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The impact of information on behavior under an ambient-based policy for regulating nonpoint source pollution

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Key Points: Experiment shows effectiveness of Ambient-based policy

Different levels of water quality information lead to different behavior

Enhanced water quality information improves social efficiency

Abstract: Stemming from Segerson [1988], literature on nonpoint source pollution shows that ambient-based regulatory policies can induce polluters in a common watershed to comply with an exogenously determined emissions standard. This study uses laboratory economic experiments in a spatially heterogeneous setting to test the effectiveness of an ambient tax/subsidy policy in a setting with realistic in-stream nutrient transport dynamics when varying levels of ambient information about the pollution is available to the agents and the regulator. We find that increasing the frequency of ambient monitoring improves the spatial allocation of emissions reductions. In particular with more frequent monitoring, the ambient-based policy induces firms further from the monitoring point to reduce emissions significantly more than downstream firms. Overall, the results suggest that enhanced information, especially enhanced temporal resolution, leads to efficiency gains.

Index terms: 6309 1880 1846 0478

Key words: Nonpoint source pollution, Ambient-based policy, Information, Laboratory economic experiment, River and Stream Water Quality Model
1. Introduction

Inefficiency in the nonpoint source pollution setting stems from information asymmetries between the environmental regulator and the agents whose activities generate pollution emissions [Xepapadeas, 2011]. The ambient-based policy instrument proposed by Segerson [1988] circumvents information challenges by providing incentives for agents to reduce pollution emission so as to achieve an exogenously determined target for “bottom of the river” ambient measurement of pollution concentration. Theory and experimental evidence shows this mechanism to be effective at achieving concentrations of pollution close to the target.

In practice, even when targeting ambient pollution, information problems exist. Currently deployed water sensing technology measures pollution concentration imperfectly. Typical nonpoint source pollutants like nitrogen, phosphorus, and bacteria pass through a point in the river in a flux following runoff events. These periods of elevated concentration can pass in a matter of hours or up to days. The “shape” of these fluxes over time at the sensor will be affected heterogeneously by land parcels of varying distance from the sensor. Current methods of water quality monitoring that can be done by city and county environmental offices, state pollution control agencies, and/or national agencies such as the U.S. Environmental Protection Agency (EPA) rely on either manual sampling, which can occur on a timeframe of weeks to months, or mechanical auto-samplers which collect and store samples on a daily or multiday basis at pre-specified monitoring points, which can be manually retrieved and analyzed at regular intervals [Pellerin et al., 2013]. This disconnect between the continuous change in contaminant concentrations and the discrete observations of water quality creates an additional level of asymmetric information. From
the context of a contaminant flux, observation times are random. Therefore, the response of policy to levels of pollution emissions is stochastic. Additionally, in a well-developed model of nutrient transport, the contribution of contaminants from individual parcels accumulates, transforms, and dissipates as it flows downstream. This spatial process induces a systematic heterogeneity between polluters.

Recent technological advances in water quality monitoring are allowing more frequent or even continuous monitoring and measurement using in-stream sensors [Pellerin et al. 2013]. Though still costly, these sensors can offer high frequency measurements of the nutrient flux at fixed points in a stream. This increase in temporal resolution of monitoring could reduce or eliminate the uncertainty in the policy response to nonpoint source pollution. Deploying an array of such sensors will increase the spatial resolution of water quality monitoring and reduce the level of heterogeneity between agents, as well as the informational asymmetry between nonpoint source polluters and the regulator.

This study examines the impact of increased water quality monitoring resolution on individual polluters’ behavior by using laboratory economic experiments to test the effectiveness of ambient tax/subsidy policies under different monitoring regimes. Previous economic experiments studies have assumed that all polluters have an equal impact on pollution at the monitoring point. We build upon this work, but embed our experiments into a realistic stream-flow model that governs the marginal damage of emissions at specific points along a waterway. Importantly, we show that given this spatial heterogeneity, the frequency of monitoring can improve the efficiency of emissions reductions by altering their allocation across polluters.
Theoretical research on nonpoint source pollution has demonstrated that ambient-based policy instruments can be designed so as to induce polluters to comply with an emission standard [e.g., Segerson, 1988; Xepapadeas, 1992; Cabe & Herriges, 1992; Xepapadeas, 1995; Horan et al., 1998]. Economic experiments have been frequently used in situations where real choice behavior is normally unobservable to examine the extent to which theoretic predictions align with actual behavior [Messer et al., 2014]. In these experiments, it has been found that some ambient-based policy instruments can induce nearly efficient outcomes [e.g., Spraggon, 2002, 2004, 2013; Alpízar et al., 2004; Poe et al., 2004; Cochard et al., 2005; Vossler et al., 2006; Suter, Vossler and Poe, 2009; Vossler, Suter and Poe, 2013]. Nearly efficient outcomes have been found both with communication [Suter et al., 2008] and with subject pools composed of professionals [Suter and Vossler, 2014].

Most previous studies on ambient-based policies assume that the ambient pollution concentration is a constant, symmetric function of polluters’ production decisions, and that regulator has perfect real-time information about this constant ambient pollution. Several studies add a symmetric error term to the measured concentration to mimic uncertainty caused by stochastic environmental factors such as weather [e.g., Spraggon, 2002; Vossler et al., 2006]. These approaches, however, do not capture the systematic, non-linear relationship between individual sources of emissions and the observed ambient pollution level at a given point in time. Spatial differences amongst polluters and the fate and transport of pollutants in a river system imply that the concentration of nonpoint source pollution at a point is unlikely to be linearly related to every polluter’s emission level [Charpa et al., 2008].
A growing body of research in experimental economics shows that spatial heterogeneity may affect agents’ behavior, especially in the context of common pool resources [e.g., Schnier, 2009; Suter et al., 2012; Li et al., 2014; Liu et al., 2014]. Adding spatial information brings one type of agent heterogeneity into experiments testing ambient instruments. Some previous nonpoint source pollution studies have introduced heterogeneous polluters by varying the parameters that affect their private benefit function [Spraggon, 2004, 2013; Suter and Vossler, 2013]; however, incorporating spatial heterogeneity and differing information sets remains an important gap in the literature that we address in our experiments.

