 18 even if the firm chooses $a_i = 0$ and $x_i = 6$ (the input choice that maximizes net production income). Therefore $a_i = 1$ reduces profit since it costs 150 and does not reduce the firm's tax liability. If $12 < z_{-i} \leq 15$ and the firm chooses $a_i = 1$, then $x_i = 6$ is the optimal input choice since in maximizes net production income and pollution does not exceed the threshold. Choosing $a_i = 1$ does not maximize profits, however, since choosing $a_i = 0$ and $x_i = 3$ allows the firm to avoid the 150 cost of the conservation technology and only reduces net production income by $10(6-3)^2 = 90$. If $z_{-i} > 15$, then firms with $a_i = 0$ face the profit function $\pi_{T2}(x_i;\ z_{-i}|a_i = 0) = 800 - 10(6 - x_i)^2 - 52(z_{-i} + x_i - 18)$. Given the discrete input levels, profit is maximized with $x_i = 3$, resulting in profit of $\hat{\pi}_{T2}(z_{-i}|a_i = 0) = 1490 - 52z_{-i}$. With $a_i = 1$ firms face $\pi_{T2}(x_i;\ z_{-i}|a_i = 1) = 650 - 10(6 - x_i)^2 - 52\left(z_{-i} + \frac{x_i}{2} - 18\right)$, which is maximized with $x_i = 5$ and a resulting profit of $\pi_{T2}(z_{-i}|a_i = 1) = 1446 - 52z_{-i}$. Maximized profit with $a_i = 0$ is therefore higher than $a_i = 1$ for all $z_{-i} > 15$. We have now shown that the profits with $a_i = 0$ are higher than with $a_i = 1$ for all possible values z_{-i}, making $a_i = 1$ strictly dominated.

Since $a_i = 1$ is a strictly dominated strategy, any NE must involve $\boldsymbol{a} = 0$. To see that a unique NE must also involve $\boldsymbol{x} = 3$, suppose that the other firms in the group all use the conventional technology ($\boldsymbol{a_{-i}} = 0$) and choose $\boldsymbol{x_{-i}} = 3$, resulting in cumulative emissions of $z_{-i} = 15$. Firm i maximizes profits by selecting $a_i = 0$ and $x_i = 3$ and the tax threshold is exactly met ($z = 18$). Choosing $x_i < 3$ reduces net production income with no benefit in terms of a lower tax liability (since it is zero with $z = 18$). Choosing $x_i > 3$ also generates lower profits since it results in a marginal increase in net production income of no more than $10[(6-3)^2 - (6-4)^2] = 50$, which is less than the 52 unit marginal cost of the tax that the firm faces with pollution greater than 18.

Further, $\boldsymbol{a} = 0,\ \boldsymbol{x} = 3$ is a unique NE. The input choice $x_i = 3$ is a best response for all $z_{-\mathrm{i}} \geq 15$ since the marginal benefit of increasing input use is less than the tax rate of 52. Choosing $x_i > 3$ is a best response to $z_{-\mathrm{i}} < 15$, since increasing input use allows the firm to increase its net production income without causing pollution to exceed the threshold. However, there cannot be an NE with any firm choosing $x_i > 3$, since we have shown that it is never a best response for any firm to choose $x_i < 3$, which is required for $z_{-\mathrm{i}} < 15$.

In the subsidy reduction treatment (T3) a firm's profit equation can be written as

$$
\begin{aligned}
(9)\quad \pi_{T3}(a_i, x_i) \;=\; & 800 - 10(6 - x_i)^2 \\
& - min[400,\ max[0, 52(z_{-i} + (1 - a_i/2)x_i - 18)]] \\
& - 150a_i \\
& s.t.\ a_i \in \{0,\ 1\},\ \ x_i \in \{0, 1, 2, 3, 4, 5, 6, 7, 8, 9\}.
\end{aligned}
$$

The profit equation is similar to the tax treatment in equation (8), except that there is an upper bound of 400 on the penalty (subsidy reduction) associated with pollution. In T3, $a_i = 1$ remains a strictly dominated strategy and $\boldsymbol{a} = 0,\ \boldsymbol{x} = 3$ remains an NE. In addition, due to the cap on the subsidy reduction, there is now a second NE with $\boldsymbol{a} = 0,\ \boldsymbol{x} = 6$. Dividing the full subsidy of 400 by the 52 unit marginal rate of subsidy reduction reveals that if pollution is more the 7 units higher than the threshold of 18, then the subsidy reduction cap is reached. Therefore, if $z_{-\mathrm{i}}$ is sufficiently high, the firm's best response is to choose $x_i = 6$, which maximizes net production income, but results in the loss of the full subsidy. Given that firms are symmetric, choosing $x_i = 6$ becomes a mutual best response for all group members and results in pollution of $z = 36$. No individual firm has an incentive to deviate by choosing $x_i < 6$ since this reduces net production income without changing the fact that the full subsidy is lost. If the existence of the $\boldsymbol{a} = 0,\ \boldsymbol{x} = 6$ NE influences behavior in the experiment, then we expect to observe higher ambient pollution levels in T3 compared to T2.

While not captured by noncooperative game theoretic predictions, the framing of the subsidy reduction as a loss may also have an impact on behavior. The framing of choices (Tversky and Kahneman 1981) coupled with loss aversion (Tversky and Kahneman 1991) has been shown to impact behavior in experiments with participant pools composed of students (Thaler et al. 1997) and professionals (Haigh and List 2005). In this case, if the framing of the penalty related to pollution in excess of the threshold as a loss influences behavior, one would expect to see lower emissions in T3 compared to T2.

