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Simulating Heterogeneous Farmer Behaviors under Different Policy Schemes: Integrating Economic Experiments and Agent-Based Modeling

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Abstract

In this paper, we develop an agent-based model that scales up results from economic experiments on technology diffusion and abatement of non-point source water pollution under the conditions of an actual watershed. The results from the economic experiments provide the foundation for assumptions used in the agent-based model. Data from geographic information systems and the US Census of Agriculture initialize and parameterize the model. This integrated model enables the exploration of the effects of several policy interventions on technology diffusion and agricultural production and, hence, on agricultural non-point source pollution. Simulation results demonstrate that information ‘nudges’ based on social comparisons increase ambient based policy performance as well as efficiency, especially individual-level tailored information on what others like them have done in past similar situations.

Key Words:

Economic Experiments, Agent-Based Model, Non-Point Source Pollution, Policy Evaluation, Farmer Behavior

1. Introduction and Literature Review

Non-point source (NPS) pollution in water systems mainly comes from rainfall and snowmelt that move over and through the ground, bringing natural and human-made pollutants into waterbodies. NPS pollution, which comes mostly from nutrients and chemicals carried by agricultural runoff, is the primary cause of water pollution in the United States today.

Unfortunately, regulation and remediation of NPS water pollution is a difficult task. It typically is hard and at times impossible to identify individual contributors to such pollution, and policies designed to address it must be designed to take polluters' hidden actions and asymmetric information into account. The cost of this type of individual monitoring and enforcement is often prohibitive (Xepapadeas, 2011).

Theoretical work (e.g., Segerson 1988, Xepapadeas, 1992) has shown that policies based on ambient levels of pollution can lead to reductions of NPS pollution to a regulator-specified target level. However, since no program has implemented an ambient-pollution-based policy on a large scale to provide empirical data, researchers have often turned to economic experiments in laboratory settings as test beds for such policies (Spraggon, 2002; Poe et al., 2004; Suter, Vossler and Poe, 2009, Miao et al., 2016). And since researchers must recruit and compensate participants in economic experiments, the experiments generally have been limited in scale and have restricted the ability to draw conclusions in contexts outside the lab. Thus, researchers have been interested in finding other ways to study the effects of these policies as part of efforts to improve their outcomes in terms of reducing NPS pollution.

Agent-based modeling (ABM) can help fill this gap by providing a mechanism for scaling up the findings in experiments to contexts that are closer to reality. With ABM, researchers can use findings from an experiment, create model agents that behave according to patterns identified in

the experiment, and conduct simulations using an environment that better mimics a real-world setting. ABM also allows the researcher to observe the results of those agent interactions, which are extremely difficult to capture using other methods. Furthermore, we compared to traditional top-bottom methods such as econometric techniques, ABM imposes less distributional restrictions or assumptions.

ABM has been applied in various fields in recent years (Farmer and Foley, 2009), such as ecological modeling (Grimm and Railsback, 2005), population growth (Axtell et al., 2002), business strategies (Khouja, Hadzikadic, and Zaffar, 2008), land use policy (Tsai et al. 2015), transportation policy (Zia and Koliba 2015) and education (Johnson, Lemasters, and Bhattacharyya, 2017). In the context of agricultural and environmental applications, it has been used mainly for problems associated with changes in land cover to develop models that simulate land use decisions by farmers facing multiple constraints (Parker, 2014; Matthews et al., 2007; Veldkamp and Verburg, 2004), especially in studying coupled human and natural systems (An, 2012). In such systems, agent decisions generate environmental consequences, which could in turn affect human decisions and behavior. Recently, Tesfatsion et al. (2017) developed the Water and Climate Change Watershed (WACCSHed) platform that allows the systematic study of interactions of hydrology, human and climate in a watershed over time. Ng et al. (2011) demonstrates an agent-based model of farmer decision making on water quality in the context of first and second generation biofuel crops and carbon trading. The ABM integrates a SWAT based hydrologic-agronomic model.

In the bottom-up construction of an ABM, modelers need to assign decision rules to agents under specific scenarios. A major challenge lies in constructing credible decision rules for ABM (Zenobia et al., 2009). Most of the previous work usually assumes perfect rationality, meaning

that the agents could perfectly solve for utility maximizing problems in various and sometimes complex scenarios. However, behavioral economics have repeatedly shown that human behavior is often, at best, rationally bounded and that individuals often use heuristics instead of optimization when making decisions. As noted by Heckbert, Baynes, and Reeson (2010), combining economic experiments with ABM offers researchers many new opportunities. Experimental economics can be used to guide calibration of ABM so that the agents' behaviors and decisions reflect patterns identified by actions in experiments.

Some researchers have used survey methods to develop decision rules for ABM (Dia, 2002). Compared to using survey-based approaches to calibrate decision-making in ABM, we can use data collected through experiments that capture the "interpersonal" and "interplayer" dynamics that arise in experimental games (and are overlooked by surveys). Furthermore, Duffy (2006) pointed out that ABM projects also could facilitate researchers' ability to interpret the aggregate findings of an experiment involving human subjects.