To the best of our knowledge, our study is the first to use an experimental design that includes a realistic physical nutrient transport model, which induces an implicit spatial heterogeneity. The in-stream water quality model (see Supporting Information Text S1) is based on a model distributed by the EPA as part of a set of tools for developing Total Maximum Daily Load (TMDL) standards [Chapra et al., 2008]. The model captures several in-stream processes including the water flow effects of a discrete runoff event; the physical behavior of nutrients within the channel associated with downstream flow and diffusion; and biochemical interactions between different forms of nitrogen, phosphorus, and algae. From an economic perspective, this model is interesting because it introduces systematic, nonlinear heterogeneity in the effect of individual decisions on environmental damages. When an ambient tax/subsidy mechanism is integrated into this setting the heterogeneity passes through to each participant’s individual payoff function.

The experimental design involves six firms producing the same good in different locations along a river, with differences in spatial location influencing the marginal damage
associated with production. The experiments implement an ambient tax/subsidy policy designed to reduce emissions under six different information treatments. While participants did not know the specific mathematical details of the nutrient transport model, they were trained on it using a calculator that displayed concentration and transfers for any set of production decisions across participants. The experiment instructions also provided the participants with a general description of the dynamics of the model. The objective of the treatments is to measure the extent to which information on ambient water quality, represented by the number of sensors (spatial resolution) and the frequency of monitoring using sensors (temporal resolution), influences firm-level decisions and social efficiency outcomes.

Based on the results of the experiments we find that polluters respond to changes in resolution of water quality information differently based on their spatial location. Upstream polluters abate more than downstream polluters in enhanced temporal information treatments. The information treatments generate differences in social efficiency where enhanced temporal information improves the allocation of emissions reductions across parcels.

2. Experimental Design

In this experiment, participants take the role of firms in a common watershed making production decisions on parcels adjacent to a river. They face an exogenous price for the produced good such that their production decision entirely determines their private income. Firms’ production creates a byproduct (hereafter referred to as emissions; an example of this byproduct would be the use of fertilizer in agricultural production.) proportional to production, which enters the river and causes damage to unspecified downstream users.
The ambient level of pollution at any point in the stream over time depends on the upstream firms’ production decisions and the in-channel nutrient dynamics. A regulator has the ability to measure the concentration of pollution in different monitoring regimes, determined by the locations and the frequency at which measurements are taken. The firms face a tax or subsidy from a regulator based on the measured ambient pollution. Typical of the nonpoint source setting, the measured ambient level of pollution is public information, while firms’ emissions are private.

The monitoring regimes are varied within participants in a two-by-three design over two levels of spatial resolution (one or two sensors) and three levels of monitoring frequency (low, high, and continuous, Table 1). A “no policy” control treatment is also implemented as a baseline. To best understand the setting, we first describe the stream and pollution dynamics followed by the details of the treatments.

2.1 Nutrient Transport Model

The nutrient transport dynamics are developed based on the QUAL2E/QUAL2K model [Chapra et al., 2008]. The physical parameters to calibrate this model are drawn from existing studies for the mid-Atlantic US, specifically from Skippack Creek in Pennsylvania [EPA, 2005] and the Pocomoke River in Delaware [DNREC, 2005], which are streams that have nonpoint source pollution problems. Previous studies have applied this water quality model in other regions of the US and internationally [e.g., NMED, 2006; USBR, 2008; Bischoff et al., 2010; Zhang et al., 2012]. This model tracks the interactions of the following nutrients: organic nitrogen (N), ammonium (NH₄), nitrogen dioxide (NO₂),
nitrate (NO₃), organic phosphorus (P), inorganic P, and algae. We focus on the dynamics of total N, which is the sum of nitrogen species mentioned above.

In this model, a stream, which is adjacent to k homogenous parcels, is divided into k+1 sections called “reaches,” labeled Rᵢ, 𝑖 = 0, 1, 2, …, k. R₀ is the “headwater”. Rₖ is the state of the river downstream from the last parcel. For the purposes of our experiment, we model six parcels, (k = 6). Water is assumed to flow from the headwater reach at a constant rate to the downstream reaches. Stream channel characteristics, including length, width, area and slope, are also assumed to be constant across reaches. We label the parcel adjacent to Rᵢ as parcel 𝑖.

Total N concentration at a given reach in the stream can be monitored using certain sensing technology over an interval of time, which we refer to as the “sensing window.” Following the Qual2K model, emissions move down the river in discrete time steps, t = 0, 1, 2, … Within the sensing window, a sensor may make an observation at any of these time step. We assume that once production decisions are made, the resulting emissions from each firm enter the river simultaneously at window = 1. Besides the loadings from firms on parcels 1 through 6, there are constant but relatively large background nutrient loads that enter each reach R₀ to R₆ at constant rates at each time step (see Supporting Information Table S1). The effect of an individual’s production decision on observed concentration at the sensor will then depend on their location, production decisions of the others and the timing of the sensing.

Water in each reach begins with low concentration of total N (855 µgN/L) and upstream water of reach R₀ always has a constant nutrient concentration (855 µgN/L). Without extra loadings from firms, the concentration of total N in each reach increases
gradually to a unique steady state of higher concentration in a later time period of the sensing window. However, when adding extra nutrient loading from each firm, concentration in each reach can have a peak at an earlier time of sensing window and then decrease to the steady state gradually or decrease to a level lower than the steady state and increase to the steady state later, depending on the location and level of the emissions.

We make the assumption that the economic damage is determined by the maximum concentration during the sensing window downstream from the sixth parcel. The marginal damage of an increase in emissions at a given parcel is therefore determined by the effect that this increase has on the maximum concentration. (This assumption derives from occurrence of algal blooms. Research has demonstrated that algal blooms are highly correlated with the maximum pollution concentrations. For example, Lapointe [1997] finds that blooms happened in reefs of Jamaica and Southeast Florida mainly because nutrient concentration exceeded a threshold level. Studies have also found that pollution damages are highest at the mouth of rivers. Tang et al. [2006] analyze spatial characteristics of harmful algal blooms in the east coast of China from 1933 to 2004 and find that the most frequent harmful algal blooms occurrence areas are at the mouth of the Yangtze River and areas located south of the Yangtze River estuary in the East China Sea.)