In the subsidy reduction with assurance treatment (T4) a firm's profit equation is identical to that for T3 (equation (9)), except that choosing $a_i = 1$ gives the firm indemnity from the subsidy reduction policy. In T4, $\boldsymbol{a} = 0,\ \boldsymbol{x} = 3$ remains an NE for the reasons described above. The assurance associated with $a_i = 1$ in T4, however, implies that $\boldsymbol{a} = 0,\ \boldsymbol{x} = 6$ is not an NE and that $a_i = 1$ is no longer strictly dominated. If $z_{-\mathrm{i}}$ is sufficiently high, then the firm's best response is to choose $a_i = 1$ and $x_i = 6$, which guarantees that they retain the subsidy payment and maximizes net production income. The resulting profit of 650 (subsidy of 400, plus net production income of 400, less the 150 cost of the conservation technology), however, is less than the profit that is earned when $\boldsymbol{a} = 0,\ \boldsymbol{x} = 3$. If the other firms in the group choose $\boldsymbol{a}_{-\boldsymbol{i}} = 1,\ \boldsymbol{x}_{-\boldsymbol{i}} = 6$, then firm i's best response is to choose $a_i = 0,\ x_i = 3$, which ensures that pollution remains below the threshold. It is a best response due to the fact that the savings associated with avoiding the 150 cost of $a_i = 1$ is larger than the 90 unit reduction in net production income from choosing the lower input level. This implies that $\boldsymbol{a} = 1,\ \boldsymbol{x} = 6$ is not an NE and that $\boldsymbol{a} = 0,\ \boldsymbol{x} = 3$ is the unique NE.

In T4, the potential for firms to receive indemnity from subsidy reductions implies that risk preferences may influence behavioral outcomes. Horan, Shortle, and Abler (2002) describe the theoretical implications for ambient-based policies with heterogeneous risk preferences when the fate and transport of pollutants as well as the social damage associated with pollution is stochastic. In our experiment, pollution and damages are assumed to be deterministically related to the technology and input choices that firms make. Firms do, however, face strategic uncertainty that arises from the fact that the tax or subsidy reduction that it faces is determined by both their own decision as well as the decisions of all other group members. This strategic uncertainty cannot be avoided in treatments T2 or T3. In other words, even if a firm chooses an input level of zero, they can still face costs associated with the tax or subsidy reduction. We therefore do not expect risk preferences to be correlated with behavior in these treatments.

In T4, however, participants that choose the conservation technology are no longer subjected to strategic uncertainty, since their profit is determined solely by their own decisions. Specifically, as described above, a participant can guarantee a profit of 650 by choosing $a_i = 1,\ x_i = 6$. Although the individual profit associated with the NE of $\boldsymbol{a} = 0,\ \boldsymbol{x} = 3$ is higher at 710, there is downside risk to a participant if other group members do not play the NE strategy and instead choose higher input levels that result in more pollution. One way to characterize the predicted impact of risk preferences on behavior is to assume that participants seek to maximize a von Neuman-Morgenstern expected utility function, which is a function of profit. For example, suppose that a participant's utility is represented by the function $u_i(\pi_i(\boldsymbol{a},\boldsymbol{x})) = \pi_i^{1-r}$, where r is the coefficient of relative risk aversion. Given this functional form, risk-seeking participants have a negative value for r, while risk neutral participants have $r = 0$ and risk-averse participants have $r > 0$.

As mentioned above, strategy $a_i = 1,\ x_i = 6$ results in a guaranteed profit of 650. The profit associated with strategy $a_i = 0,\ x_i = 3$ depends on the behavior of other group members. Suppose the firm expects pollution from other firms to be uniformly distributed with a mean of 15 and a range between 11 and 19 ($z_{-i} \sim U[11,\ 19]$). The expected profit given this distribution of z_{-i} is higher than 650, which implies that a risk neutral ($r = 0$) participant would be expected to choose $a_i = 0,\ x_i = 3$. If r is greater than 0.481, however, the expected utility associated with strategy $a_i = 1,\ x_i = 6$ is higher than with strategy $a_i = 0,\ x_i = 3$. This example demonstrates that participants that are relatively more risk averse (have higher values of r) can have a greater incentive to choose the conservation technology. The results from the Holt-Laury lottery provide an interval of r for each participant and allow us to test the extent to which these values are correlated with the choice of $a_i = 1$.

Based on the theoretical predictions for the treatments described above, we formulate four testable hypotheses.

> Hypothesis 1: *The aggregate level of pollution from a group is not affected by the type of penalty—a tax (T2) versus a subsidy reduction (T3 and T4)—imposed on excess pollution.*

Each of the treatments implements an ambient-based policy that generates an NE wherein the pollution threshold is achieved with equality. The marginal penalty for pollution in excess of the threshold is the same in each case. The cap on subsidy reductions creates a second NE in T3, in which all firms choose the conventional technology and an input level of $x_i = 6$, leading to total pollution of 36. Given the existence of two equilibria in the subsidy-reduction treatment it remains an open question how the subsidy reduction will affect total pollution relative to the tax. We test the null hypothesis that there will be no significant differences in pollution under the three policy treatments.

> Hypothesis 2: *Participants are more likely to adopt the conservation technology in T4, compared to T2 and T3, where adoption of the conservation technology does not affect the risk of penalties.*

In C1, T2, and T3, the conservation technology is a strictly dominated strategy, and we therefore do not expect participants to choose it. In T4, adoption of the conservation technology is not strictly dominated, due to the fact that it assures participants that they will retain their full subsidy. Given the added benefit in T4, we expect higher rates of conservation technology adoption in this treatment, despite the fact that it is not an equilibrium strategy due to the high cost of adoption.

> Hypothesis 3: *Risk aversion is positively correlated with adoption of the conservation technology in T4.*

As we have shown, risk preferences can influence a participant's incentives for choosing the conservation technology in T4. Specifically, participants can eliminate strategic uncertainty and earn a guaranteed profit by selecting the conservation technology. Given the potential to reduce uncertainty, this strategy is particularly attractive to individuals that are classified as risk-averse.

