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Impact of peer comparisons and firm heterogeneity on nonpoint source water pollution: An experimental study

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ABSTRACT

Greg Poe was a pioneer in using experimental economics to test theories and potential policies for controlling ambient pollution. His foundational work showed that, in some settings, policies could induce groups to reduce their nonpoint source (NPS) pollution to socially-efficient levels. Poe's earlier studies assumed firms were homogeneous, which laid the groundwork for subsequent research to investigate the effect of firm heterogeneity on policy outcomes. We build on the research foundation laid by Poe and his colleagues by using an economic experiment to test the effects of four types of firm heterogeneity and three social norm information treatments on the performance of an ambient tax/subsidy policy. Our experimental results show that heterogeneity reduces the effectiveness of the ambient tax/subsidy policy, but that information nudges can improve outcomes even when there is considerable heterogeneity in the policy environment. Participants were also better able to find and retain their dominant strategies when they were provided with information about similar firms, suggesting that individually-targeted information is more effective than information about aggregate group-level decisions.

1. Introduction

Reducing nonpoint source (NPS) water pollution is a difficult task because of hidden actions on the part of polluters and information asymmetries regarding the true cost of reducing their emissions. Consequently, designing and implementing policies based on individual behavior is often impossible or prohibitively costly (Xepapadeas, 2011; Miao et al., 2016). In extensions of Segerson (1988) considering homogeneous NPS contributors, numerous researchers have shown both theoretically (e.g., Xepapadeas, 1991; Horan et al., 1998; Segerson and Wu, 2006) and experimentally (e.g., Alpízar et al., 2004; Poe et al., 2004; Spraggon, 2002; Vossler et al., 2006) that ambient pollution policies involving a monetary policy instrument (taxes and/or subsidies) can induce groups to reduce their collective emissions to a socially efficient level. In such schemes, the regulator usually compares the ambient pollution reading to a target level and applies the monetary instrument to every firm in the watershed. Suter et al. (2009) and Poe et al. (2004) extended the classic ambient-based policy setting to scenarios involving heterogeneous polluters that could cooperate, and they showed empirically that introducing heterogeneity changes policy outcomes.

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Our study builds upon fundamental research by Greg Poe and his colleagues on policies to reduce NPS pollution. We extend that work to a watershed composed of firms that are heterogeneous and in which contributors make multiple decisions that more closely reflects the complex environments in which firms actually operate. We further consider the potential for two types of information nudges – social comparisons and information about peers' actions – to improve the effectiveness of a pollution abatement policy.

Adequately modeling the complexity of the decision-making environment is particularly important when addressing agricultural firms, which are leading contributors of NPS pollution in the United States. Several studies have examined the effects of single types of heterogeneity (size or location) on the efficiency of ambient pollution policies (Spraggon, 2004; Miao et al., 2016) but, to our knowledge, no studies have analyzed a policy's performance in the presence of multiple forms of firm heterogeneity and when firms must make more than one management decision. In reality, agricultural firms often differ significantly in terms of their spatial location in a watershed and their production capacities, and those differences are likely to affect the firms' decisions, their ability to reduce their emissions, and the overall outcome of a policy. A firm's location, for example, may dictate the amount of marginal environmental damage it contributes because of differences in how the pollution diffuses in the water and other biophysical factors.

Management decisions regarding intensity of production and adoption of pollution abatement technologies also affect the amount of runoff and nutrient loss produced by a firm. Increasingly, local, state, and federal initiatives are promoting technologies that reduce nutrient runoff, such as conservation buffers, which can remove 50 % or more of the nutrients and pesticides that normally run off the surface of agricultural land (Conservation Technology Information Center, 2018). Another advantage of such technologies is that they can be observed by regulators, confirming the producer's commitment to environmental stewardship. That has not been the case with prior programs such as limiting producers' use of fertilizer, which is difficult to monitor. Few prior studies have considered these types of technology decisions (Palm-Forster et al., 2019a).

In recent years, public and private sectors have recognized the benefits of using behavioral economic principles such as information "nudges" to influence behavior and improve private and social welfare (Thaler and Sunstein, 2008). These tools are attractive to policymakers because they are usually simple and highly cost-effective to incorporate in policies (Johnson and Goldstein, 2003; Ferraro et al., 2017; Messer and Allen, 2018). However, studies of NPS pollution management have focused primarily on monetary policies.

We use an economic laboratory experiment to identify the effects of multiple layers of firm heterogeneity and two nudges on the performance of the classic ambient tax/subsidy policy aimed at reducing water pollution. Specifically, we test two types of informational nudges – one is a social comparison in which the individual learns about the actions of similar individuals and the other nudge involves the individual receiving information about peer behavior by learning about aggregate outcomes in their group. We incorporate an extended decision space in which participants make multiple decisions so we can more-accurately represent the realities of the complex environments in which agricultural producers operate. Our results demonstrate that greater heterogeneity among firms in a watershed reduces the effectiveness of the tax/subsidy policy and that information nudges can improve policy efficiency. Participants are better able to find and maintain their dominant strategy when they receive information about decisions made by similar firms, suggesting that providing individually-targeted information is more effective than providing information about aggregate group-level decisions. Our results suggest that traditional ambient pollution policies may be less effective when agents are heterogeneous and that information nudges can improve policy performance in those cases.

2. Background

Segerson (1988) showed that NPS pollution can be reduced to a socially optimal level using taxes and subsidies linked to the ambient pollution level in the watershed, which generates an incentive for individuals to internalize the full cost of their pollution contributions. Ambient-based policies have not been widely implemented due, in part, to obstacles such as lack of political feasibility and concerns about fairness since a minority of firms could be primarily responsible for the pollution and not have to pay their fair share (Cason and Gangadharan, 2013; Xepapadeas, 2011). Despite a lack of empirical data regarding the effectiveness of these policies in the field, economic experiments have been used to test potential and existing policy schemes. Early studies demonstrated theoretically and experimentally that various types of ambient schemes could lead to attainment of targeted levels of pollution (Xepapadeas, 1992; Spraggon, 2002; Alpízar et al., 2004; Poe et al., 2004).

The focus on homogeneous agents arose partly as a way to simplify modeling and partly because of evidence from several studies that ambient-based policies would be most successful in watersheds that consisted of a small number of homogenous farmers (Weersink et al., 1998; Suter et al., 2009). A few researchers have analyzed such policies in settings involving heterogeneous actors. Spraggon (2004, 2013) and Suter et al. (2009) considered heterogeneity in the size of the polluting firms. Spraggon (2004) examined NPS pollution without specifying the context and compared the results of homogeneous and heterogeneous contributors for a tax/subsidy policy. He concluded that one could design a policy that would achieve the ambient abatement target in a context in which the firms varied in size but not without substantial losses of efficiency and equality. Suter et al. (2009) extended Spraggon's (2004) research by adding a watershed context. They showed that heterogeneity in the size of the firms had an impact on group decisions and that whether the resulting changes were desirable or undesirable depended on specific conditions.

A second type of heterogeneity has drawn attention recently as evidence has mounted that the location of an agricultural firm within a watershed can significantly affect its contribution to the ambient level of pollution in the water and the amount of environmental damages measured at particular points in the watershed. Studies have shown that location heterogeneity can influence agents' decisions, especially when addressing a common-pool resource (e.g., Schnier, 2009; Suter et al., 2012; Li et al., 2014; Liu et al., 2014; Wu et al., 2017). Miao et al. (2016) used an economic experiment to test an ambient tax/subsidy policy that was informed by water quality readings and a realistic nutrient transport model, which were used to calculate the marginal damages contributed by spatially-explicit polluters within a watershed. The authors found that increasing the frequency of water quality readings reported to the regulator from an in-stream sensor improved the spatial allocation of emissions reductions leading to improved policy outcomes.

Others have investigated informal ways to reduce NPS pollution using laboratory experiments. Cason and Gangadharan (2013) incorporated location heterogeneity in terms of proximity to a pollution monitoring station to study the effectiveness of informal neighbor-based punishment versus a formal ambient tax. They found that a formal ambient tax was more effective than empowering neighbors to engage in informal sanctions after observing their group members' emissions and that the outcome of the ambient tax policy could be improved by adding peer-based punishment. Suter et al. (2008) showed that communication amongst landowners facing the pollution policy could reduce emissions below the socially optimal level. Butler et al. (2019) showed that how the pollution information was shown and how groups were encouraged or discouraged through public communications, such as mascots, impacted landowner behavior.

Using behavioral information ̎nudges̈to improve decision-making in agri-environmental contexts is a promising new area of research (Palm-Forster et al., 2019b). Information nudges typically use narrative messages—especially about how a participant's behavior compares with the behavior of others—to influence a participant's decisions. The concept of a nudge originates in the theory of social comparison by Festinger (1954), which posits that people evaluate the appropriateness of their behaviors by comparing themselves to others. Earlier research demonstrated that this principle could be used to promote conservation behaviors such as reducing power consumption (Allcott, 2011) and water use (Ferraro and Price, 2013; Bernedo et al., 2014), encourage water conservation behavior in hotels (Goldstein et al., 2008), and motivate agricultural producers to conserve land (Banerjee, 2018). Thus, it is reasonable to assume that information nudges can be used to improve efforts to abate NPS pollution, but few studies have addressed this question. Spraggon (2013) varied the information available to participants in an experiment regarding the number of other polluters and their payoffs. He concluded that information and heterogeneity did not affect a policy's aggregate-level effectiveness but did reduce its efficiency. Spraggon and Oxoby (2010) showed that providing participants with a more-detailed description of how to maximize their total payoff increased how often their behavior aligned with the socially optimal outcome, thus increasing the policy's efficiency. This "recommended play" approach, however, does not involve influencing private decisions with decisions made by others.

In this study, we determine how information about the behavior of others influences participants' decisions by testing two types of information provided to participants: (i) individual decisions made by similar firms and (ii) aggregate group-level outcomes, including average group production and the rate of technology adoption in their watershed in the previous round.

Our study makes several important contributions. We extend the participant decision space to include both production and technology decisions and, unlike prior studies, examine the effects of two types of firm heterogeneity (size and location in a watershed). We further examine the ability of two types of information nudges (social comparison and aggregate peer actions) to improve the policy performance in an NPS pollution context. By combining an extended decision space, two layers of heterogeneity, and information nudges, we evaluate the performance of an ambient-based policy in a rich decision-making environment.