There are two components that influence how the decision made by a particular parcel influences the maximum concentration. The first component is the duration of the impact and the second is the magnitude of the impact. The production decision made at a given parcel is more likely to influence the maximum in situations where emissions from that parcel have a longer duration of impact in the sensing window. Increases in emissions from upstream parcels have a larger duration of impact than downstream parcels, since
their emissions tend to diffuse over a larger area of the stream over time. Emissions from parcels close to the sensor pass by the sensor more quickly and therefore have a more limited duration of impact. The production decision made at a given parcel is also more likely to influence the maximum concentration the higher the magnitude of its impact. Parcels closer to the sensor may have a higher magnitude of impact than parcels further upstream, since the emissions do not have the opportunity to diffuse over time before reaching the sensor.

The dynamics through which these two competing impacts influence the maximum concentration are complex, but generally follow the following characterization. When emissions at a parcel are sufficiently low, increases in emissions have little effect on the maximum concentration. However, above a parcel-specific threshold level, additional emissions can have a larger effect on the maximum concentration. This parcel-specific threshold depends on the emissions decisions of other parcels, but, in general, is higher for parcels closer to the sensor (downstream parcels), than parcels further away (upstream parcels). This means that relatively low emissions levels can impact the maximum concentration for firms further away from the sensor while only relatively high emissions levels impact the maximum for the downstream firms. Two features of the calibrated QUAL2K model cause this outcome. Firstly, emissions from upstream firms mix with a large amount of accumulated background nutrient loading later in the sensing window. As a consequence, even relatively low emissions from upstream firms can induce a maximum concentration higher than the steady state. Secondly, emissions from the downstream firms pass through the sensor early in the sensing window when the background nutrient level has not accumulated. Therefore, when emissions from upstream firms are relatively low,
relative high emissions of downstream firms only induce a peak early in the sensing window. Thus, the marginal impact of emissions from upstream firms on the maximum concentration is generally greater than that of emissions from downstream firms.

The experiment instructions described the process that as the byproduct flows downstream, it spreads out and dilutes so that the concentration decreases with distance (see Supporting Information Text S2) Emissions from upstream firms can have less marginal impact on maximum concentration depending on the parameter values in QUAL2K. In our parameterized model, the background loading was set at a high level relative to the parameters associated with the dilution process. As a result, the diluted emissions from upstream firms have a larger marginal impact on maximum concentration at the sensor, and conversely, emissions from downstream firms (which have not diluted when the pollutants pass the sensor) have a smaller marginal impact. This difference was not explained to subjects. Given the complexities of the stream flow dynamics, this design focused on providing participants with opportunities to learn of these dynamics through experience instead of relying solely on a written description to explain this difference. Participants were given time to learn the dynamics of their position on the stream and relative impact on emissions at the sensor through practice rounds and the calculator which provided insight into the stream flow dynamics.

The ability of an ambient-based policy to affect the behavior that influences the maximum concentration just downstream of parcel 6 depends on the ability of the monitoring technology to observe concentrations near the maximum. With continuous monitoring, the timing of the maximum concentration is observed with certainty. For the discrete monitoring case, the observed maximum will depend on the randomly selected...
time when the monitoring occurs. With continuous monitoring, the duration effect dominates the magnitude effect such that parcels further away from the sensor have a larger impact on the observed maximum concentration than parcels downstream. Importantly, under discrete monitoring the magnitude effect becomes relatively more important such that the impact of emissions of downstream firms on the observed maximum concentration is inversely related to the monitoring frequency. The intuition here is that the average marginal impact of emissions from downstream firms on the observed maximum concentration increases because the peak caused by emissions of downstream firms early in the sensing window is taken into the expectation of the measured concentration.

2.2 Experiment Protocol

Six sessions of the experiment were run using 108 undergraduate students at a large public university on the East Coast of the United States. All decisions were made on networked computers. The experiment was implemented with a computer interface, Willow [McCabe and Weel, 2010], and a Python framework, which integrates the QUAL2K model described above.

Each session consists of 18 participants, organized randomly into independent stream groups of six participants. Each participant is assigned to one of the six parcels for each treatment. Stream groups and parcel locations within each stream group are randomly shuffled between treatments. To control for potential order effects across treatments, we systematically vary the treatment orders in each session. Each treatment consists of six decision rounds. In each round, participants make one confidential production decision and learn the measured level of ambient pollution, the tax/subsidy that they face, and their total
profit from the round. Rounds are independent in that production decisions and concentration outcomes do not affect outcomes in future rounds.

Prior to making any decisions, experiment participants have approximately fifteen minutes to read the instructions (see Supporting Information Text S2) for the first treatment. They then hear an oral presentation that emphasizes how production decisions affect their profit, the underlying water quality model, and the ambient tax/subsidy structure. The exact details of the water quality model are not explained. Instead participants receive a qualitative explanation of the model and several numerical examples.

To help participants understand the experiment and formulate their production decisions, they are given time to use the calculator which allows them to enter hypothetical production decisions for each parcel and then see the measured concentration, tax/subsidy, and profits. In treatments with discrete rather than continuous monitoring frequency, the measured concentration is stochastic for a given production set. In these cases, the calculator reports the expected concentration, tax/subsidy and profits based on the distribution of possible sensing values. These calculations change with each treatment. The written instructions include a guided training on the use of the calculator and require that participants use the calculator to identify the outcomes for several different levels of production. The participant answers are checked by the experiment administrators to ensure that participants know how to correctly operate and interpret the calculator.

The first three rounds for all sessions are practice rounds with hypothetical payoffs, which follow the “no policy” treatment. Additional instructions and an oral presentation are provided to the participants before each new treatment to explain the relevant sensing regime. Each session takes roughly one hour and 45 minutes for participants to complete.
The financial payoff earned by participants is determined based on the outcomes of each round and it is paid in cash at the end of the experiment. The average payoff was $29 with a standard deviation of $2.