> Hypothesis 4: *The social net benefit will be lower in T4 than in T2 or T3.*

This hypothesis stems from the fact that firms that adopt the conservation technology choose a relatively costly way to reduce their emissions. *Ex ante*, we do not know how emissions and technology decisions will change under these three treatments. If we reject hypothesis 1 and fail to reject hypothesis 2, the effect of the treatments on social net benefits is ambiguous. We acknowledge that the resulting level of social net benefits depends on the relative magnitudes of social damages from emissions and the cost of selecting a conservation technology that we have chosen in the experiment. Given the high cost of the conservation technology, we hypothesize that social net benefit (equation 2), will decline when individual assurances are offered (T4) because of the increase in the cost of emission reduction rather than because of excessive emissions.

Analytical Methods

We formally test the effects of the treatments on individual technology choices, group-level pollution, and social net benefits. Random effects estimators with clustered standard errors are employed to account for the panel structure of our experimental data. The data are generated in a repeated game in which individuals make decisions in twenty separate rounds (four treatments with five rounds per treatment). The random effects model captures individual heterogeneity and accounts for the correlation across responses for individuals and groups, depending on the level of analysis. Additionally, because the experimental parameters are exogenously assigned, we can assume that there is no correlation between the unobserved heterogeneity and the explanatory variables, thus the random effects estimator is consistent and efficient (Wooldridge 2010).[4] Clustered standard errors are used to account for correlation among error terms across clusters (Cameron and Miller 2015).

Hypothesis 1 is tested using a linear random effects model to analyze how the groups'

[4] Results from fixed effects models are presented in the online supplementary material, appendix III.

emissions are affected by the policy treatments. We specify our model as

$$(10)\quad POLLUTION_{gr} = \alpha_0 + \sum_{k=2}^{4} \beta_k TREAT_{k,gr} + \sum_{m=2}^{4} \gamma_m ORDER_{m,gr} + \theta_1 ROUND + \theta_2 \frac{1}{ROUND} + \varphi_g + \varepsilon_{gr},$$

where $POLLUTION_{gr}$ is a continuous variable that reflects the aggregate pollution by group g in round r. $TREAT_k$ represents binary variables that take a value of one when the treatment number corresponds to the k subscript, and $k \in \{2,\ 3,\ 4\}$ represents the three policy treatments. $ORDER_m$ is a binary variable that controls for the order in which the four treatments were presented to participants. $ROUND$ identifies the round number and takes an integer value between 1 and 20. We also include the reciprocal of the round ($1/ROUND$) to allow for potential nonlinear learning processes that would have a diminishing effect as the experiment progressed. The estimable parameters from this model are $\alpha_0,\ \beta_k, \gamma_m,\ \theta_1$, and θ_2. We specifically analyze β_k, which provides an estimate of differences in group pollution in each of the policy treatments relative to the control treatment to determine whether the policy treatments differentially affect the group's total pollution.

To test hypotheses 2 and 3, we use a random effects probit model to examine how individual technology adoption decisions are affected by the policy intervention treatments,

$$(11)\quad TECH_{ir} = \alpha_0 + \sum_{k=2}^{4} \beta_k TREAT_{k,ir} + \sum_{m=2}^{4} \gamma_m ORDER_{m,ir} + \theta_1 ROUND + \theta_2 \frac{1}{ROUND} + \varphi_i + \varepsilon_{ir},$$

where $TECH_{ir}$ is a binary variable that equals zero when individual i uses the conventional technology and one if the individual uses the conservation technology in round r. We analyze β_k to test whether the treatments affect the likelihood that an individual will adopt the conservation technology, where $k \in \{2,\ 3,\ 4\}$ represent the three policy treatments.

In this analysis, we also incorporate data about risk preferences from the Holt-Laury task to determine whether the participants' risk attitudes change their likelihood of adopting the conservation technology in T4 in which adopters are protected from financial penalties (hypothesis 3). Our model is specified as

$$(12)\quad TECH_{ir} = \alpha_0 + \sum_{k=2}^{4} \beta_k TREAT_{k,ir} + \sum_{m=2}^{4} \gamma_m ORDER_{m,ir} + \theta_1 ROUND + \theta_2 \frac{1}{ROUND} + \omega RISKAVERSE_i + \sum_{k=2}^{4} \delta_k TREAT_{k,ir} * RISKAVERSE_i + \varphi_i + \varepsilon_{ir},$$

where risk-aversion is introduced as a binary variable ($RISKAVERSE_i$) that equals one if the subject is risk-averse. Following Holt and Laury (2002, table 3), we define "risk-averse" individuals as those with a relative risk aversion parameter strictly greater than 0.41, and we conduct sensitivity analyses to examine the robustness of our results using risk parameter thresholds of 0.15 and 0.68. Risk preference parameter ranges were assigned to individuals based on the decision row in which they first chose the riskier choice (option B). Individuals should switch from choosing option A to choosing option B only once between decision rows 1 and 10; however, 14 participants ($\sim$9%) selected option A after choosing option B in a prior decision row. This type of behavior has been observed in previous research. Andersen et al. (2006) suggest that switching in-between options indicates a subject's indifference, and this behavior can be accounted for by widening the range of their risk preference parameter. Therefore, we do not remove individuals who switched between A and B more than once. Choosing option A in decision row 10, on the other hand, likely indicates that the subject did not understand the task because choosing option A generates a lower payout with certainty in the final row. We remove three participants from our individual-level analysis because they chose option A in decision row 10.