3. Model and experiment setup

Using the classic set-up of NPS pollution experiments, we had participants act as firms operating along a river, and the firms made decisions that would affect the ambient pollution level within the river. Though the firms were designed to reflect agricultural operations, the experiment was context free and did not refer to agriculture in the instructions. The firms were set up as price-takers in a market with an exogenously determined price for their products, and each firm's production generated a byproduct that we referred to as emissions (e.g., excessive nutrients in runoff) which generated a social environmental cost (e.g., damage to downstream watersheds).

The firms were then given an opportunity to adopt a pollution-abatement technology (e.g., buffers that could reduce runoff of excessive nutrients). The technology cost was a fixed amount that was scaled based on the size of the firm. Participants were told that the technology would reduce the firm's pollution at a percentage rate tied to their production. Therefore, each firm made a production decision and a technology-adoption decision.

A regulator monitored the density of emissions downstream from the firms and thus had perfect information on the aggregate level of pollution. We assumed that the regulator had no information about the individual firms' production decisions and emissions but knew the average production quantity and the groups' rate of technology adoption. In the experiment, the regulator imposed a tax for excessive pollution or provided a subsidy for adequate reductions in pollution as described in the next section.

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3.1. Model setup

Suppose there are N heterogeneous firms along the river indexed as $i = 1, 2, \ldots, N$. Following Spraggon (2002) and subsequent studies (e.g., Suter et al., 2009; Spraggon, 2013; Cason and Gangadharan, 2013; Miao et al., 2016), we define production income as

$$b_i(x_i) = \gamma_0 - \gamma_1(\gamma_{2i} - x_i)^2 \tag{1}$$

where γ_0 and γ_1 are parameters in the income function and x_i is the production intensity for firm i. Following Spraggon (2002), we introduce production heterogeneity by varying firm capacity (size), which is represented by γ_{2i} (size heterogeneity).

By producing any level of $x_i > 0$, the firm generates pollution emissions, $e_i(x_i, \tau_i)$, that can be reduced by adopting an abatement technology, τ_i. We model technology adoption as a binary decision in which $\tau_i = 1$ if the technology is adopted and $\tau_i = 0$ otherwise. The cost of adopting the technology is $c\gamma_{2i,}$ which is scaled to the capacity of the firm ($\gamma_{2i,}$). When the firm adopts the technology, its emissions are reduced by a fixed proportion, α, such that $0 < \alpha < 1$. We model the firm-level emission function as $e_i(x_i, \tau_i) = \beta_i x_i(1 - \alpha\tau_i)$ where β_i is a parameter that represents the effect of location heterogeneity on emissions. In other words, the location of the firm in the watershed affects the marginal contribution of its production on the ambient pollution concentration downstream (location heterogeneity).

Following Cason and Gangadharan (2013), we position the firms at different geographical proximities to the downstream monitoring point. We assume that emissions from firms closer to the monitoring point generate greater environmental damage than firms farther away because pollutants from firms farthest upstream are more dilute than pollutants from closer firms when they arrive at the monitoring point. Miao et al. (2016) also introduced location heterogeneity by imposing a nutrient transport model to calculate the marginal damage of farmers. That model included two effects in determining the pollutants' concentration: duration, which increased the marginal damage from upstream farmers, and magnitude, which increased marginal damage from downstream farmers. Parameterization of the model determined which effect was dominant. We followed the approach introduced in Cason and Gangadharan (2013) because that specification allowed us to solve for a closed-form solution and created less complexity for participants in the experiment.

Aggregate emissions, E, are a function of the emissions of all firms, and the damage function is defined as $D(E) = \delta E$ where δ denotes the marginal social cost of the emissions. Total environmental damage can therefore be expressed as

$$D(E) = \delta \sum_{i=1}^{N} \beta_i x_i(1 - \alpha\tau_i).$$

Each firm maximizes its individual profit function,

$$\pi_i = b_i(x_i) - \tau_i c\gamma_{2i}.$$

Since adoption of the pollution-abatement technology imposes a cost without increasing income from production, a profit-maximizing firm is predicted to choose not to adopt the technology ($\tau_i = 0$) and to choose an input quantity, $x_i = \gamma_{2i}$, that satisfies $\partial b_i / \partial x_i = 0$.

The social planner's problem is to maximize the social benefit, which is denoted as SP:

$$SP = \sum_{i=1}^{N} \pi_i(x_i) - D(E) \tag{2}$$

The first-order condition indicates that the optimal level of production is $x_i = \gamma_{2i} - \frac{\delta\beta_i}{2\gamma_1}$, which is smaller than the private optimal level of production for the individual firm, γ_{2i}, since $\beta_i > 0$, $\gamma_1 > 0$, and $\delta > 0$.

Previous research has shown that designing a scheme in which the tax/subsidy rate equals the marginal damage from pollution provides an incentive for a firm to internalize the full cost of its pollution. The total tax/subsidy equals $D_i^{'}(e_i)\left(E - \bar{E}\right)$ where $\bar{E}$ is the targeted limit on environmental damage set by the regulator and $D_i^{'}(e_i) = \delta$ is the marginal social damage from emissions. An individual, profit-maximization firm's problem involves choosing the optimal input quantity, x_i, and technology, τ_i:

$$\max_{x_i, \tau_i} b_i(x_i) - \tau_i c\gamma_{2i} - \delta\left(E - \bar{E}\right) \tag{3}$$

For the firm to prefer adopting the technology, the firm's profit when it does not adopt the technology (π^N) must be less than its profit when it does (π^A). We find the equilibrium by backward induction. Consider firm i in a watershed in which there is a given level of pollution, e_{-i}, contributed by others in the group. Firm i's profit function from producing x_i and adopting the technology is

$$\pi_i^A = \gamma_0 - \gamma_1(\gamma_{2i} - x_i)^2 - \delta(e_{-i} + \beta_i x_i(1 - \alpha) - \bar{E}) - c\gamma_{2i} \tag{4}$$

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Table 1
Parameters used in the experiment.

Parameter	Value
γ_0	40
γ_1	0.0025
$\gamma_{2i} \in i = \{1, 2, 3\}$	75, 100, 125
β_0	0.30
$\beta_i \in i = \{1, 2, 3, 4\}$	0.24, 0.28, 0.32, 0.36
c	0.082
α	0.5
δ	1

We can solve for the optimal production level, ${x_i}^A$, by computing the derivative of Eq. 4 with respect to x_i:

$$\frac{\partial {\pi_i}^A}{\partial x_i} = 2\gamma_1 \left(\gamma_{2i} - x_i\right) - \delta\beta_i(1-\alpha) = 0 \tag{5}$$

Then, we rearrange Eq. 5 to solve for the optimal production level:

$$x_i^A = \gamma_{2i} - \frac{\delta\beta_i \left(1-\alpha\right)}{2\gamma_1} \tag{6}$$

Finally, we combine Eqs. 6 and 4 to compute the maximum profit achievable when adopting the technology:

$$\pi^A = \gamma_0 - \frac{\delta^2 {\beta_i}^2 \left(1-\alpha\right)^2}{4\gamma_1} - \delta \left(e_{-i} + \beta_i \left(1-\alpha\right) \left(\gamma_{2i} - \frac{\delta\beta_i \left(1-\alpha\right)}{2\gamma_1}\right) - \bar{E}\right) - c\gamma_{2i}. \tag{7}$$

Next, consider firm i given the same pollution level from others, e_{-i}. Firm i's profit function when not adopting the technology and producing at x_i is

$$\pi^N = \gamma_0 - \gamma_1(\gamma_{2i} - x_i)^2 - \delta(e_{-i} + \beta_i x_i - \bar{E}) \tag{8}$$

$$\frac{\partial \pi^N}{\partial x_i} = 2\gamma_1 \left(\gamma_{2i} - x_i\right) - \delta\beta_i = 0 \tag{9}$$

$$x_i^N = \gamma_{2i} - \frac{\delta\beta_i}{2\gamma_1} \tag{10}$$

The maximized profit of not adopting is

$$\pi^N = \gamma_0 - \frac{\delta^2 {\beta_i}^2}{4\gamma_1} - \delta \left(e_{-i} + \beta_i \left(\gamma_{2i} - \frac{\delta\beta_i}{2\gamma_1}\right) - \bar{E}\right) \tag{11}$$

The condition under which firm i would not prefer to adopt the pollution-abatement technology is

$$\frac{\delta^2\beta_i^2}{4\gamma_1} \left(1 - (1-\alpha)^2\right) - \alpha\delta\beta_i\gamma_{2i} + c\gamma_{2i} < 0 \tag{12}$$

Therefore, the optimal strategy of each firm in the watershed depends on the firm's size and spatial location.

The model presented above is used to generate theoretical predictions about how firms will behave when attempting to maximize profits. We test whether informational nudges cause behavior to deviate from theoretical predictions for different types of firms with and without a tax/subsidy.[1]

3.2. Parameterization

The parameters used in the experiment, which mostly follow parameters used in prior studies, are shown in Table 1. The parameters for size heterogeneity are based on Spraggon (2002) and the parameters for location heterogeneity are based on Cason and Gangadharan (2013). Specifically, when there is no heterogeneity, the size of all firms is set to 100 and the location parameter is set to 0.3. Under size heterogeneity, the size parameters are set to 75 for "small" firms and 125 for "large" firms. Under location heterogeneity, the location parameters are set to 0.24, 0.28, 0.32 and 0.36 for regions 1, 2, 3,

[1] In this paper, we do not model the behavioral pathway(s) through which informational nudges influence firm decision making. Recent studies analyzing pro-environmental consumer behavior use a moral cost adjustment in the utility function to model the effect of nudges involving social norms (See Levitt and List, 2007; Ferraro and Price, 2013; Allcott and Kessler, 2019). A similar approach could be used to model firm decision making by identifying the pathways that influence producer behavior, which may deviate from pure profit maximizing motives. We leave this investigation for future research.

Table 2
Treatment Order.