In each round, participants make anonymous individual production decisions, which directly determine their emissions level and private payoff. The profit a participant receives is the sum of the private payoff and the tax/subsidy determined by the regulator. The private payoff function is based on Spraggon [2002] and is quadratic in production, $x_n$, and takes the form

$$I_n(x_n) = 35 - 0.0075(50 - x_n)^2, \text{ for } n = 1, 2, ..., 6,$$

where $I_n$ represents the private payoff and $x_n$ is the production level of participant $n$.

Participants choose a production level between 0 and 50. The individual emissions contributed from a parcel are equivalent to that parcel’s production level. We assume that one unit of production leads to 1000 $\mu$gN/L emission of nitrogen dioxide at one time step. As such, we refer to production and emissions interchangeably. If a participant chooses a production level of zero, their emissions equal zero. The distribution of the pollutant concentration over time at one location in the river is determined by the joint decisions of all upstream participants, conforming to the nutrient transport model described above.

In each of the treatments it is assumed that damage from pollution occurs just downstream of the six parcels and the damage is determined by the maximum concentration of the pollutant. The damage function takes the form

$$D(x_1, x_2, \ldots, x_6) = 10^*C_{\text{max}}(x_1, x_2, \ldots, x_6),$$
where $D(x_1, x_2, \ldots, x_6)$ is the damage and $C_{\text{max}}(x_1, x_2, \ldots, x_6)$ is the maximum concentration just downstream of all parcels in a given round. We assume the regulator seeks to maximize the net social benefit, given by

$$\text{NSB} = \sum_{n=1}^{6} I_n (x_n) - D(x_1, x_2, \ldots, x_6).$$

(3)

We calculate the socially optimal emission array of $x_1, x_2, \ldots, x_6$ using numerical techniques (Table 2, also see Supporting Information Text S3). Under the calibrated stream and pollution dynamics, the optimal total emissions across all firms are 200, with heterogeneity across firms based on spatial location. Specifically, the marginal effect of increases in emissions on maximum concentration is higher for upstream parcels than for downstream parcels. The furthest downstream parcel (parcel 6) optimally has the highest emissions while the parcel furthest upstream (parcel 1) has the lowest emissions.

Based on Segerson [1988], an ambient tax/subsidy instrument is used to incentivize firms to reduce emissions and improve efficiency. The tax/subsidy that each firm must pay in each round is a linear function of measured concentration and is contingent on each participant’s decision. The tax/subsidy is defined as follows:

$$T(x_1, x_2, \ldots, x_6) = 10(\text{Threshold} - C(x_1, x_2, \ldots, x_6)),$$

(4)

where $T(x_1, x_2, \ldots, x_6)$ is the tax/subsidy, $C(x_1, x_2, \ldots, x_6)$ is the measured maximum concentration level, and the Threshold is an exogenously determined concentration level set by the regulator. When $T$ is negative, all six participants pay a tax; otherwise they all receive a subsidy. Note that all participants pay the same tax (or receive the same subsidy) depending on the measured maximum concentration and the marginal tax/subsidy rate is equal to the marginal damage from pollution.
2.3 Treatments

There are two primary treatment variables: the number of sensors (one or two) and the frequency of sensing (low, high, and continuous, Table 1). The treatments have either one sensor located just downstream of parcel 6 (Treatments B, C and D) or two sensors placed just downstream of parcels 3 and 6 (Treatments E, F and G). Moreover, the treatments have the sensor(s) measure the concentration of pollutant at low sensing frequency (Treatments B and E), high sensing frequency (Treatments C and F), or continuously (Treatments D and G). We also implement a treatment without the ambient tax/subsidy as a “no policy” baseline (Treatment A). Next, we describe the seven treatments and the computed Nash equilibria in detail.

Treatment A: Treatment A is a baseline treatment in which there is no policy implemented to control pollution level. As such, we expect that every participant will choose an emissions level of 50 to maximize their payoff. In the other treatments, the tax/subsidy policy is imposed and we expect emissions levels and emissions to be lower than in Treatment A.

Treatments B, C, & D: For these three treatments, one sensor is placed just downstream of parcel 6, which measures the concentration resulting from the emissions decisions of all six firms. The frequency of measurement is varied across the three treatments. In Treatment B, the sensor measures the concentration at one random moment during the sensing window. In Treatment C, the sensor measures the concentration at four random moments and the maximum observation is chosen to be the measured concentration. In Treatment D, the sensor measures the concentration continuously and thus observes the maximum concentration with certainty. The ambient tax/subsidy is
determined by the difference between the measured concentration and the threshold determined by the regulator. The threshold varies by treatment and is designed such that the average ambient tax/subsidy is approximately zero when each participant chooses an emission level of 25.

Importantly, as explained previously, the differences in monitoring frequency across treatments influence the extent to which emissions at a particular parcel influence the magnitude of the tax/subsidy. Emissions by firms that are far away from the sensor have a bigger impact on the maximum concentration. Therefore, with the continuous sensing in Treatment D upstream firms have a larger impact on the magnitude of the tax/subsidy than downstream firms. When monitoring occurs less frequently, the impact of emissions from downstream (upstream) firms on the measured maximum concentration level increases (decreases).

Since participants are not allowed to communicate, we focus on exploring potential non-cooperative outcomes. Using numerical optimization (see Supporting Information S3), the theoretic prediction of each participant’s emission for Treatments B, C and D is presented in Table 2. These arrays of emission levels represent Nash equilibria (NE), since no one participant gets more benefit if he/she deviates from the predicted emission level. In Treatment D, the NE is equivalent to the social optimum, a result that is determined based on the parameterization of the tax/subsidy rate.

**Treatments E, F, & G:** In these three treatments, a second sensor is placed just downstream of parcel 3, which changes the spatial resolution of ambient pollution monitoring. The measurement frequency of each sensor in Treatments E, F, and G are determined identically to the measurements in Treatments B, C and D, respectively. The
tax/subsidy for participants located in the lower (upper) three parcels is determined by the difference between the measured concentration from the sensor just downstream of parcel 6 (parcel 3) and the threshold is determined by the regulator. To maintain consistency with the treatments that involve one sensor, the threshold for the participants in the upper three parcels is reduced such that the average ambient tax/subsidy is 0 when each participant produces 25. Thresholds for participants at the lower three parcels in these three treatments are the same as the threshold in Treatments B, C and D, respectively.