To provide a richer understanding of the behavioral motivations that underlie the technology choices, we also estimate a model in which we control for participants' past experiences in the experiment by adding a variable that equals the cumulative amount of penalties (taxes and subsidy reductions) that the individual has incurred in previous rounds ($CPENALTIES_{ir}$). The units for this variable are 100 s of experimental dollars. We also interact this new variable with the binary treatment variables to test for differential effects of penalties within the four treatments. This model is specified as

$$(13) \quad TECH_{ir} = \alpha_0 + \sum_{k=2}^{4} \beta_k TREAT_{k,ir} + \sum_{m=2}^{4} \gamma_m ORDER_{m,ir} + \theta_1 ROUND + \theta_2 \frac{1}{ROUND} + \omega RISKAVERSE_i + \sum_{k=2}^{4} \delta_k TREAT_{k,ir} * RISKAVERSE_i + \varphi CPENALTIES_{ir} + \sum_{k=2}^{4} \rho_k TREAT_{k,ir} * CPENALTIES_{ir} + \varphi_i + \varepsilon_{ir}.$$

We test hypothesis 4 using a random effects model to compare group-level SNB for the control policy versus the treatment policies. This model is similar to equation (10), but the group-level SNB (SNB_{gr}) is used as the dependent variable

$$(14) \quad SNB_{gr} = \alpha_0 + \sum_{k=2}^{4} \beta_k TREAT_{k,gr} + \sum_{m=2}^{4} \gamma_m ORDER_{m,gr} + \theta_1 ROUND + \theta_2 \frac{1}{ROUND} + \varphi_g + \varepsilon_{gr}.$$

We also compute a measure of social efficiency as described in Spraggon (2004) and Suter et al. (2008) to compare social efficiency across policy treatments. In the model, social efficiency measures the percentage of the SNB attributable to the policy intervention. Here, SNB is the social welfare defined in equation (2), which includes the income of firms minus the economic damages caused by water pollution. Social efficiency for treatment k is computed as

$$(15) \quad \text{Social Efficiency}_k = \frac{SNB_{observed} - SNB_{status\ quo}}{SNB_{SO} - SNB_{status\ quo}}.$$

$SNB_{observed}$ is the actual SNB achieved in a given group and round while $SNB_{status\ quo}$ is the SNB that results when there is no policy intervention and firms maximize their private net benefits (competitive equilibrium). SNB_{SO} is the SNB that occurs when firms reduce their emissions to the socially optimal level using the least-costly method of abatement.

Results

We analyze the impacts of the three policy interventions on the level of ambient pollution, firms' technology choices, and social welfare. Table 4 reports mean values for the proportion of individuals who chose the conservation technology, group emissions, SNB, and social efficiency. Based on the descriptive statistics, it is evident that pollution is greatest when there is no policy (C1) and significantly less under each of the three policy treatments. A similar trend is evident when comparing the SNB for the four treatments, although the relative differences are smaller. The outcomes of C1, T2, and T3 align with theoretical predictions, as one would expect based on our experimental design, and these outcomes serve as important reference points when discussing key results. Contrary to theoretical predictions, but as hypothesized, the proportion of participants who chose the conservation technology is highest under T4 (subsidy reduction with assurance). These results, in conjunction with the parameter estimates from the formal econometric models described in the previous section, allow us to assess our four hypotheses related to the effects of the policy treatments.

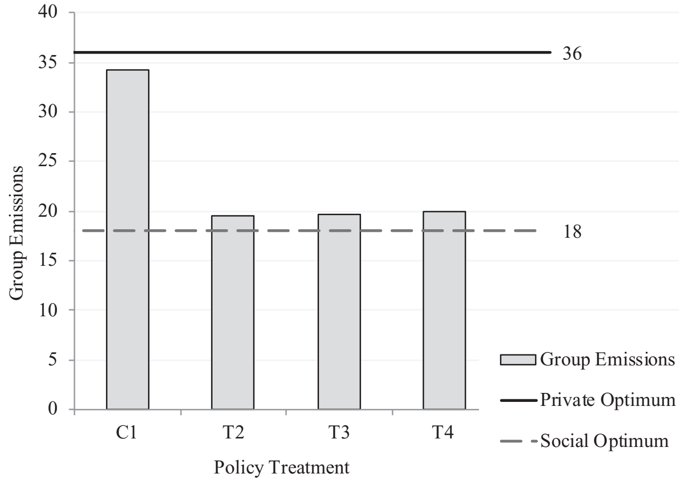

Figure 1. Mean group emissions for each treatment: Control (C1), Tax (T2), Subsidy reduction (T3), Subsidy reduction with assurance (T4)

Result 1: *Subsidy-reduction policies (with and without individual assurance) are as effective as the tax policy in reducing aggregate pollution.*

Compared to the no-policy control treatment, all three policy treatments reduce the level of ambient pollution to just above the socially optimal level of 18 units (figure 1). Table 5 reports the results from the random effects model in equation (10) (Model 1). The parameter estimates indicate the differences in group pollution under each policy treatment relative to the control treatment. Group emissions in each of the policy treatments are statistically different and lower than the control treatment ($p < .01$). Analysis of variance in the outcomes for group pollution for each round indicates that there are no statistically significant differences in the amount of ambient pollution from the groups across the policy treatments (N=390; Prob > $F = 0.220$). However, the amount of pollution generated under each policy treatment is statistically different from the social optimum of 18 ($p < .01$ in each case). Average group pollution for T2, T3, and T4 is 19.48, 19.66, and 20.03, respectively (table 4). This result is promising for policymakers interested in using a subsidy-reduction policy to reduce ambient pollution since it suggests that the effects of the policies on behavior do not vary with how they are framed or the existence of degenerate equilibria. However, to reduce pollution to the social optimum, policymakers would need to reduce the pollution threshold that triggers the penalty or increase the penalty rate.