Treatment Order									
NoInfo	Session 1	No Policy				Policy			
		H0	HT1	HT2	HT3	H0	HT1	HT2	HT3
	Session 2	No Policy				Policy			
		HT3	HT2	HT1	H0	HT3	HT2	HT1	H0
	Session 3	Policy				No Policy			
		H0	HT1	HT2	HT3	H0	HT1	HT2	HT3
	Session 4	Policy				No Policy			
		HT3	HT2	HT1	H0	HT3	HT2	HT1	H0
Info1	Sessions 5–8	Four identical sessions but with Information Treatment 1 – decisions by similar firms							
Info2	Sessions 9–12	Four identical sessions but with Information Treatment 2 – aggregate outcomes for their group in the preceding round.							

and 4 where *region1* is farthest upstream and *region4* is farthest downstream. For simplicity, but without losing generality, we assume that the marginal social cost of pollution damage is $\delta = 1$.

We parameterize the model so that it is always privately optimal for profit-maximizing firms to produce at the maximum level possible and not adopt the pollution-abatement technology in the absence of a tax/subsidy policy. Under the subsidy/tax policy, the social planner's optimal strategy, which is to maximize social welfare, aligns with the dominant strategy of each firm acting as a profit maximizer. When the tax/subsidy policy is in effect, the optimal decision of homogeneous firms (in both size and location) is to adopt the abatement technology. Under the three heterogeneity treatments, the model is parameterized so that the optimal decision for half of the firms is to adopt the technology and the optimal decision for the other half is not to adopt. In each treatment, the target pollution level equals the dominant strategy aggregate pollution level based on parameterization for that treatment; in the policy treatments, the target is also equal to the socially-optimal aggregate pollution level.

4. Experimental design

Our analysis is based on observations from 192 undergraduate student participants (16 per session) recruited in November and December of 2016 at a large public university on the East Coast of the United States.[2] Twelve sessions were conducted to analyze the effect of the information treatments—four each for the no-information baseline, provision of information on decisions by similar firms, and provision of information on the past aggregate outcome from the same group.

In each of the twelve experiment sessions, participants were randomly assigned a number and seated at the computer identified with that number. They were first asked to read through written instructions and then to view and listen to a recorded PowerPoint presentation of the instructions to help them understand the experiment and ensure that the instructions were presented consistently across sessions.

After the presentation, participants were asked to complete two exercises on the computer to evaluate their understanding of the experiment instructions. To calculate the correct answer for each exercise, participants had to use materials provided to them and could proceed to the next part of the session only after solving both exercises correctly. In a final preparatory step, the participants made production and technology decisions in five practice rounds that did not affect their earnings in the experiment.

The formal experiment session consisted of 40 production/adoption decisions—five rounds in each treatment period for eight within-subject treatments: presence/absence of the policy and firms that were homogeneous (H0), heterogeneous by location in the watershed (HT1), heterogeneous by size (HT2), and heterogeneous by size and location (HT3). Table 2 further describes the sessions and treatments. At the beginning of each treatment period, imperfect stranger-matching[3] was used to randomly assign the sixteen participants in each session to two eight-member groups representing firms in two watersheds.

In each round of the experiment, participants made a production intensity decision and a technology decision. Participants were provided with a decision calculator that could be easily accessed on the decision page. They were given time and were

[2] Past economic experiments have examined differences in how student and professional participants perform in economic experiments that can potentially be used to inform policymaking and have found minimal participant pool effects in agricultural and nonagricultural contexts (e.g., Cummings et al., 2004; Duquette et al., 2012; Fooks et al., 2016; Krause et al., 2003; Vossler et al., 2009; Vossler and McKee, 2013). In an experiment involving NPS pollution, Suter and Vossler (2013) tested how dairy farmers differed from students in a lab setting. They found that an ambient-based tax induced group-level compliance in both groups. At an individual level, owners of small farms tend to abate more and owners of large farms tend to abate less than student participants. However, as the authors noted, the difference in responses could relate to farmers treating the experiment as a pre-policy evaluation and trying to influence the resulting policy by behaving strategically and signaling policymakers. The groups of farmers in the study tended to contribute less than the optimal amount of pollution even in no-policy treatments, which could indicate their signaling that a tax was not needed. Nevertheless, it is important to keep in mind potential differences between agricultural producers and students in such experiments. The current study could be extended by conducting a similar economic experiment with agricultural producers in a field setting.

[3] This matching technique randomly assigns group membership but does not preclude participants from being assigned to the same group multiple times throughout the experiment. In this study, the identity of group members was not known; therefore, participants did not know if they shared group membership with another participant more than once.

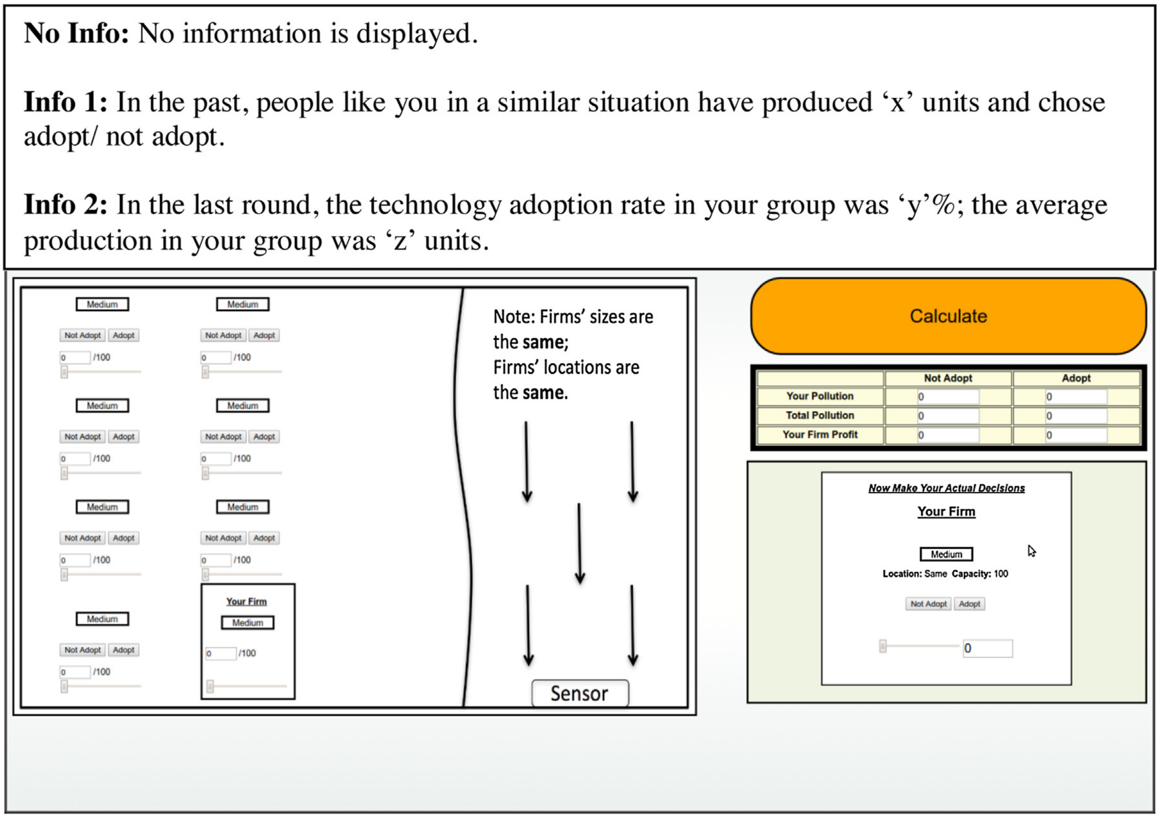

Fig. 1. Screenshot of the Decision Page.

encouraged to use the decision calculator before they make each decision. Each participant also went through training on how the calculator was used and had to correctly answer two practice questions before they make any actual decisions to ensure that they understood how their choices would impact outcomes.

4.1. Information treatments

The between-subject information treatments consisted of the no-information baseline (the control), provision of information on decisions by similar firms (Info1), and provision of information on the aggregate outcome from their group in the preceding round (Info2). The information in the treatments was presented at the top of the decision page on the computer screen as shown in Fig. 1.

The Info1 treatment presented testimonial information about production and technology-adoption decisions people "like them" had made in the past: "In the past, people like you in a similar situation have produced *x* units and chose adopt/not adopt." To ensure that the information participants received was truthful, we generated it using previously observed behavior of participants in no-information sessions. Conditioning on size and location, we identified the actual decisions made by the participant firms that were closest to the Nash equilibrium (NE) of the information-treatment firms. Details of the NE calculations are provided in Appendix A.

Table 3 presents the NE predictions for each type of firm and the information provided to participants in Info1. Sharing this information with participants resembles a policy change in which people are informed about the actions of firms of a similar size in a similar location prior to making individual management decisions.

In Info2, we gave participants information about the technology-adoption rate and average production level in their group in the preceding round: "In the last round, the technology adoption rate in your group was *y*%; the average production in your group was *z* units." With this information, participants could compare their actions to those of others, effectively providing information on the average decisions of peers in the same region (e.g., a watershed or county).

5. Hypotheses and analytical methods

We formally test the effects of two types of firm heterogeneity and two information treatments on group and individual decisions about technology adoption and production under an ambient-based tax/subsidy policy and analyze the effects of our treatments on the policy's efficiency. Statistical t-tests and regression analyses are used to test the hypotheses. Given the

Table 3
Nash Equilibrium and Information Treatment 1 Given by Size and Location.

			Nash Equilibrium Predictions		Information Provided in Info1	
Type of heterogeneity	Firm Capacity/ Size (γ_{2i})	Marginal Damage of production (β_i)	Technology Adoption (τ_i)	Production (x_i)	Technology Adoption (adopt = 1)	Average Production (units)
No Policy						
H0 (no heterogeneity)	100	0.3	0	100	0	100
HT1 (location)	100	0.24	0	100	0	100
	100	0.28	0	100	0	100
	100	0.32	0	100	0	100
	100	0.36	0	100	0	100
HT2 (size)	125	0.3	0	125	0	125
	75	0.3	0	75	0	75
HT3 (location and size)	125	0.24	0	125	0	125
	75	0.24	0	75	0	75
	125	0.28	0	125	0	125
	75	0.28	0	75	0	75
	125	0.32	0	125	0	125
	75	0.32	0	75	0	75
	125	0.36	0	125	0	125
	75	0.36	0	75	0	75
Policy						
H0 (no heterogeneity)	100	0.3	1	70	1	70
HT1 (location)	100	0.24	0	52	0	51
	100	0.28	0	44	0	43
	100	0.32	1	68	1	70
	100	0.36	1	64	1	64
HT2 (size)	125	0.3	1	95	1	95
	75	0.3	0	15	0	15
HT3 (location and size)	125	0.24	1	101	1	100
	75	0.24	0	27	0	28
	125	0.28	1	97	1	96
	75	0.28	0	19	0	20
	125	0.32	1	93	1	95
	75	0.32	0	11	0	10
	125	0.36	1	89	1	90
	75	0.36	0	3	0	25

panel structure of the dataset,[4] we use random effects models with clustered standard errors at an individual or group level (depending on the level of analysis) to address correlation among error terms across clusters (Cameron and Miller, 2015). Since the treatment variables in the experiment are randomly assigned to each participant, unobserved heterogeneity is not correlated with the independent variables.