Measured concentration by the sensor just downstream of parcel 3 is only dependent on emissions from the upper three parcels, and the observed concentration at the sensor just downstream of parcel 6 is determined by all six parcels. Like in treatments B and C, the actual tax/subsidy faced by participants in treatments E and F is determined by the timing of the monitoring. Predicted emissions from each parcel are presented in Table 2. The NE for Treatment G is equivalent to the social optimum and the NE in Treatments E and F are approximately the same as the equilibrium predictions in Treatments B and C respectively.

Interestingly, the predicted emissions show that adding sensor just downstream of parcel 3 does not affect the equilibrium of the three upstream parcels even though intuition suggests otherwise. This result stems from two opposing effects of the additional sensor. The distance between the upper sensor and the upstream parcels become shorter, and hence the ‘duration effect’ is expected to be smaller. This would reduce the expected damage. Simultaneously, the ‘magnitude effect’ increases the marginal damage of the upstream parcels. In our parameterized model, this effect offsets the duration effect and increases the
expected damage of the upstream parcels. Combined, increasing the number of sensors is therefore not expected to influence behavior if participants follow the NE.

2.4 Testable hypotheses

The experimental design allows us to form four basic hypotheses related to the impact of the tax/subsidy policy and changes in the sensing regime on individual behavior and social efficiency.

**Hypothesis 1**: Emissions are lower in treatments that include the tax/subsidy policy than in the baseline (“no policy”) Treatment A.

This first basic hypothesis stems directly from the expectation that the tax/subsidy policy acts as a disincentive for emissions given that every unit increase in the maximum pollution concentration level observed at the sensor reduces each firm’s payoff by 10 experimental dollars. If the tax/subsidy policy does not influence behavior then altering the monitoring regime will not influence outcomes.

**Hypothesis 2**: Enhanced temporal resolution of pollution concentration measurements influence the allocation of emissions, with parcels further away from the sensor reducing emissions relatively more than parcels close to the sensor.

Hypothesis 2 emphasizes that differences in temporal resolution are expected to induce different emission levels at specific parcels across treatments. Going from discrete to continuous sensing changes the extent to which each parcel influences the observed maximum concentration level. In the low frequency sensing treatment, all firms are
predicted to abate about the same amount because each firm has the same impact on measured concentration. However, in the enhanced temporal measurements treatments, upstream firms are predicted to emit less than downstream firms since upstream firms have more impact on measured maximum concentration than downstream firms (Table 2). As such, we hypothesize that increases in the frequency of sensing will alter the allocation of emissions, with more emissions occurring downstream.

Hypothesis 3: Enhanced spatial resolution of pollution concentration measurements will not influence individual behavior.

The treatments are parameterized such that increasing the number of sensors from one to two does not have a large impact on the NE emissions prediction at each parcel (treatments B vs. E, C vs. F, and D vs. G; Table 2).

Hypothesis 4: Social welfare is highest under the ambient tax/subsidy policy with continuous sensing.

In Treatment A, behavior is predicted to generate net social benefits that are lower than the optimal net social benefits both because of excessive emissions levels and because of an inefficient allocation of emissions across firms. Social efficiency is predicted to be higher in all treatments that involve the ambient tax/subsidy given that the policy provides incentives to reduce emissions (Hypothesis 1). Social efficiency is also expected to increase with more frequent sensing given that it improves the allocation of emissions decisions by providing incentives for upstream firms to reduce emissions more than downstream firms (Hypothesis 2). In addition, increasing the spatial resolution of sensing is not predicted to
impact behavior (Hypothesis 3). These three outcomes taken together suggest that the highest levels of social efficiency are expected in Treatments D and G, which involve the ambient tax/subsidy policy based on continuous sensing.

3. Results

In this section, we highlight four key results from the experiment, organized by the four hypotheses.

RESULT 1: Emissions levels in treatments with the ambient tax/subsidy policy are lower than emissions in the “no policy” Treatment A. (Supports H1)

The first result is based off of a simple inspection of the mean observed emissions levels provided in Table 2. In Treatment A, observed emissions at each parcel are never significantly different from the predicted emissions level of 50. When the ambient tax/subsidy policy is introduced in Treatments B – G, aggregate emissions are lower than the aggregate emissions in Treatment A (p < 0.01). In addition, mean emissions for each parcel are lower in Treatments B – G than in Treatment A. These results provide support for Hypothesis 1.

It is noteworthy that in every treatment, the ambient tax/subsidy policy results in lower aggregate emissions than that predicted by the NE. In other words, the tax/subsidy policy leads to excessive reductions in emissions in each case. This result is consistent with results from experimental economics studies of the tax/subsidy policy reported in Vossler et al. [2006] and Poe et al. [2004] with participants that are able to communicate given the possibility of group subsidies in low emission situations. Although the participants in our
experiment were not able to communicate, the collusive equilibrium provides incentives for groups to reduce emissions levels below the NE. It appears that the experimental setting that participants confronted in our sessions leads to tacit collusion that is similar to the collusion possible under communication. This is particularly dramatic in Treatment B, where aggregate emissions are significantly lower than they are in any other treatment setting. Not surprisingly, Treatment B has a collusive equilibrium in which, if all firms emit zero, they can earn higher profits from collusion than in any other treatment.

**RESULT 2:** *Under the ambient tax/subsidy policy, increasing the frequency of sensing leads to higher emissions for downstream parcels relative to upstream parcels (supports H2).*

The effect of increased sensing frequency can be observed in Table 2. In Treatments B and E, which involve sensing at one random moment during the sensing window, emissions are relatively constant across the parcels, consistent with the theoretic prediction. In Treatments D and G, with continuous sensing, emissions are higher, on average, for the three downstream parcels than for the three upstream parcels, although the increase in emissions levels are not monotonic as one moves from upstream to downstream parcels. Additionally, going from low to high frequency sensing appears to have a larger effect on behavior than going from high to continuous frequency sensing.