Table 5 also provides evidence regarding any potential order effects in the sequence of the treatments. The results reveal no significant ordering effect and no evidence that the level of group emissions was influenced by experience (learning) during the experiment.[5] Thus, the results uniformly point to there being no significant differences in total emissions of pollution across the policy treatments.

Result 2: *Individuals are more likely to adopt a costly technology to reduce emissions when they are offered individual assurance that limits their exposure to penalties for excessive group emissions (T4).*

In the experiment, firms could reduce their emissions (and boost the likelihood that the group's pollution not exceed the threshold) by choosing a management approach with relatively low inputs and by adopting the conservation technology. In T4, adopting the costly conservation technology also protected them from being penalized for excessive group pollution. As shown in figure 2, participants are substantially more likely to adopt

[5] We also analyzed the results considering only the first round of each treatment. Results from the first round of each treatment are generally consistent with the results when all rounds are considered. We present results from the full data set, and first round results are available from the authors upon request.

Table 5. Random Effects Regression on Group Pollution Emissions (Model 1) and Social Net Benefits (Model 2)

Variable	Parameter	Model 1 Coefficient (Robust SE)	Model 2 Coefficient (Robust SE)
Treatment effect			
C1 (no policy)	β_1	Base group	Base group
T2 (tax)	β_2	−14.740***	275.954***
		(0.481)	(12.799)
T3 (subsidy reduction)	β_3	−14.580***	284.313***
		(0.591)	(14.557)
T4 (subsidy reduction with assurance)	β_4	−14.212***	130.278***
		(0.467)	(20.354)
Order			
2 (T2 first)	γ_2	0.254	−29.311
		(0.454)	(20.881)
3 (T3 first)	γ_3	–0.703	−33.250
		(0.540)	(23.357)
4 (T4 first)	γ_4	–0.136	−6.711
		(0.357)	(24.049)
Round	θ_1	−0.012	1.305
		(0.038)	(1.639)
1/Round	θ_2	−0.328	−33.476
		(1.060)	(37.665)
Constant	α_0	34.473***	2962.005***
		(0.553)	(20.202)
N		520	520
Groups		26	26
Wald χ^2		$\chi^2(8) = 1416.13$	$\chi^2(8) = 699.33$

Note: The asterisks ***, **, and * denote statistical significance at the 1% level, 5% level, and 10% level, respectively. Robust standard errors clustered at the group-level are presented in parentheses.

the conservation technology when offered the individual assurance.[6]

To evaluate differences in technology decisions more formally, we estimate the random effects models specified in equations 11, 12, and 13 (see table 6). The parameter estimate for T4 in model 3 is significantly different and larger than for T2 ($p < .01$) and T3 ($p < .05$). The marginal effects of the parameter estimates from Model 3 imply that participants are 10.8% more likely under T2 and 7.6% more likely under T3 to adopt the conservation technology than participants in the control treatment. Under T4, participants are 35.8% more likely to adopt the conservation technology.

Results from Models 3 and 4 demonstrate that participants are less likely ($p < .05$) to choose the conservation technology when T4 is the first treatment in a session. This result suggests that observing pollution outcomes and the resulting penalties in prior treatments increases the likelihood that participants choose to guarantee their immunity from the subsidy reduction. To disentangle the effect of prior penalties, we present results from a model that includes variables to control for the incidence of previous penalties, which include both taxes and general subsidy reductions (Model 5). We find that previous penalties increase the probability that an individual will adopt the conservation

[6] In treatments C1, T2, and T3, there is no financial advantage to reducing pollution using the conservation technology because pollution reductions can be achieved more cost-effectively by reducing input choices (i.e., choosing a different management decision). However, contrary to theoretical predictions, we find that 2.7%, 8.5%, and 6.8% of subjects chose the conservation technology in C1, T2, and T3, respectively. There are two feasible explanations for these results. First, participants may not have fully understand the payoff structure, and as a result, made decisions in which they incurred unnecessary costs. A second explanation is that participants want to adoption pollution-reducing technologies to signal their desire for stewardship. In an experimental study with Midwest farmers, Palm-Forster, Swinton, and Shupp (2017) observed participants making costly decisions in an artefactual field experiment that reduced their final payoffs. In focus groups that followed the experiment sessions, the farmers acknowledged that they made costly decisions because, in real-world situations, they would be willing to assume some costs to improve water quality. Furthermore, preliminary evidence suggests that people are willing to make costly experimental decisions if they can signal their environmental stewardship to other participants in laboratory experiments (Griesinger et al. 2017).

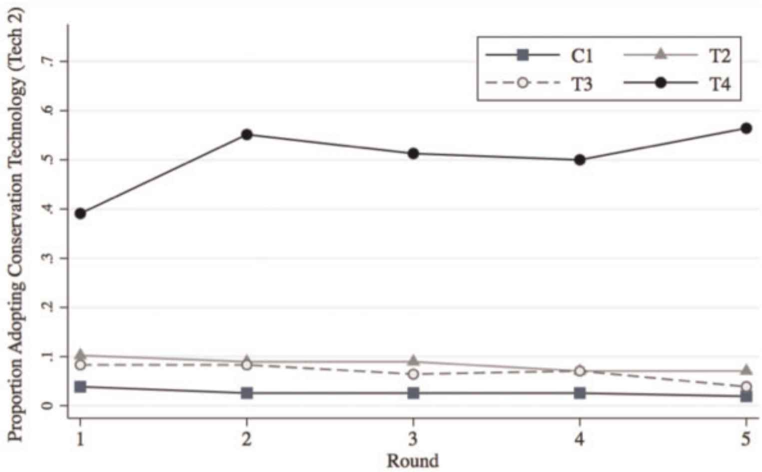

Figure 2. Adoption of the costly, conservation technology by round for each treatment: Control (C1), Tax (T2), Subsidy reduction (T3), Subsidy reduction with assurance (T4)

technology in T4 when this adoption prevents them from being subject to general earnings reductions ($p < .05$). A 100 dollar increase in previous penalties increases the likelihood that an individual will adopt the conservation technology in T4 by 1.5 percentage points.