5.1. Hypothesis 1

The ambient-based subsidy/tax policy will reduce pollution to the socially optimal level regardless of the presence and type of firm heterogeneity and the presence of an information treatment.

When there is no ambient pollution policy in place, we expect that subjects will maximize their profits by producing at the maximum level possible without considering the cost of environmental damage. When a tax/subsidy ambient-based policy is introduced, we hypothesize that group-level pollution will be reduced to the target level despite firm heterogeneity and the presence of an information treatment.

To test this first hypothesis, we analyze how group pollution levels compare to the target level in each treatment. We aggregate the data from the five rounds completed by each group under a particular treatment and calculate the average level of pollution contributed collectively by the group in those rounds. We then use t-tests to determine whether the group pollution under each treatment is statistically different from the policy's target level.

5.2. Hypothesis 2

Under a tax/subsidy policy, the information treatments will not affect the firms' individual pollution decisions.

[4] In the session, the participants make one production decision and one adoption decision in each of the 40 independent rounds (eight treatments, five rounds per treatment).

Under the ambient-based abatement policy, there is a unique dominant-strategy NE for each participant, and we expect that the participants will play those strategies regardless of whether they have information about the actions of others. We are ultimately interested in whether the information treatments improve decision-making and therefore lead to ambient pollution levels that deviate less (for over-pollution and under-pollution) from the socially optimal target level. Therefore, we test whether the treatments influence the absolute deviation in pollution from the target level.

To test hypothesis 2, we calculate predicted pollution levels based on predictions of the firms' production and adoption decisions. Instead of simply taking the difference between an individual's contribution and the theoretical level, we calculate the percent absolute deviation (PerAbsDiff) of the two values, which we standardize in line with the metric used in Spraggon (2013):

$$\mathrm{PerAbsDiff}_i = \left| \frac{p_i - p_i^*}{p_i^{max}} \right| \tag{13}$$

where p_i represents the actual pollution level contributed by participant i, p_i^* stands for the theoretical predicted NE level of pollution contributed by participant i, and p_i^{max} is the maximum pollution level of participant i. Using this metric allows us to analyze all deviations from the theoretical optimum regardless of whether the actual deviations are positive or negative.

To test the effects of the treatments on the deviation from the theoretically optimal level of pollution, we specify a random effects model:

$$PerAbsDiff_{it} = \alpha + \sum_{k=1}^{3}\beta_k HT_{k,it} + \sum_{h=1}^{2}\theta_h INFO_{h,it} + \sum_{k=1}^{3}\varphi_k HT_{k,it}{}^{*}INFO1_{it} + \sum_{k=1}^{3}\psi_k HT_{k,it}{}^{*}INFO2_{it} + \rho_1 ROUND_{it} + \rho_2 ROUND\_SQ_{it} + v_i + e_{it} \tag{14}$$

in which the outcome variable is the percent absolute deviation between the actual and predicted levels of pollution by individual i in round t as defined in Eq. 14. HT_k represents binary treatment variables that equal 1 when the subscript $k \in \{1, 2, 3\}$ corresponds to the correct heterogeneity treatment (HT1, HT2, HT3). $INFO_h$ represents binary treatment variables that equal 1 when the subscript $h \in \{1, 2\}$ corresponds to the correct information treatment ($INFO1$, $INFO2$). $ROUND$ identifies the round number and takes an integer value between 1 and 40, and $ROUND\_SQ$ is an integer equal to the squared round number to allow for potential nonlinear learning effects. Finally, v_i represents individual-level random effects and e_{it} represents an individual-specific and time-specific error term.

To test for the effects of the size (production) and location variables, we specify a random effects model with size and location indicators:

$$PerAbsDiff_{it} = \alpha + \sum_{h=1}^{2}\theta_h INFO_{h,it} + \lambda_1 LARGE_{it} + \lambda_2 SMALL_{it} + \sum_{h=1}^{2}\eta_h INFO_{h,it}{}^{*}LARGE_{it} + \sum_{h=1}^{2}\sigma_h INFO_{h,it}{}^{*}SMALL_{it} + \sum_{k=1}^{4}\gamma_k REGION_{k,it} + \sum_{k=1}^{4}\phi_k REGION_{k,it}{}^{*}INFO1_{it} + \sum_{k=1}^{4}\omega_k REGION_{k,it}{}^{*}INFO2_{it} + \rho_1 ROUND_{it} + \rho_2 ROUND\_SQ_{it} + v_i + e_{it} \tag{15}$$

in which $LARGE$ and $SMALL$ represent firm capacities of 125 and 75 units, respectively, and $REGION_m$ represents binary variables that equal 1 when the subscript $m \in \{1, 2, 3, 4\}$ corresponds to the correct region. Since the information treatments may have disparate effects on heterogeneous firms, we include information and heterogeneity interaction terms to allow for such variation.

5.3. Hypothesis 3

Policy efficiency at the group level will not be affected by firm heterogeneity or the information treatments.

Under Info1, participants are given individually tailored information about the decisions made by similar firms in past sessions. In Info2, participants are given information on the average adoption rate and production level for their group in the preceding round. We test the policy's efficiency in achieving the pollution targets under each information treatment and hypothesize that the provided information will have no effect since every participant's decision space has a dominant NE strategy.

To test hypothesis 3, we define efficiency per Spraggon (2013) as the change in the value of the social planner's problem (achievement of a target level of pollution) expressed as a percentage of the optimal change in the social planner's problem. We specify the social planner's problem for a group as

$$SP = \sum_{i=1}^{8}\left[\gamma_0 - \gamma_1(\gamma_{2i} - x_i)^2 - c\tau_i\gamma_{2i} - \delta\beta_i x_i(1 - \alpha\tau_i)\right] \tag{16}$$

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Table 4
Average Decisions by Treatment.

		Target	No Info	Info1	Info2	Total
No Policy	Adoption Rate	H0	6.88 %	6.56 %	5.63 %	6.35 %
		HT1	4.69 %	3.44 %	6.25 %	4.79 %
		HT2	6.56 %	2.19 %*	6.25 %	5.00 %
		HT3	5.94 %	1.88 %**	5.31 %	4.38 %
	Production	H0	98.10	98.68	99.06	98.61
		HT1	97.33	99.00*	98.93*	98.42
		HT2	98.14	99.13	99.49*	98.92
		HT3	97.54	99.56	98.66	98.59
	Profit	H0	39.25	39.34	39.46	39.35
		HT1	39.30	39.59	39.41	39.43
		HT2	39.38	39.72	39.52	39.54
		HT3	39.15	39.83*	39.47	39.48
Policy	Adoption Rate	H0	69.69 %	90.63 %***	86.88 %***	82.40 %
		HT1	72.81 %	69.06 %	74.69 %	72.19 %
		HT2	77.50 %	66.25 %**	75.31 %	73.02 %
		HT3	76.88 %	69.38 %	75.31 %	73.85 %
	Production	H0	58.86	64.64**	63.26*	62.25
		HT1	64.58	62.89	62.97	63.48
		HT2	57.12	56.00	57.51	56.88
		HT3	60.86	54.70*	58.81	58.12
	Profit	H0	22.70	30.37*	29.08	27.38
		HT1	30.26	31.34	35.90	32.50
		HT2	20.44	26.01	22.20	22.88
		HT3	14.66	26.40**	19.88	20.31

The Info1 and Info2 columns provide *t*-test significance indicators of Info1 and Info2 values against the corresponding values in the no-information. *, **, and *** indicate significance at a 10 %, 5 %, and 1 % level, respectively. H0 represents homogenous firms, HT1 represents location heterogeneity, HT2 represents size heterogeneity, and HT3 represents both location and size heterogeneity.

and efficiency is calculated as

$$E = \frac{SP_{Actual} - SP_{StatusQuo}}{SP_{Optimal} - SP_{StatusQuo}} \tag{17}$$

SP_{Actual} is the value of the social planner's problem calculated using the participants' actual decisions, $SP_{Optimal}$ is the value when the participants all choose their optimal production levels and technology-adoption strategies, and $SP_{StatusQuo}$ is the value when all participants choose to produce the maximum amount possible and do not adopt the technology. Theoretically, $SP_{Optimal}$ and $SP_{StatusQuo}$ should correspond to the upper and lower bounds of the social planner's problem, resulting in efficiency taking values between 0 and 1.

A random effects model with standard errors clustered at the group level is defined as

$$\begin{aligned} Efficiency_{jt} &= \alpha + \sum_{k=1}^{3}\beta_k HT_{k,jt} + \sum_{h=1}^{2}\theta_h INFO_{h,jt} + \sum_{k=1}^{3}\varphi_k HT_{k,jt}{}^{*}INFO1_{jt} + \sum_{k=1}^{3}\psi_k HT_{k,jt}{}^{*}INFO2_{jt} + \beta_{12}ROUND_{jt} \\ &\quad + \beta_{13}ROUND\_SQ_{jt} + v_i + e_{jt} \end{aligned} \tag{18}$$

in which j represents the group of firms, t represents the round, v_j is the group-level random effect, and e_{jt} is a group- and time-specific error term.

6. Results

We conducted 12 experiment sessions that each involved 16 participants, resulting in 192 participants, and used the resulting data to identify the effects of a tax/subsidy policy, firm heterogeneity, and information treatments on individual and aggregate contributions of pollution to a watershed and the policy's efficiency in achieving its ambient pollution target.