To evaluate the effect of sensing frequency on emissions, we use pairwise comparisons between treatments at each parcel location (Table 3). The numbers reported in the table reflect the difference in going from a lower to a higher frequency of sensing at a given parcel. If increasing the frequency influences behavior as suggested by the NE,
then we should observe negative numbers for upstream parcels (reflecting a decrease in emissions) and positive numbers for downstream parcels (reflecting an increase in emissions).

The results show that varying the frequency of sensing changes individual behavior at some parcels. For the single sensor treatments, both high and continuous frequency sensing (Treatments C and D) lead to higher emissions in downstream parcels relative to low frequency sensing (Treatment B). At parcels 4 and 5, high frequency leads to higher emissions relative to continuous sensing, a result not predicted by theory. The frequency of sensing with one sensor does not appear to have a statistically significant impact on the behavior of upstream parcels.

When there are two sensors, we observe some differences. Compared to low frequency in Treatment E, the high and continuous frequency sensing in Treatments F and G generally leads to significantly lower emissions in upstream parcels. Higher frequency sensing leads to higher emissions in some cases at downstream parcels 5 and 6, but this result is not as robust as it is with only one sensor.

Taken together, these results show a general tendency of a reallocation of emissions from upstream parcels to downstream parcels with increases in the frequency of sensing. The impacts of enhanced temporal resolution on each parcel’s emission, however, are not as strong as predicted and the effect of increased sensing is more dramatic when moving from low frequency sensing to high frequency sensing than it is going from high frequency to continuous sensing.

**RESULT 3:** Under the ambient tax/subsidy policy, enhanced spatial resolution of ambient concentration measurement does not have a systematic impact on emissions.
There are no significant differences in aggregate emissions across Treatments C – G, which suggests that increasing the number of sensors does not have a dramatic impact on average behavior. The one anomaly is Treatment B, which has aggregate emissions that are significantly lower than in all other treatment settings \((p < 0.05)\). Evaluating differences in individual emissions across parcels, pairwise comparison of individual emissions paired by frequency (similar to regression analysis in Table 3) reveals a few noteworthy outcomes. Emissions by upstream firms in treatments with enhanced frequency of sensing are generally lower with two sensors than they are with one sensor (only one difference is statistically significant). This outcome is not predicted by non-cooperative theory, but does align to some extent with the collusive equilibria, which predict lower emissions amongst the three upstream firms relative to the three downstream firms. Increasing spatial resolution of sensors has mixed impacts on downstream parcels with five differences of pairwise comparisons being positive and four negative. However, only two of them are statistically significant at the 5% level.

**RESULT 4:** Social efficiency is highest in treatments that involve the ambient tax/subsidy policy with high frequency and continuous sensing (partial support for H4).

Relative to the no policy setting, efficiency can be enhanced by both reducing total emissions and reallocating emissions from upstream firms to downstream firms. We follow Spraggon [2002] and define efficiency as the change in the value of net social benefits as a percentage of the optimal change in social benefits from the status quo:

\[
SE = \frac{\text{NSB}_{\text{actual}} - \text{NSB}_{\text{status quo}}}{\text{NSB}_{\text{optimal}} - \text{NSB}_{\text{status quo}}},
\]

\[
(5)
\]
where \( SE \) represents the social efficiency, \( \text{NSB}_{\text{actual}} \) is the actual net social benefit, \( \text{NSB}_{\text{status quo}} \) is the net social benefit when their emissions are equivalent to the competitive level of emissions, and \( \text{NSB}_{\text{optimal}} \) is the net social benefit with socially optimal behavior. This measure of efficiency ignores the regulator’s cost of acquiring, implementing, and operating sensors.

Additionally, we follow Suter et al. [2008] to decompose \( SE \) as a product of Emission Efficiency (EE) and Allocative Efficiency (AE), which provides insight into the sources of inefficiency. EE measures the efficiency loss arising from the differences between actual aggregate emissions and optimal aggregate emissions. A low EE indicates that aggregate emissions are far from the optimal level. AE measures the efficiency loss arising from imperfect allocation of individual emissions on each parcel given a specific level of aggregate emissions. AE is equal to 100% if individual emissions are perfectly allocated across parcels.

Both the predicted and actual efficiency outcomes are provided in Table 4. As expected, with no policy in place in Treatment A, the observed efficiency level is near zero. Efficiency levels are higher in all treatments with the tax/subsidy policy and are significantly higher in treatments that involve high frequency or continuous sensing compared to low frequency sensing. The emissions and allocative efficiencies that are reported in Table 4 provide some interesting insights into the sources of these differences. Consistent with the aggregate emissions results discussed earlier, the emissions efficiency is lowest in Treatment B given that participants in the treatment engage in excessive emissions reductions. Across the remaining five treatments that involve the ambient tax/subsidy policy there is no appreciable differences in the emissions efficiency that is
observed. The increase in overall efficiency therefore comes primary from higher allocative efficiency in treatments that involve higher frequency sensing. This is consistent with Result 2, which showed that emissions tend to be allocated more heavily towards downstream firms as the frequency of sensing is increased.

Interestingly, the observed efficiency associated with treatments that involve enhanced temporal resolution tends to increase over time (Figure 1). This result comes about primarily due to improvements in allocative efficiency over time as participants experience the impacts of the tax/subsidy policy and adjust emissions decisions to reflect the incentives that vary based on their location.