The choice of technology also has the expected impact on the management decisions selected by participants. Figure 3 shows the distribution of management decision selections by participants in every round. The distribution in the policy treatments T2 and T3 are clearly uni-modal, with most participants choosing management decision D. In contrast, the distribution of management choices in T4 is bi-modal, with the majority of participants with the conventional technology choosing D and the majority of participants with the conservation technology choosing decision G. Across all five rounds, under the control treatment with no policy intervention, 86.8% of the participants choose the private profit-maximizing combination of decision G (involving the highest net production income of 400) and the conventional technology. Under both T2 and T3, approximately 54% of participants reduce their emissions by selecting decision D (net production income of 310) and the conventional technology, while nearly 18% choose decision E (net production income of 360) and the conventional technology. Of the minority of participants who choose the conservation technology in T2 and T3, almost 50% choose decision G, which provides the greatest net profit for that technology. The largest shift in management and technology decisions is evident in the subsidy reduction with assurance. Under T4, 50% of participants select decision G, whereas in T2 and T3 almost 90% of participants choose management decisions with lower net production income.

Result 3: *Participants' risk preferences have no effect on the likelihood of adopting the conservation technology in T4.*

The histogram in figure 4 shows the distribution of the first decision row in which participants choose option B, the riskier choice (see table 3). Nearly 58% ($n = 88$) of participants first choose option B in decision rows 7–10. Using the risk-aversion classifications proposed by Holt and Laury (2002, table 3, pg. 1649), their decisions imply that their relative risk aversion parameter (r) is strictly greater than 0.41, thus classifying them as risk averse.

Based on the results reported in table 6 (Model 4) for the model that incorporates risk preferences, risk averse participants are no more likely to adopt the conservation technology than individuals with other risk preferences. We also test for interaction effects for risk aversion in different treatments, but we find no effect on technology decisions. This result is robust when we control for the participants' previous experience with penalties (Model 5). Our results are also robust when risk aversion is defined more conservatively to include only "very risk averse" individuals ($r > 0.68$) and when risk aversion is defined more broadly to

Table 6. Random Effects Probit Regression on Conservation Technology Adoption

Variable	Parameter	Model 3 Coefficient (Robust SE)	Model 4 Coefficient (Robust SE)	Model 5 Coefficient (Robust SE)
Treatment effect				
C1 (no policy)		Base group	Base group	Base group
T2 (tax)	β_2	0.782***	0.996***	0.702*
		(0.219)	(0.335)	(0.375)
T3 (subsidy reduction)	β_3	0.546***	0.702**	0.516
		(0.206)	(0.349)	(0.398)
T4 (subsidy reduction with assurance)	β_4	2.589***	2.761***	2.196***
		(0.226)	(0.376)	(0.420)
Risk preferences				
Risk averse ($r > 0.41$)	ω		0.239	0.248
			(0.427)	(0.448)
Risk averse * T2	δ_2		−0.357	−0.405
			(0.440)	(0.459)
Risk averse * T3	δ_3		−0.248	−0.272
			(0.433)	(0.466)
Risk averse * T4	δ_4		−0.281	−0.279
			(0.457)	(0.476)
Previous penalties				
Cumulative previous penalties	ϕ			−0.065
				(0.056)
Cumulative previous penalties * T2	ρ_2			0.096*
				(0.054)
Cumulative previous penalties * T3	ρ_3			0.061
				(0.060)
Cumulative previous penalties * T4	ρ_4			0.112**
				(0.056)
Order				
2 (T2 first)	γ_2	−0.211	−0.210	−0.204
		(0.234)	(0.234)	(0.266)
3 (T3 first)	γ_3	−0.053	−0.052	0.034
		(0.246)	(0.247)	(0.275)
4 (T4 first)	γ_4	−0.569**	−0.558**	−0.297
		(0.222)	(0.224)	(0.243)
Round	θ_1	−0.023*	−0.023*	−0.038**
		(0.013)	(0.013)	(0.019)
1/Round	θ_2	0.064	0.070	0.038
		(0.272)	(0.273)	(0.260)
Constant	α_0	−2.158***	−2.317***	−2.080***
		(0.297)	(0.412)	(0.416)
N		3,060	3,060	3,060
Individuals		153[a]	153[a]	153[a]
Wald χ^2		$\chi^2(8) = 254.35$	$\chi^2(12) = 261.78$	$\chi^2(16) = 259.66$

Note: ***, **, * Denote statistical significance at the 1% level, 5% level, and 10% level, respectively. Robust standard errors clustered at the individual subject-level are presented in parentheses. [a]Data from three respondents are removed. These three respondents chose Option A in row 10 of the Holt-Laury task (see table 3). This irrational response gives us reason to believe that they did not understand the task; therefore, we remove these observations from our analysis.

include individuals who are "slightly risk averse" ($r > 0.15$).