Table 4 summarizes participants' adoption and production decisions and the corresponding profit earned by the firms at the group level. T-tests are used to compare the outcomes under the two information treatments to the outcome of the no-information control. Asterisks indicate statistical significance of the result.

As expected, regardless of the heterogeneity and information treatments applied, under the no policy scenario, the technology-adoption rate is low and production is close to the maximum capacity allowed for each participant.

When the policy is in effect, under the homogeneous treatment the optimal technology decision is to adopt and the optimal production decision is 70 units for all firms (see Table 3). In the homogeneous-firm no-information treatment, the average adoption rate is 69.69 % and average production is 58.86 units. Therefore, participants are under-adopting and under-producing. When the information treatments are applied to homogeneous firms, the technology-adoption rates and production levels increase significantly, as do profits under Info1.

Table 5
Mean Group Pollution by Treatment under Policy.

	Pollution Level				
	Target[a]	No Info	Info1	Info2	Average of All Information Treatments
Policy					
H0	84	89.96	82.23	83.56	85.25
		(5.13)	(2.65)	(3.41)	(2.25)
HT1	94.4	93.41	92.81	87.70*	91.31
		(6.49)	(2.54)	(3.99)	(2.61)
HT2	75	81.42*	76.79	80.20*	79.47**
		(3.43)	(4.72)	(3.09)	(2.14)
HT3	73	85.93**	73.87	80.79**	80.20***
		(4.99)	(3.19)	(3.50)	(2.42)
Average of H0, HT1, HT2, and HT3	81.6	87.68**	81.42	83.06	84.06**
		(2.56)	(2.07)	(1.75)	(1.26)

Means (standard errors) of t-tests of pollution level vs. corresponding NE (target) level. *, **, and *** indicate significant at the 10 %, 5 %, and 1 % level, respectively.
[a] In the No Policy scenarios, no target was provided.

For the heterogeneous firms, the optimal decision for half of the participants is to adopt and for the other half not to adopt. However, we find adoption rates of 72 %–77 %, suggesting over-adoption in the heterogeneous treatments. The Info1 treatment led to a decrease in the adoption rates to 66 %–70 %, which is statistically significant in the HT2 case (production/size heterogeneity). We find no significant differences in level of production or profits in response to the information treatments. The only change is a marginal decrease in production and increase in profit in HT3 (size and location heterogeneity) under the Info1 treatment.

6.1. *Pollution reduction under an ambient tax/subsidy policy*

Since firms' production and adoption rates both affect the target pollution level under an ambient-based policy, we pay particular attention to the group level pollution and how they differ from the target pollution levels. Table 5 summarizes group-level pollution (measured by environmental damage) under each treatment with the policy and presents *t*-test standard error in parentheses.

The information treatments do not influence the theoretical NE calculations. Therefore, the target pollution levels vary based on the parameters of the size and location treatments but are identical across the information treatments.

6.1.1. *Firm heterogeneity reduces the effectiveness of the tax/subsidy policy in the absence of an information treatment*

The results presented in Table 5 show that pollution generated under the homogeneity and HT1 (location) treatments does not differ significantly from the target level. Under the HT2 (size) and HT3 (size and location) treatments, however, the group pollution levels are significantly different from the targets at the 10 % and 5 % levels respectively. Therefore, in the no-information case, as greater heterogeneity is introduced, group pollution levels deviate further from the socially optimal level.

6.1.2. *For heterogeneous firms, both information treatments are associated with a level of group pollution that is closer to the target than under the no-information control*

Under Info1, the group pollution levels for all of the location and size heterogeneity treatments are not significantly different from the target levels. For example, the group average pollution is 73.87 in HT3, which is not significantly different than the target level 73. Under Info2, only the homogeneous treatment leads to achieving the target level of pollution. Group pollution levels in the treatments involving heterogeneous firms differ significantly at a 10 % or 5 % level.

The results indicate that the information treatments have no significant effect on the amount of pollution contributed by homogeneous firms and that the policy is relatively effective in achieving its targets when all firms in the watershed are similar. Introducing heterogeneity in terms of the firms' locations in the watershed does not have a negative effect on group pollution in the no-information and Info1 treatment (peer information) and only a small effect on group pollution in the Info2 treatment. However, when size heterogeneity is introduced, group pollution exceeds the target level by 8.6 % under no-information and 6.9 % under Info2 (aggregate information). Those results are significant at a 10 % level. Upon introducing both location and size heterogeneity, we observe group-level deviations in pollution that are significant at the 5 % level in the no-information treatment (17.7 %) and Info2 (10.7 %) but none in Info1. And though group pollution under Info2 is statistically different from the target, the deviation (10.7 %) is about 40% smaller than the deviation in the no-information treatment (17.7 %). Therefore, both information treatments reduce the amount of group pollution and peer-based information (Info1) is more effective than aggregate information (Info2).

We further analyze the effects of the information treatments by computing the average pollution level for the three information treatments combined (Table 5). We again find that group-level pollution in the homogeneous and HT1 treatments

Table 6
Random Effects Regression of Percent Absolute Deviation (PerAbsDiff) on Individual Pollution and Treatment Variables.

	Without Policy			With Policy		
	Coeffi.	Std. Err.	P-value	Coeffi.	Std. Err.	P-value
HT1	−0.002	0.008	0.788	0.006	0.009	0.517
HT2	−0.002	0.008	0.762	0.032	0.009	0.000
HT3	−0.001	0.008	0.888	0.054	0.009	0.000
Info1	−0.008	0.018	0.671	−0.072	0.162	0.000
Info2	−0.018	0.018	0.310	−0.056	0.162	0.001
Info1_HT1	−0.017	0.011	0.107	0.043	0.012	0.001
Info1_HT2	−0.025	0.011	0.016	0.017	0.012	0.181
Info1_HT3	−0.030	0.011	0.004	0.012	0.012	0.351
Info2_HT1	0.006	0.011	0.580	0.028	0.012	0.027
Info2_HT2	0.003	0.011	0.754	0.038	0.012	0.003
Info2_HT3	0.002	0.011	0.824	0.028	0.012	0.026
Round	−0.006	0.006	0.250	−0.002	0.007	0.731
Round_sq	0.001	0.001	0.379	0.0004	0.001	0.708
Constant	0.063	0.015	0.000	0.137	0.014	0.000
Observations	3,840			3,840		
No. of groups	192			192		
Wald chi2	26.68			229.13		
Prob > chi2	0.0138			0.0000		

All standard errors are clustered at the individual level.

is not significantly different from the target and that pollution levels are significantly different from the target at a 5 % level in the HT2 treatment and at the 1 % level in the HT3 treatment.

Analyzing the average effect of each information treatment across all of the homogeneity/heterogeneity treatments (Table 5), we find that the average group pollution level is significantly different from the average target level in the no-information treatment at a 5 % level and not significantly different from the target level in Info1 and Info2.

6.2. *Pollution deviation at the individual level*

As previously discussed, there is a unique dominant-strategy NE for each participant's decisions. We previously predicted the amount of pollution emitted by each firm based on its predicted production and adoption decisions (see Table 3). Ultimately, we are interested in how the firms' actual decisions under various treatments deviate from the theoretical predictions (which are also the socially optimal decisions) and how to reduce deviations in both directions (i.e., reduce both over-polluting and under-polluting). Therefore, we calculate percent absolute deviation (PerAbsDiff) values (see Eq. 13) to standardize absolute deviation of the individual pollution levels and the associated theoretical levels. Specific individual-level analyses are discussed in the following two subsections.

6.2.1. *At the individual decision level, introducing greater firm heterogeneity leads to larger deviations in pollution contributed by each firm from the predicted level, and both information treatments reduce the magnitude of the deviation from theoretical predictions*

Results of separate regressions of the no-policy and policy treatments are presented in Table 6 (the regression specification follows Eq. 14). In the no-policy treatments, the heterogeneity and information treatments alone do not affect the pollution-level deviations. However, under the Info1 treatment, the deviations in the HT2 and HT3 treatments decrease significantly. Therefore, providing individual information to participants reduces their likelihood of deviating from their optimal NE strategies.

In the presence of the tax/subsidy policy, the HT2 (size) and HT3 (size and location) treatments have significantly positive coefficients, meaning that the firms in those treatments deviated more from the Nash predictions than firms in the homogeneous treatment. The coefficients on Info1 and Info2 indicate that receiving either of the information treatments decreases deviation from the predicted values.

Analyzing the interactions between the information and heterogeneity treatments, we find that deviation in HT1 (location) is slightly greater under the Info1 treatment while there is no statistically significant effect from Info1 in the homogeneous treatment or in the HT2 and HT3 treatments.

The results in Table 6 further show that the coefficients on the interaction terms for Info2 and all of the heterogeneity treatments are positive and significant at the 5 % level. This indicates that individual-level deviations under the Info2 (aggregate) treatment are larger for heterogeneous firms than for homogeneous firms.

In summary, then, we find that heterogeneity in location and in size and location combined lead to increased deviations from the theoretically predicted values. The firms are better able to find and retain their NEs when provided information about past decisions relative to receiving no information. Also, heterogeneity of the firms has less of an effect on deviation from the NE under the Info1 (peer) treatment than under the Info2 (aggregate) treatment, suggesting that relatively tailored, individual-level information most effectively improves the outcome of a policy when the firms are heterogeneous.

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Table 7
Random Effects Regression of Percent Absolute Deviation (PerAbsDiff) on Individual Size, Location, and Information Treatments.