4. Conclusion

In this paper, we incorporate a spatial nutrient transport model into a nonpoint source water pollution economic experiment to test the impact of information on emission decisions and on efficiency of ambient tax/subsidy policy. Economic experiments are well suited for studies where the real behavior is generally unobservable. We specifically investigate how technological limitations to pollution monitoring can affect social efficiency. Imperfect information can be caused by technology constraints and constrained monitoring budgets. The results from our experiment show that the ambient tax/subsidy policy influences producer behavior, reduces pollution, and increases social efficiency. Though all policy treatments exhibit lower ambient pollution concentrations, enhanced information, especially enhanced temporal information, helps the regulator implement the policy in a way that induces polluters to allocate emissions reductions more efficiently. In addition, the results suggest that increased frequency of sensor measurements can help move behavior closer to the social optimum.
The results offer the regulator some insight into the tradeoffs related to investing in monitoring technology and effort. They suggest that it may not always be true that more information is better in an ambient/tax subsidy instrument. In the experiment, the treatment that involved the lowest frequency of sensing and the fewest sensors also induced the highest emissions reductions. Note, however, that the emissions reductions were substantially larger than optimal and thus this treatment involved the lowest observed social efficiency. Increasing the resolution of ambient pollution measurement increases efficiency, but it would also likely involve increased cost of monitoring that we do not explicitly account for in this experiment design. We also find rapidly diminishing marginal returns to increasing the frequency of sensing given that the social efficiency improvements associated with going from high frequency sensing to continuous sensing are negligible. In addition, when implementing high frequency sensing, the effect of a second sensor is limited. While additional sensors may be valuable for purposes of education, scientific knowledge, and perhaps identifying the true source of the pollution, the results of this research suggest the need to consider the tradeoff between social outcomes and the cost of improved monitoring technology.

To enhance our ability to reach general conclusions related to the relationship between monitoring and the efficiency of ambient-based instruments targeting water quality improvements, several of our assumptions could be modified in future research. For example, in our model we assume constant background loadings into the surface water system. The inclusion of stochastic inflows due to storm events would be an interesting extension, since diffusion and concentration of pollutants may change under these scenarios. Similarly, an important future extension would be to test the robustness of our
results to other types of pollutants such as phosphorous and suspended solids which may display different fate and transport characteristics that alter the incentives generated by an ambient-based policy. Behaviorally, the introduction of communication among participants is also likely to influence behavior and observed social efficiency as groups could more easily coordinate on collusive outcomes.
Acknowledgements: This material is based upon work supported in part by the National Science Foundation EPSCoR Track-2 Cooperative Agreement #IIA-1330406, Collaborative Research: North East Water Resources Network. We are grateful to the comments from Scott C. Merrill. This article has also benefited from comments during presentations at 2015 summer conferences organized by Association of Environmental and Resource Economists and Northeastern Agricultural and Resource Economics Association.

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NMED, (2006), San Juan River Watershed TMDLs, New Mexico Environment Department, Santa Fe, NM.


Table 1: Treatment conditions

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Label</th>
<th>Number of Sensors</th>
<th>Frequency of Sensing</th>
<th>Ambient Tax/Subsidy</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Baseline</td>
<td>-</td>
<td>-</td>
<td>No</td>
</tr>
<tr>
<td>B</td>
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<td>1</td>
<td>Low</td>
<td>Yes</td>
</tr>
<tr>
<td>C</td>
<td>One Sensor, High Frequency</td>
<td>1</td>
<td>High</td>
<td>Yes</td>
</tr>
<tr>
<td>D</td>
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<td>1</td>
<td>Continuous</td>
<td>Yes</td>
</tr>
<tr>
<td>E</td>
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<td>Low</td>
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</tr>
<tr>
<td>F</td>
<td>Two Sensors, High Frequency</td>
<td>2</td>
<td>High</td>
<td>Yes</td>
</tr>
<tr>
<td>G</td>
<td>Two Sensors, Continuous</td>
<td>2</td>
<td>Continuous</td>
<td>Yes</td>
</tr>
</tbody>
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### Table 2: Comparison of predicted emission levels (Nash equilibrium) and observed average emission levels by treatment.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Label</th>
<th>Emissions</th>
<th>Upstream</th>
<th>Downstream</th>
<th>Aggregate Emissions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Parcel 1</td>
<td>Parcel 2</td>
<td>Parcel 3</td>
</tr>
<tr>
<td>A</td>
<td>Baseline</td>
<td>Predicted</td>
<td>50</td>
<td>50</td>
<td>50</td>
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<tr>
<td></td>
<td></td>
<td>Observed</td>
<td>47.68</td>
<td>48.64</td>
<td>49.01</td>
</tr>
<tr>
<td>B</td>
<td>One Sensor, Low Frequency</td>
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<td>33.4</td>
<td>33.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Observed</td>
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<td>22.08</td>
<td>25.64</td>
</tr>
<tr>
<td>C</td>
<td>One Sensor, High Frequency</td>
<td>Predicted</td>
<td>21.8</td>
<td>22.8</td>
<td>28.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Observed</td>
<td>25.43</td>
<td>22.81</td>
<td>26.54</td>
</tr>
<tr>
<td>D</td>
<td>One Sensor, Continuous</td>
<td>Predicted</td>
<td>20</td>
<td>24</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Observed</td>
<td>26.72</td>
<td>25.63</td>
<td>27.93</td>
</tr>
<tr>
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<td>33.3</td>
<td>33.3</td>
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<td>32.48</td>
<td>29.25</td>
<td>21.55</td>
</tr>
<tr>
<td>F</td>
<td>Two Sensors, High Frequency</td>
<td>Predicted</td>
<td>22</td>
<td>20.2</td>
<td>29</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Observed</td>
<td>21.20</td>
<td>26.78</td>
<td>25.34</td>
</tr>
<tr>
<td>G</td>
<td>Two Sensors, Continuous</td>
<td>Predicted</td>
<td>20</td>
<td>24</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Observed</td>
<td>25.89</td>
<td>21.77</td>
<td>20.31</td>
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</table>

Optimal emission based on linear damage
Mean of observed average emission (excluding Treatment A)