In table 7, we present results from a model in which we analyze observations from T4 only (Model 6). Again, we find no effect of risk preferences on behavior in T4; however, results from this analysis suggest that participants are more likely ($p < .05$) to adopt the conservation technology in T4 when T4 is the first treatment presented. This result appears to be driven by factors other than risk aversion. When T4 is presented first, participants have less experience converging to the NE; therefore, they may seek a simple, salient strategy to reduce

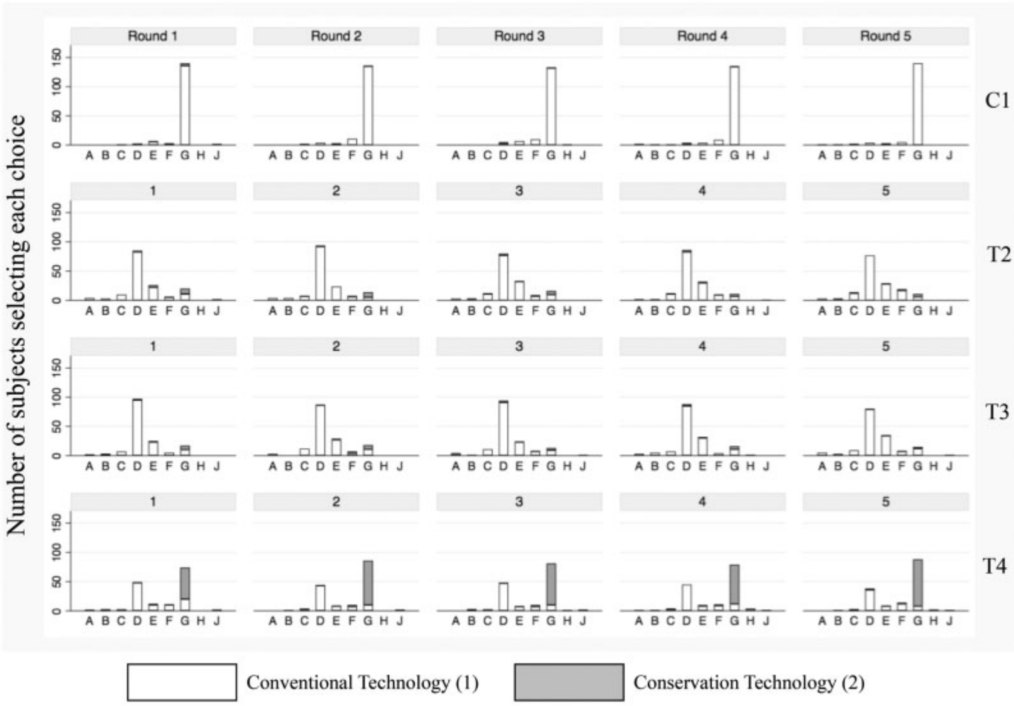

Figure 3. Management and technology decisions of firms in each round

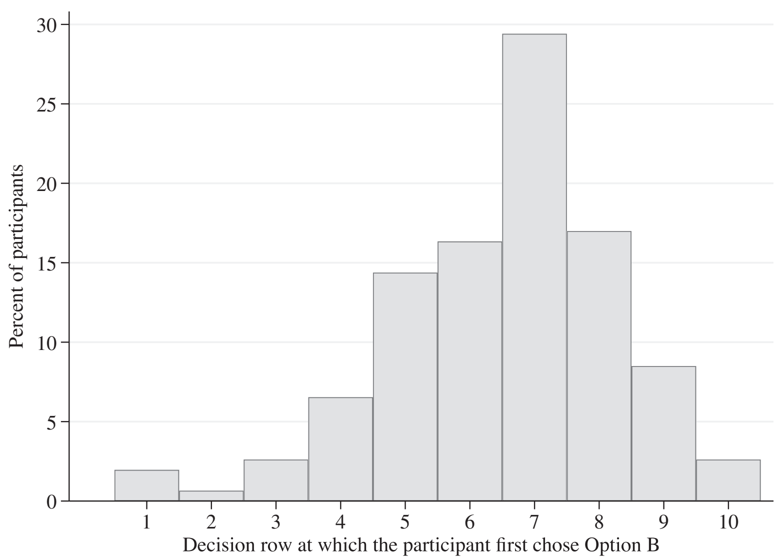

Figure 4. Distribution of the first decision row at which participants chose Option B during the Holt-Laury risk elicitation task (see table 3)

Note: Participants who chose Option B for the first time in decision row 7–10 are classified as being risk averse as defined by Holt and Laury (2002, table 3)

losses in the experiment. Choosing the conservation technology in T4 provides a straightforward way for individuals to avoid losses with certainty. On the other hand, if participants are presented with other treatments first, they are more likely to have discovered the NE by the time they make decisions in T4, and thus they are less likely

Table 7. Random Effects Probit Regression on Conservation Technology Adoption in Treatment 4 (T4)- General Earnings Reduction with Individual Assurances

Variable	Parameter	Model 6
Risk averse ($r > 0.41$)	ω	−0.136
		(0.251)
Cumulative previous penalties	ϕ	0.076**
		(0.032)
Order 2 (T2 first)	γ_2	0.343
		(0.528)
Order 3 (T3 first)	γ_3	0.942
		(0.661)
Order 4 (T4 first)	γ_4	1.749**
		(0.816)
Round	θ_1	0.068
		(0.057)
1/Round	θ_2	−0.146
		(0.515)
Constant	α_0	−2.008*
		(1.037)
N		765
Individuals		153[a]
Wald χ^2		$\chi^2(7) = 13.21$

Note: The asterisks ***, **, and * denote statistical significance at the 1% level, 5% level, and 10% level, respectively. Robust standard errors clustered at the individual subject-level are presented in parentheses. [a]Data from three respondents are removed. These three respondents chose Option A in row 10 of the Holt-Laury task (see table 3). This irrational response gives us reason to believe that they did not understand the task; therefore, we remove these observations from our analysis.

to choose the costly conservation technology in T4.