	Without Policy			With Policy		
	Coeffi.	Std. Err.	P-value	Coeffi.	Std. Err.	P-value
Info1 (peer)	−0.0108	0.018	0.556	−0.060	0.017	0.001
Info2 (aggregate)	−0.0166	0.020	0.407	−0.047	0.020	0.020
Large size	0.0003	0.009	0.968	0.005	0.014	0.725
Small size	−0.0017	0.011	0.876	0.075	0.017	0.000
Region1 (most upstream)	0.0035	0.017	0.832	0.013	0.015	0.412
Region2	−0.0054	0.008	0.521	0.002	0.020	0.928
Region3	−0.0080	0.006	0.214	0.006	0.013	0.655
Region4 (most downstream)	0.0082	0.013	0.525	0.034	0.018	0.065
Info1_large	−0.0193	0.011	0.072	−0.003	0.017	0.882
Info1_small	−0.0196	0.013	0.138	−0.012	0.024	0.610
Info1_region1	−0.0089	0.019	0.637	0.016	0.023	0.501
Info1_region2	−0.0148	0.012	0.220	0.024	0.026	0.361
Info1_region3	−0.0035	0.010	0.728	0.019	0.019	0.296
Info1_region4	−0.0164	0.016	0.315	0.017	0.026	0.507
Info2_large	−0.0074	0.014	0.584	0.016	0.018	0.387
Info2_small	0.0073	0.015	0.630	0.022	0.023	0.344
Info2_region1	−0.0123	0.018	0.488	0.023	0.022	0.286
Info2_region2	−0.0015	0.013	0.909	0.022	0.025	0.391
Info2_region3	0.0245	0.016	0.137	0.008	0.024	0.744
Info2_region4	−0.0008	0.021	0.968	−0.017	0.026	0.510
Round	−0.0065	0.006	0.290	−0.002	0.006	0.684
Round_sq	0.0008	0.001	0.366	0.0004	0.001	0.649
Constant	0.0618	0.018	0.000	0.133	0.018	0.000
Num. of Obs.	3840			3840		
Num. of groups	192			192		
Wald chi^2	35.02			148.06		
Prob > chi^2	0.0385			0.0000		

All standard errors are clustered at the individual level. The regions are numbered in order of increasing marginal damage (upstream to downstream).

A potential explanation for the robustness of the Info1 treatment is that it provides the social comparison at an individual level and thus takes the firm's heterogeneous characteristics into account whereas Info2 provides only group-level information about average peer actions. As greater heterogeneity is introduced, the range of a group's individual optimal strategies expands and group-level averages are likely less valuable to individuals trying to find the best strategy.

6.2.2. *Firms with different sizes and locations have different response to the ambient policy, but both information treatments increase the performance of the policy overall, regardless of the size and location of the firm*

Table 7 presents the results of our analysis of how the information treatments affect deviations from theoretical predictions for each size and location (following Eq. 15) with and without the policy. In the absence of a policy, most of the coefficients are not significantly different from zero. Thus, in the absence of a tax/subsidy policy, most of the firms pollute at the maximum level regardless of the information treatment applied, their size, and their location, which aligns with our theoretical predictions.

We next analyze the individual effects of size and location in the presence of the tax/subsidy policy, emphasizing four key results. First, the coefficient on small firms is positive and significant, meaning that, relative to medium-sized firms, small ones tend to deviate more from the target pollution level. Second, we observe only one effect of the firms' locations—a marginally significant (10 % level) deviation from the target for Region4 (farthest downstream). This suggests that the firms took their location in the watershed into account when making their production and technology decisions. Third, both of the information treatments have significant and negative coefficients and thus significantly reduce deviation from the theoretical predictions. Fourth, none of the interactions between the information treatments and size and location are significant, meaning that the information treatments are effective in improving the policy's efficiency regardless of a firm's size and location.

In particular, the results of this analysis demonstrate that both types of information nudges positively influence firms' decisions. Moreover, the impacts appear to be essentially identical for all firms so the information nudges are robust to the firms' relative sizes and locations. These results support the use of information nudges based on social comparisons as a policy intervention since they are equally effective for various types of firms.

Table 8
Policy Efficiency by Treatment.

	No information	Info1	Info2	Average for All Information Treatments
H0	81.87 %	91.95 %	90.56 %	88.13 %
HT1 (location)	79.61 %	87.38 %	86.76 %	84.59 %
HT2 (size)	67.91 %	82.95 %	74.95 %	75.27 %
HT3 (location and size)	66.81 %	77.51 %	74.01 %	72.77 %
Avg for all Hetero Treatments	74.05 %	84.95 %	81.57 %	80.19 %

Means of efficiency by treatment.

Table 9
Policy Efficiency by Treatment.

	Coefficient	Std. Err.	P-value
HT1 (location)	0.002	0.046	0.962
HT2 (size)	−0.141	0.040	0.000
HT3 (location and size)	−0.134	0.047	0.005
Info1 (peer)	0.101	0.035	0.004
Info2 (aggregate)	0.087	0.048	0.072
Info1_HT1	−0.040	0.055	0.468
Info1_HT2	0.052	0.058	0.371
Info1_HT3	0.018	0.061	0.774
Info2_HT1	−0.017	0.063	0.791
Info2_HT2	−0.017	0.069	0.805
Info2_HT3	−0.015	0.063	0.816
Round	0.002	0.010	0.833
Round_sq	−0.001	0.002	0.705
Constant	0.819	0.033	0.000
No. of Obs.	480		
No. of groups	96		
Wald chi^2	111.52		
Prob > chi^2	0.000		

All standard errors are clustered at the group level.

6.3. *Social efficiency*

6.3.1. *Social efficiency decreases as firm heterogeneity increases but both types of information treatments increase policy efficiency*

Table 8 presents the results of our analysis of the tax/subsidy policy's efficiency for each type of firm heterogeneity and the information treatments. We find that that policy's efficiency is greatest under the Info1 treatment, followed by the Info2 treatment, and the no-information treatment. And, as greater heterogeneity is introduced, the policy's efficiency decreases: in the homogeneous treatments, the tax/subsidy policy achieves 88.1 % efficiency on average versus 72.8 % in the heterogeneous treatments.

Table 9 presents the results of an analysis of the policy's efficiency for each information treatment and heterogeneity value individually and for their interactions (following Eq. 18). We find that firm size (HT2) and firm size and location (HT3) decrease efficiency by 14.1 % and 13.4 %, respectively ($p < 0.01$). The Info1 treatment increases efficiency by 10.1 % ($p < 0.01$) and the Info2 treatment increases efficiency by 8.7 % ($p < 0.10$). None of the interactions of information and heterogeneity or of the rounded and rounded-squared controls are significant at the 5 % level. Collectively, these results suggest that the policy's efficiency decreases as greater heterogeneity is introduced and increases under both of the information treatments. The Info1 treatment leads to greater policy efficiency than the Info2 treatment.

In this study, information provided in the social/peer comparison treatment reported peer behavior that aligned most closely with the Nash Equilibrium to reinforce and promote efficient behaviors. This illustrates a specific type of peer comparison, but in general, providing information about peer behavior may not improve someone's decisions if their original behavior was already more efficient than that of their peers. Therefore, it is important to understand how information about sub-optimal behavior affects decisions and to carefully design programs involving peer comparisons to promote behavior that is welfare enhancing. Results from prior research are mixed. Banerjee (2018) suggests that individuals may respond to strategic uncertainty by changing their behavior to conform with the reported behavior of peers even when that involves making less efficient choices. Research on energy conservation programs has also identified a so-called “boomerang effect” that can occur when consumers with low energy usage increase consumption in response to information about social norms; however, results suggest that incorporating advice and tips about conservation and the inclusion of injunctive norms may help reduce concerns about adverse behavioral responses to peer comparisons (Allcott, 2011; Schultz et al., 2007). Our results

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suggest that decisions are positively influenced by information about efficient behaviors, while participants are more likely to disregard information about behavior that is less efficient than their current behavior.[5]

Determining what type of peer comparison information to provide is an important consideration for program administrators and advocacy groups. Our results suggest that information specifically about efficient peer behavior can promote pro-environmental behavior. Although not explored in our study, providing decisions makers with information about the benefits of the reported peer behavior may increase their confidence in their ability to improve outcomes. Decision support tools that allow people to determine how specific outcomes would change in response to a management change could also increase confidence in following management recommendations.

7. Conclusions and discussion

In this study, we conducted an economic laboratory experiment on NPS water pollution for firms that were heterogeneous in terms of their location within the watershed and their size (production) and that operated in an extended decision space that required participants to make decisions about production and adoption of a pollution-abatement technology. We find that, as greater heterogeneity is introduced, the ability of the tax/subsidy policy to reduce group pollution to the target level decreases. However, informational nudges can increase the effectiveness of the policy. The first treatment provided information on decisions made by other firms in the past that was tailored to the size and location of the firm receiving it. The second treatment provided information on mean production and technology adoption rates in the group in the preceding round.

Our results demonstrate that policy efficiency is negatively affected by firm heterogeneity but can be improved using informational nudges based on social norms. We find that individually-tailored information about decisions made by others is more likely to reduce pollution to the socially optimal level than more general aggregated information on mean rates of production and technology adoption. We also find that both of the information treatments tested in this study are associated with the individual firms' abilities to align their decisions with their NE strategies in both homogeneous and heterogeneous cases.

Our results indicate that ambient-based abatement policies addressing water pollution will prove to be less effective once greater heterogeneity and more-complex decision spaces are incorporated into economic studies and that additional tools such as behavioral information nudges based on social norms may be needed for such policies to be effective in practice. The results of our analysis of two types of nudges based on social norms indicates that general, aggregated information is less effective in motivating producers than specific information about actions actually taken by the producers' peers. These findings are important because they suggest that ambient-based policies that lack such effective behavioral nudges are unlikely to be effective and/or efficient given the complexity of actual water-improvement projects.

The information treatments analyzed in this study could be easily and inexpensively incorporated into many pollution-abatement policy schemes and significantly improve their outcomes. Policymakers could, for example, use the types of nudges documented in Ferraro and Price (2013) and inform participants in the abatement program about the average production levels and rates of technology adoption by similar producers in nearby watersheds and present "efficient producer's" decisions as a "social norm" to encourage similar behavior. A valuable extension of this research could investigate how firms respond to another information treatment comprised of expert advice about production and technology decisions for different types of firms.[6] Our study demonstrates that policies that use information nudges can potentially overcome the tendency of heterogeneous producers to under-provide abatement and achieve a more efficient outcome.

Declaration of Competing Interest

None.

Acknowledgments

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[5] This finding is based on a chi-square test comparing the proportion of decisions that improve or worsen in response to information about more efficient or less efficient behaviors compared to the participants' previous decision. When people receive more efficient information, they improve their decisions 67% of the time. People receiving information about less efficient decisions make better decisions significantly less, but they still improve their decisions 56% of the time.

[6] We thank an anonymous reviewer for this thoughtful suggestion.

Appendix A. Calculation of Nash Equilibrium

For the no policy case, each firm maximizes production income subject to size constraint. Taking the derivative of Eq. (1), we can see that the dominate strategy is $\{a_i = 0$ (not adopt); $x_i = \gamma_{2i}\}$ without policy.