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Label</th>
<th>Emissions</th>
<th>Upstream</th>
<th>Downstream</th>
<th>Aggregate Emissions</th>
</tr>
</thead>
<tbody>
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<td></td>
<td></td>
<td>Parcel 1</td>
<td>Parcel 2</td>
<td>Parcel 3</td>
</tr>
<tr>
<td>A</td>
<td>Baseline</td>
<td>Predicted</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Observed</td>
<td>47.68</td>
<td>48.64</td>
<td>49.01</td>
</tr>
<tr>
<td>B</td>
<td>One Sensor, Low Frequency</td>
<td>Predicted</td>
<td>33.5</td>
<td>33.4</td>
<td>33.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Observed</td>
<td>22.18</td>
<td>22.08</td>
<td>25.64</td>
</tr>
<tr>
<td>C</td>
<td>One Sensor, High Frequency</td>
<td>Predicted</td>
<td>21.8</td>
<td>22.8</td>
<td>28.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Observed</td>
<td>25.43</td>
<td>22.81</td>
<td>26.54</td>
</tr>
<tr>
<td>D</td>
<td>One Sensor, Continuous</td>
<td>Predicted</td>
<td>20</td>
<td>24</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Observed</td>
<td>26.72</td>
<td>25.63</td>
<td>27.93</td>
</tr>
<tr>
<td>E</td>
<td>Two Sensors, Low Frequency</td>
<td>Predicted</td>
<td>33.3</td>
<td>33.3</td>
<td>33.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Observed</td>
<td>32.48</td>
<td>29.25</td>
<td>21.55</td>
</tr>
<tr>
<td>F</td>
<td>Two Sensors, High Frequency</td>
<td>Predicted</td>
<td>22</td>
<td>20.2</td>
<td>29</td>
</tr>
<tr>
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<td>Observed</td>
<td>21.20</td>
<td>26.78</td>
<td>25.34</td>
</tr>
<tr>
<td>G</td>
<td>Two Sensors, Continuous</td>
<td>Predicted</td>
<td>20</td>
<td>24</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Observed</td>
<td>25.89</td>
<td>21.77</td>
<td>20.31</td>
</tr>
</tbody>
</table>

Optimal emission based on linear damage
Mean of observed average emission (excluding Treatment A)

Notes: Predicted emissions and optimal emission based on linear damage are computed by algorithm described in Text S3 in Supporting Information. Observed emission is averaged across all rounds by treatment and parcel. Aggregate emission (last column) is the sum of observed average emission across six parcels by treatment. Mean of observed average emission (last row) is averaged across Treatments B through G for each parcel.
Table 3: Effects of increased sensing frequency based on pairwise comparison of individual emissions by parcel, treatments paired by number of sensors.

<table>
<thead>
<tr>
<th>Parcels</th>
<th>Treatments B vs. C (one sensor)</th>
<th>Treatments B vs. D (one sensor)</th>
<th>Treatments C vs. D (one sensor)</th>
<th>Treatments E vs. F (two sensors)</th>
<th>Treatments E vs. G (two sensors)</th>
<th>Treatments F vs. G (two sensors)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parcel 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.25 (2.78)</td>
<td>4.53 (2.69)</td>
<td>1.28 (2.88)</td>
<td>-11.27***</td>
<td>-6.58**</td>
<td>4.69*</td>
</tr>
<tr>
<td>Parcel 2</td>
<td>0.73 (2.42)</td>
<td>3.55 (2.59)</td>
<td>2.82 (2.53)</td>
<td>-2.47</td>
<td>-7.48**</td>
<td>-5.01*</td>
</tr>
<tr>
<td>Parcel 3</td>
<td>0.89 (3.77)</td>
<td>2.28 (3.23)</td>
<td>1.38 (3.08)</td>
<td>3.78</td>
<td>-1.24</td>
<td>-5.02***</td>
</tr>
<tr>
<td>Parcel 4</td>
<td>10.49*** (3.62)</td>
<td>4.29 (3.64)</td>
<td>-6.19* (3.54)</td>
<td>2.51</td>
<td>-2.03</td>
<td>-4.55</td>
</tr>
<tr>
<td>Parcel 5</td>
<td>10.86*** (2.34)</td>
<td>5.99** (2.32)</td>
<td>-4.87** (2.34)</td>
<td>1.48</td>
<td>13.13***</td>
<td>11.65***</td>
</tr>
<tr>
<td>Parcel 6</td>
<td>5.80* (3.40)</td>
<td>8.64** (3.77)</td>
<td>2.84 (2.83)</td>
<td>8.09**</td>
<td>-0.06</td>
<td>-8.15**</td>
</tr>
</tbody>
</table>

Notes: These 36 pairwise comparisons are OLS regressions in which dependent variable is individual emission and the independent variable is frequency dummy which is equal to one if frequency is higher. Standard errors in parentheses and are clustered at individual level. * p < 0.10, ** p < 0.05, *** p < 0.01. N = 216 in each cell.
Table 4: Average efficiency of treatments based on linear damage

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Label</th>
<th>Predicted Efficiency</th>
<th>Predicted Efficiency</th>
<th>Emission Efficiency</th>
<th>Allocative Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Baseline</td>
<td>0%</td>
<td>5.92% (0.09)</td>
<td>N/A</td>
<td>N/A</td>
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<tr>
<td>B</td>
<td>One Sensor, Low Frequency</td>
<td>71.24%</td>
<td>27.16% (0.33)</td>
<td>67.77% (0.26)</td>
<td>54.97% (0.23)</td>
</tr>
<tr>
<td>C</td>
<td>One Sensor, High Frequency</td>
<td>93.41%</td>
<td>63.75% (0.18)</td>
<td>84.78% (0.15)</td>
<td>72.99% (0.17)</td>
</tr>
<tr>
<td>C</td>
<td>One Sensor, Continuous</td>
<td>100%</td>
<td>64.44% (0.18)</td>
<td>85.38% (0.12)</td>
<td>75.26% (0.17)</td>
</tr>
<tr>
<td>E</td>
<td>Two Sensors, Low Frequency</td>
<td>71.55%</td>
<td>43.70% (0.24)</td>
<td>77.59% (0.21)</td>
<td>58.66% (0.23)</td>
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<tr>
<td>F</td>
<td>Two Sensors, High Frequency</td>
<td>93.71%</td>
<td>61.12% (0.23)</td>
<td>82.80% (0.17)</td>
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</tr>
<tr>
<td>G</td>
<td>Two Sensors, Continuous</td>
<td>100%</td>
<td>57.03% (0.22)</td>
<td>76.73% (0.19)</td>
<td>72.93% (0.18)</td>
</tr>
</tbody>
</table>

Notes: Standard deviation in parentheses (for example, s.d. = 0.09 means standard of efficiency is 9%)
Notes: Each point on the figure is the efficiency averaged across six experiment sessions for each treatment. $N = 18$ for each point.

**Figure 1:** Mean efficiency level by round