RESULT 4: *The three policy treatments all increase the SNB and social efficiency relative to the control treatment, but the SNB and social efficiency are significantly lower under the subsidy reduction with assurance (T4) than under the tax (T2) and subsidy reduction (T3).*

Table 4 presents group mean SNB and social efficiency measures by treatment. Relative to the control treatment, the mean SNB is more than 9% greater in T2 and T3 and 4% greater in T4. Social efficiency for the policy treatments, defined as the percentage of SNB under the treatment that exceeds the SNB of the no-policy control treatment (equation 14), is approximately 70% higher in T2 and T3. This supports our previous finding that the subsidy-reduction policy has a similarly positive impact on social welfare as the tax policy. Under T4, social efficiency is 32% higher than the control on average, but this is significantly lower than the efficiency achieved in T2 ($t = 11.72$; $p < .001$) and T3 ($t = 11.68$; $p < .001$).

The results of the random effects regression in which the dependent variable is the observed level of SNB are presented in table 5 (Model 2). The coefficients indicate that, relative to the control, the SNB is approximately 276, 284, and 130 experimental dollars greater under T2, T3, and T4, respectively. Neither the order of the treatments nor experience (learning) have a significant effect as indicated by the insignificant γ and θ coefficients.

Discussion and Conclusion

The results of our experiment suggest that subsidy reductions tied to the level of ambient pollution of a water resource can potentially reduce NPS emissions to near the socially optimum level. The subsidy reduction in this experiment is similar to a tax on the level of ambient pollution at the margin because the reduction is equal to the marginal social damage from each unit of pollution. There is, however, a cap on the subsidy reduction; once pollution reaches a level that completely dissipates an individual's subsidy, there is no additional penalty for further emissions. Under the parameters of our experiment, two equilibria exist—one in which abatement of emissions results in a socially optimal level of pollution and another in which emissions remain at a higher privately optimal level. Despite the multiple equilibria, emissions decline under the subsidy reduction to the same level achieved by the tax. However, when participants have the opportunity to ensure that their subsidies will not be reduced by adopting a lower-emission production technology, many choose to secure that assurance even though the cost to do so is significant. We found that participants' risk preferences have no effect on which technology they adopt. Additional risk-elicitation procedures should be used in future research to test the robustness of this result. Our results suggest that factors such as loss aversion may have influenced behavior in some of our policy treatments; however, we cannot rule out other behavioral drivers. Further investigation of other behavioral frameworks that may explain the behavior observed in this experiment is also warranted, especially in field settings in which numerous psychological, cognitive, and social factors may affect behavior.

The subsidy examined in this study represents benefits from federal farm programs that producers currently receive regardless of the outcome of efforts to improve water quality. By linking subsidies and payments to the level of ambient pollution, the subsidy reduction policies can be viewed as analogous to the policy that progressively taxes producers when the level of ambient pollution does not meet program objectives. Such tax-based policies have faced opposition in the past (Boyd 2003), in part because producers do not want to be held responsible and penalized for the actions of others. One way to ameliorate such concerns is to include provisions that protect producers from penalties when they demonstrate a commitment to improving water quality using a visible technology[7]—so-called assurances that protect producers from being fined even if water pollution exceeds the target threshold.

In this study, subjects could reduce pollution by adopting a costly production technology. They are significantly more likely to choose that technology when offered assurance that they will not be liable for excessive group pollution. Without such an assurance, subjects choose the lowest-cost abatement method available—they reduce emissions by selecting a less-intensive management approach (input level) and foregoing the cost of the conservation technology.

Although the results indicate that providing individual assurances increases the likelihood that producers will adopt a costly technology to reduce pollution, it is not clear how adoption of the conservation technology affects social welfare relative to other policy interventions. Under the parameters chosen for this experiment, adoption of the visible technology to reduce pollution is costlier than adjusting the level of production. While the level of ambient pollution declines as a result, so does the producers' relative profits. Given this setup, one could view the reduction in welfare associated with providing assurance relative to the other interventions as the policy cost associated with creating a process seen as more equitable. Varying the parameters used in the experiment would provide additional information about the effects of such policies on firms' abatement behavior. For example, if adoption of the technology led to excessive abatement (far below the target level), some firms might attempt to under-abate their own emissions in an effort to free-ride on the effort and expense of others. Expanding the decision space and introducing firm heterogeneity in profit functions are important steps for future work to determine if these results hold when additional complexity is introduced. Additionally, future research could explore alternative behavioral frameworks to explain the results observed in the experiment. We also think that important information could be gleaned from future experiments that vary the cost and number of available production technologies and explore how the extent to which choices related to specific production technologies are observable by other producers. The experiment assumes that the choice of technology can be verified by a policymaker, but it may also be true that other producers in the watershed could at least partially observe these decisions, which could then have important implications for the behavior of firms.

A limitation of this experimental design is that it does not fully account for the voluntary nature of programs that provide subsidies to producers. For example, producers are not required to participate in federally subsidized crop insurance programs or other programs that provide tax credits or subsidies. Therefore, a pollution policy tied to receipt of subsidized crop insurance would not affect those who do not participate in the program. This research also does not account for heterogeneity in the program benefits received by individual producers. We examine a situation in which all firms receive the same initial subsidy. Tying the policy to a benefit that is proportionally distributed would be an important consideration for promoting greater equity in the policy.

The policy mechanisms that we implement in the experiment do not currently exist in practice. Decisions made by participants in an economic experiment provide insight into people's behavioral responses to policy mechanisms, but there is still much to learn about how the policies would be implemented and the actual responses of stakeholders. A recent study (Arbuckle 2013) found

[7] The type of technology connected to the assurance is important because it must both effectively reduce pollution and be easily observable to reduce the cost of monitoring and verification.

general support among producers for extending conservation-compliance programs to water quality and other environmental concerns but did not investigate preferences for policies that would link eligibility for subsidies to ambient water quality. Future research should engage key stakeholders, including producers and program administrators, to gain a fuller understanding of the administrative feasibility, acceptance, and effectiveness of the types of agri-environmental policies explored in this study.

Supplementary Material

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

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