For the policy case, as shown in Section 3.1, for a firm with size parameter γ_{2i} and location parameter β_i, the dominant strategy could be defined as:

$\{$*if* $\frac{\delta^2\beta_i^2}{4\gamma_1}\left(1-(1-\alpha)^2\right)-\alpha\delta\beta_i\gamma_{2i}+c\gamma_{2i}<0$: $a_i^* = 1$ (adopt); $x_i^* = \gamma_{2i}-\frac{\delta\beta_i(1-\alpha)}{2\gamma_1}$.

if $\frac{\delta^2\beta_i^2}{4\gamma_1}\left(1-(1-\alpha)^2\right)-\alpha\delta\beta_i\gamma_{2i}+c\gamma_{2i}>0$: $a_i^* = 0$ (not adopt); $x_i^* = \gamma_{2i}-\frac{\delta\beta_i}{2\gamma_1}$.$\}$

The values of the parameters are given in Table 1.

Using these parameters, we can derive the Nash Equilibrium for each size and location combination.

For example, for a firm with size parameter 75, location parameter 0.3, we use Eq. (12) $\frac{\delta^2\beta_i^2}{4\gamma_1}\left(1-(1-\alpha)^2\right)-\alpha\delta\beta_i\gamma_{2i}+c\gamma_{2i} > 0$, and the corresponding adoption and production equilibrium decisions are: $a_i^* = 0$ (not adopt); $x_i^* = \gamma_{2i}-\frac{\delta\beta_i}{2\gamma_1} = 15$.

Meanwhile, for a firm with size parameter 125, location parameter 0.3, we use Eq. (12) $\frac{\delta^2\beta_i^2}{4\gamma_1}\left(1-(1-\alpha)^2\right)-\alpha\delta\beta_i\gamma_{2i}+c\gamma_{2i}<0$, and the corresponding adoption and production equilibrium decisions are: $a_i^* = 1$ (adopt); $x_i^* = \gamma_{2i}-\frac{\delta\beta_i}{2\gamma_1} = 95$.

In a similar fashion, we can derive the equilibrium decisions for all the size and location combinations (listed in Table 3).

Appendix B. Experiment Instructions

Thank you for participating!

Please return the signed consent form to the administrator.

Please read and follow the instructions carefully and do not communicate with others during the experiment.

Introduction

This is an experiment about the economics of decision making. You will earn money during this experiment if you follow these instructions carefully and make informed decisions; otherwise, you may end up losing money. Any money earned during this experiment will initially be recorded as experimental dollars. At the end of this experiment, we will convert your experimental dollars into actual US dollars that will be handed to you as you leave. The more experimental dollars you earn the more actual US dollars you will receive. At the end of the experiment, your earnings will be converted at a rate of $1 US dollar for 50 experimental dollars. Please read these instructions carefully and do not communicate with any other participants during the experiment.

General Instructions: Today's experiment has several parts. Each part will have five rounds. Each round is independent, meaning that decisions during a round do not affect future rounds in any way. The only value that gets carried over across rounds is the cumulative amount of money you earn, which will be used to calculate your cash earnings at the end of the experiment.

Your role: You own and operate a firm. You will make decisions that affect the amount of money your firm earns. This money will be called your **Firm Profit**.

Groups: Throughout the experiment, you will be in a group of eight people, each will play the role of a firm. Think of your firm and the seven other firms as being located near a river. Groups are randomly reassigned after each part of the experiment and you will not know who is assigned to each group.

Production and Production Income: Each business owner produces output that creates **Production Income**. Production income only depends on how much is produced. The more a firm produces, the more production income the firm will get.

Pollution: Production also generates pollution that goes into the river. In general, the higher the output being produced, the more pollution is being generated. Some concentration of this pollution is harmless. However, if the concentration is too large, the pollution has negative effects to the environment.

Total Pollution: This is measured by a sensor downstream and is the sum of pollution for everyone in the same group.

Capacity: The firms may have a different production capacity, which is the maximum amount your firm can produce. Each firm's capacity will be shown on the calculator in the corresponding part for that firm. There are three types of capacities: Large firms with a capacity of 125; medium firms with a capacity of 100; small firms with a capacity of 75.

Technology: At the beginning of each round, the firms may choose to adopt a technology at a cost proportional to your firm capacity. When adopted, the technology will reduce the firm's pollution to a certain percentage of the original level for that round.

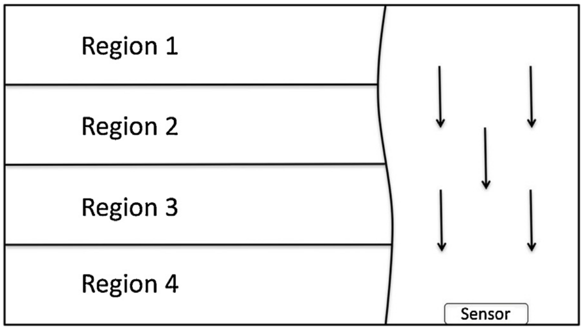

Fig. B1. Different Locations.

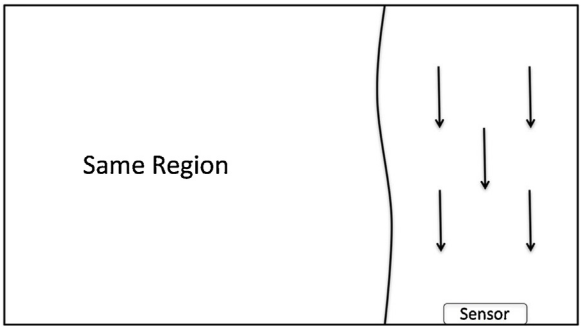

Fig. B2. Same Location.

Location: The firms may either be located in the same location or at different locations along a river. As shown in Fig. B1, when the region is separated by lines, it means the region is being divided into Region 1 to Region 4. In this case, Region 1 is the most upstream and Region 4 is the most downstream. The further downstream your firm is the more pollution per unit of production will be recorded by the sensor. As shown in Fig. B2, when there are no lines separating the region, it means all of the firms are placed in the same region. The actual capacity and location of the firm that you operate will be shown on your computer screen.

Decisions: In each round, you will make two decisions:

(1) **Production Decision** – You will decide your firm's production level, between 0 and your firm's capacity.
(2) **Technology Decision** – You will choose whether to adopt a technology at a certain cost, labeled "Not Adopt" or "Adopt".

Pollution Table: To help you better understand the relationship of production, technology, location and pollution, you are given a **Pollution Table** that has pollution levels of a firm corresponding to different production decisions, technology decisions and location. Use this table to understand how your production would affect pollution based on your location and technology decision.

Firm Profit: Your **firm profit** is calculated based on your production decision and technology decision and will be explained to you in further details in each part of the experiment.

Decision Calculator: A **Decision Calculator** is provided to test different scenarios to see how the decisions of other firms in your group could affect Total Pollution and your Firm Profit. Follow the instructions on how to use this calculator provided on the next page.

In summary:

- In each part of the experiment, you will be given additional instructions and all calculations will be described.
- Your earnings from the experiment depend on your cumulative firm profit.
- Use the decision calculator to test out different scenarios and determine your own production and technology decision.
- Choose your own production and technology decision and click "Confirm".
- Your production income is affected by your production decision, technology decision, and firm capacity.
- Your pollution depends on your production decision, technology decision and firm location.
- A round of the experiment is complete when all eight players have made their production and technology decisions.
- After each part, participants will be randomly reassigned to a new group.

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How to use the decision calculator and make decisions

In each round, you will be provided with a decision calculator like the one in the attached handout.
The layout of all firms and their corresponding capacity in your group is shown in the calculator.
Your firm is labeled "Your Firm" and marked with a black box.

Step 1. On the left part of the page, assume what everyone in your group will be doing by choosing a production and technology decision for every firm. To choose a production decision, move the slider or type in the amount that you think other firms will be producing; to choose a technology decision, simply choose between the "Not Adopt" and "Adopt" options. Note that your firm is labeled in the black box and you do not have to choose technology decision for your firm.

Step 2. On the top right part of the page, click "Calculate" and your pollution, total pollution and your profit of "Not adopt" and "Adopt" will be shown to you in the table right under the "Calculate" button.

Keep in mind that the decisions you make in the decision calculator are for informational purposes only and other firms can make their own decisions regardless of what you choose for them.

After you decide what your decision will be, make your actual decision in Step 3.

Step 3. On the bottom right part of the page, choose your actual production decision with the slider, and pick your actual technology decision. When you are done, click "Confirm". Once you have clicked this button, the button will turn gray and it is no longer possible to change your decisions for that round.

Results – While you are waiting for the other players to make their decisions, you can review the results of past rounds, which will be shown on your screen. After all eight players have clicked the Confirm button, the results of the current round will appear, including Your Pollution, the Total Pollution from all members of your group, your Production Income, and Your Firm Profit.

Decision calculator

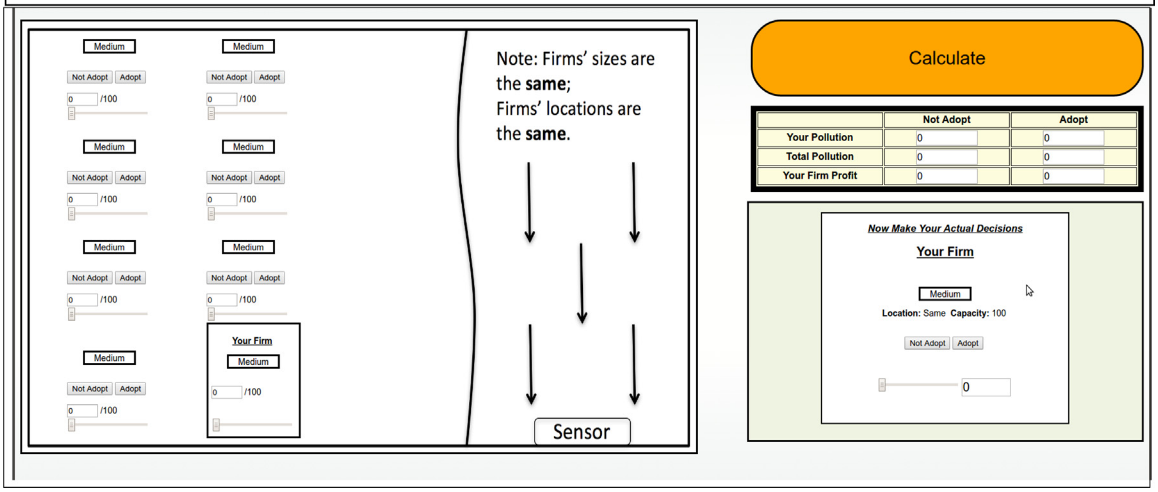
The image below are examples of the interactive Decision Calculator that you will use on your computer.

Note: In the information treatments, a message will be displayed in the top part of the page above the decision calculator. In the no information treatment, no text is displayed.

No Info: No information is displayed.

Info1: In the past, people like you in a similar situation have produced 'x' units and chose adopt/ not adopt.

Info2: In the last round, the technology adoption rate in your group was 'y'%; the average production in your group was 'z' units.



Pollution Table

This Pollution Table helps you to better understand how your firm's production decision, technology decision and location affect your pollution. Use this table along with the Decision Calculator to help you make more informed decisions.

How to read this table?

1 The first column (Production) indicates how much is being produced.
2 Find where your firm is located from the Decision Calculator. If every firm is in the same region, use the last two columns (marked as "Same Region").
3 Your firm's pollution for each level of production under "Not Adopt" and "Adopt" are listed in the columns corresponding to your region.

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	Your Firm Pollution									
Production	Region 1		Region 2		Region 3		Region 4		Same Region	
	Not Adopt	Adopt	Not Adopt	Adopt	Not Adopt	Adopt	Not Adopt	Adopt	Not Adopt	Adopt
0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	1.20	0.60	1.40	0.70	1.60	0.80	1.80	0.90	1.50	0.75
10	2.40	1.20	2.80	1.40	3.20	1.60	3.60	1.80	3.00	1.50
15	3.60	1.80	4.20	2.10	4.80	2.40	5.40	2.70	4.50	2.25
20	4.80	2.40	5.60	2.80	6.40	3.20	7.20	3.60	6.00	3.00
25	6.00	3.00	7.00	3.50	8.00	4.00	9.00	4.50	7.50	3.75
30	7.20	3.60	8.40	4.20	9.60	4.80	10.80	5.40	9.00	4.50
35	8.40	4.20	9.80	4.90	11.20	5.60	12.60	6.30	10.50	5.25
40	9.60	4.80	11.20	5.60	12.80	6.40	14.40	7.20	12.00	6.00
45	10.80	5.40	12.60	6.30	14.40	7.20	16.20	8.10	13.50	6.75
50	12.00	6.00	14.00	7.00	16.00	8.00	18.00	9.00	15.00	7.50
55	13.20	6.60	15.40	7.70	17.60	8.80	19.80	9.90	16.50	8.25
60	14.40	7.20	16.80	8.40	19.20	9.60	21.60	10.80	18.00	9.00
65	15.60	7.80	18.20	9.10	20.80	10.40	23.40	11.70	19.50	9.75
70	16.80	8.40	19.60	9.80	22.40	11.20	25.20	12.60	21.00	10.50
75	18.00	9.00	21.00	10.50	24.00	12.00	27.00	13.50	22.50	11.25
80	19.20	9.60	22.40	11.20	25.60	12.80	28.80	14.40	24.00	12.00
85	20.40	10.20	23.80	11.90	27.20	13.60	30.60	15.30	25.50	12.75
90	21.60	10.80	25.20	12.60	28.80	14.40	32.40	16.20	27.00	13.50
95	22.80	11.40	26.60	13.30	30.40	15.20	34.20	17.10	28.50	14.25
100	24.00	12.00	28.00	14.00	32.00	16.00	36.00	18.00	30.00	15.00
105	25.20	12.60	29.40	14.70	33.60	16.80	37.80	18.90	31.50	15.75
110	26.40	13.20	30.80	15.40	35.20	17.60	39.60	19.80	33.00	16.50
115	27.60	13.80	32.20	16.10	36.80	18.40	41.40	20.70	34.50	17.25
120	28.80	14.40	33.60	16.80	38.40	19.20	43.20	21.60	36.00	18.00
125	30.00	15.00	35.00	17.50	40.00	20.00	45.00	22.50	37.50	18.75

For Example:

1 A firm in Region 1, producing 75 units. Firm Pollution for not adopt: 18; adopt: 9.
2 A firm in Region 4, producing 75 units. Firm Pollution for not adopt: 27, adopt: 13.5.
3 A firm in Same Region, producing 100 units. Firm Pollution for not adopt: 30; adopt: 15.

ID# _________

Understanding the experiment

This short exercise is designed to help you understand how the experiment works. The profit you earn in this section does not affect your real earnings.

Please use the decision calculator on the computer in front of you to figure out what your firm profit will be under the following scenarios:

You will be guided through Scenario A, and you will complete scenario B by yourself.

Scenario A:

Please fill in your profit for the following hypothetical decisions. The steps listed below will guide you through scenario A.

Everyone else		You		
Technology	Production	Your Production	Your Technology	Your Profit
Not Adopt	80	50	Not Adopt	
Not Adopt	80	50	Adopt	

Step 1: On the left part of the page, select “Not Adopt” for everyone else except your firm.

Step 2: Use the slider or type in the boxes to change everyone else’s production to 80 units.

Step 3: Still on the left part of the page, find the box that lists “Your Firm”, change the production decision to 50 units.

Step 4: Click “Calculate”. Your pollution, total pollution and your firm profit should be shown to you.

Step 5: Find “Your Firm Profit” for “Not Adopt”, which should be “33.75” in this case. Type in “33.75” in the first row under profit for scenario A.

Step 6: Find “Your Firm Profit” for “Adopt”, which should be “25.55” in this case. Type in “25.55” in the second row under profit for scenario A.

Step 7: Click “Check answer for scenario A” when you are done. If the program asks you to try again, please check answers for the highlighted parts.

Now please complete scenario B on your own, please raise your hand if you have any questions.

Scenario B:

Please fill in your profit for the following hypothetical decisions on the computer screen.

Everyone else		You		
Technology	Production	Your Production	Your Technology	Your Profit
Adopt	100	100	Not Adopt	
Adopt	100	100	Adopt	

You may refer to instructions for Scenario A to help you complete Scenario B.

Input your firm profit for Scenario B on the computer program and check if it is correct by clicking "check answers". When the program asks you to "try again", it means your answer is not correct and will be highlighted. In that case, please use the calculator to recalculate the answer.

When you get both scenarios correct, you may click the continue button to move on to the next part.

Instructions for practice

You will now play five practice rounds to learn how the experiment works. The outcomes of these rounds will not affect your cash earnings.

In each round of this part, you will make your Production Decision and your Technology Decision. Use the Decision Calculator to see how your decision and others' decisions affect your earnings.

In this practice part, pollution does not affect firm profits. The more you produce, the more your firm profit will be.

After everyone makes their decisions, you will see the results screen that will display your Firm Profit and Pollution. In this part, your Firm Profit will be calculated as follows:

Firm Profit = Production Income.

MOVING on to PART 1 through PART 8

After you have finished the practice rounds, you will participate in Part 1 through Part 8 of the experiment. In these parts, the experimental dollars you earn from your firm's profits in each round will affect your cash earnings.

In each round of Part 1 through Part 8, you will make a Production Decision and a Technology Decision. Groups will be randomly reassigned after each part.

Instructions for part 1-4

1 In these parts, your Firm Profit only depends on your production and technology decisions; the production and pollution generated by other firms do not affect your Firm Profit.
2 Note that the location and capacity of firms may or may not be different. The capacity of each firm is shown on the calculator. When firms have different locations, the region will be divided in 4 sub-regions by solid lines; when firms have the same location, the region will not be divided. Refer to the **Pollution Table** to see how location influences pollution. We will indicate each scenario at the beginning of each part.
3 Use the **Decision Calculator** to make more informed decisions. Although the results are for informational purposes only, the location and capacity of each firm is the same as the real decisions.
4 To make your actual decision for this round, choose a Production Decision and a Technology Decision. Once done, click "Confirm".
5 In these parts, pollution does not affect firm profits. The more you produce, the more your firm profit will be.

In these parts: Firm Profit = Production Income.

Instructions for part 5-8

In these parts, an **environmental regulator** has set a **target total pollution level**. There will be a tax or subsidy based on the total pollution of your firm compared with the target level. The target will change between parts and the specific value will be shown to you.

Your profit will be adjusted by a tax or subsidy (from here on referred to as **tax/subsidy**). This tax/subsidy can be either negative (a tax) or positive (a subsidy) and is determined based on how much pollution is in the river relative to the **Target** determined by the regulator. The pollution level in the river is the aggregation of pollution from all firms. There will be a subsidy for zero concentration, but the amount of subsidy gets smaller as concentration increases. If the measured concentration level is exactly the same as the target, there will be neither a tax nor a subsidy. As concentration increases beyond the target, the tax gets larger.

Pollution in one round does not affect pollution in other rounds. However, at the end of the experiment, your earnings will be the sum of the profits you earned from all of the rounds.

In each round, you will make a Production Decision and a Technology Decision. **Total Pollution** in your group affects the profits of firms in your group.

The **Tax Payment for each firm** in your group is calculated as follows:

Total Pollution ≤ Target	Subsidy Received = Target – Total Pollution
Total Pollution > Target	Tax Payment = Total Pollution – Target

For example, if the target is set at 60, then

- If the Total Pollution in your group is less than or equal to 60, each firm in your group receives 1 experimental dollar in subsidy for every unit of total pollution under 60 units.
- If the Total Pollution in your group is greater than 60, each firm pays 1 experimental dollar in taxes for every unit of total pollution above 60 units.

The amount of the Tax/Subsidy Payment is determined by decisions of everyone in your group. Your Firm Profit in these parts will be calculated as:

If Total Pollution ≤ Target,

Firm Profit = Production Income + Subsidy Payment

If Total Pollution > Target,

Firm Profit = Production Income – Tax Payment

Use the Decision Calculator to help you make more informed decisions, otherwise, you may lose money. Note that in these parts, it is not true that the more you produce, the more profit you will get.

Appendix C. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.reseneeco.2019.101142.

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