Not many studies have combined experimental economics and ABM. Evans, Sun, and Kelley (2006) compared results from a spatially explicit lab experiment to outputs of a simulation from a land-use ABM involving utility-maximizing agents. They concluded that the participants in the experiment deviated from revenue-maximizing actions and that it was thus valuable to use non-maximizing agents in ABM. Heckbert (2009) also acknowledged the value of combining experiments and ABM, reporting a study in which a participant replaces the role of an agent and the participant's behavior under several treatments can be used to recalibrate the ABM.

A few studies have attempted to integrate economic experiments and ABM in NPS pollution management context. Zia et al. (2016, in review) constructed agent-based models using an

economic experiment documented in Miao et al. (2016). The agents were categorized to pursue different behavioral strategies under alternate policy and sensor information regimes, and the agents' type categories were predicted by a multi-level multinomial logistic regression model built from experimental data. Our research extends this idea by designing an experimental setting that includes technology adoption decisions and two layers of heterogeneity, meanwhile building a closer link between the experiment and the ABM.

We also include two information treatments to examine the ability of information 'nudges' to induce desired outcomes from the participants. Originating from the social comparison theory by Festinger (1954), it has been shown that information 'nudges' on social comparison and peer actions can promote environmental conservation behavior (e.g., Allcott, 2011; Ferraro and Price, 2013; Goldstein, 2008). These information 'nudges' are attractive from a policy design perspective since they are more cost-effective compared to traditional monetary based programs. However, not much research has considered incorporating information 'nudges' in NPS pollution management. We are interested in if information 'nudges' based on social comparison and peer action could help the performance of ambient based policies. In the first information treatment, participants are provided with information about what people "like them" have chosen in a similar situation in the past. In the second treatment, participants are provided with information regarding average production and average rate of adoption of technology by their group in the preceding round. Participants' responses to the policy and the information treatments given the heterogeneity of production types are used to guide the agent's behavior in the models under various scenarios.

In this study, we scale up findings from an economic experiment with ABM in a spatially explicit watershed setting to provide insight into the effects of different policy interventions

addressing NPS pollution. The models capture interactions among heterogeneous agents in terms of diffusion of technology adoption by farmers, which is difficult to model using other techniques. Specifically, we test how tax/subsidy policies based on ambient levels of water pollution work in scenarios involving heterogeneous production and pollution schemes and focus on cases in which the decision space of the agents is extended from making a single production decision to making a production and a technology decision. We also investigate how information influences people's behavior and whether policies can be designed to incorporate information 'nudges' to induce more-desired outcomes.

Our study makes two significant contributions to the literature. In environmental and resource economics, our experiment investigates the effect of information 'nudges' in an experimental setting that simultaneously incorporates an extended participant decision space and multiple layers of heterogeneity. Moreover, we use an ABM that features heterogeneous agents in a spatially explicit context to understand implications of the complex actions and interactions created based on experimental data. In the field of ABM, despite rising interest in using non-fully rational agents, not much work has actually done so. We are one of the first to introduce bounded rational agents into an ABM based on an economic experiment. The ABM agent decision rules are closely linked with human decisions in the economic experiment using an underlying game-theoretical model. Our research demonstrates that economic experiments can be useful to capture bounded rationality and guide ABM development. This study provides an example to incorporate human-based decision rules and a possible framework to integrate experiments and ABM in future research.

2. Experimental Design and Theoretical Foundation

In this part, we discuss the experimental design of our economic experiment. We first lay out the theoretical model, and describe the treatments in the experiment.

2.1 Theoretical Model

We build upon and extend the classic model framework in the environmental economics literature. Consider a group of agricultural producers indexed by $i = 1 \dots N$ operate farms or ranches adjunct to a common watershed. The farmers' operations generate pollution as byproduct. A regulator monitors water quality by a sensor at the downstream of the watershed. The farms may differ both in their capacity and their distance to the sensor. The farmers may choose to adopt a pollution abatement technology (e.g., buffer, cover crop) at a cost (τ) proportional to farm size. Each year, the farmers make two decisions: a production decision x_i and a decision on whether to adopt an abatement technology a_i . $\frac{\partial PE_i(x_i, a_i)}{\partial x_i} > 0$, $\frac{\partial PE_i(x_i, a_i)}{\partial a_i} < 0$, indicating lower production and the adoption of the technology are associated with lower private earnings through $PE_i(x_i, a_i)$.

The environmental damage generated by each farm is $D_i(x_i, a_i) = \alpha\beta_i x_i a_i + \beta_i x_i (1 - a_i)$, where $\frac{\partial PE_i(x_i, a_i)}{\partial x_i} > 0$, $\frac{\partial PE_i(x_i, a_i)}{\partial a_i} < 0$, and β_i depends on the location of the farm relative to the sensor and α denotes the effect of the technology. We assume that the total environmental damage is $TD = \sum_{i=1}^N D_i(x_i, a_i)$. Without any regulation, a profit maximizing farm will produce at their capacity level and not adopt the technology. The social planner's problem is to maximize social benefits (denoted as SP), where $SP = \sum_{i=1}^N PE_i(x_i, a_i) - \sum_{i=1}^N D_i(x_i, a_i)$. Suppose the regulator hopes to achieve a pollution standard D and imposes a tax/subsidy policy, where the tax/subsidy equals to the environmental damage minus the target level of pollution, $t(TD) = (TD - \bar{D})$. Following the literature, suppose $PE_i(x_i, a_i)$ takes a quadratic form $\gamma_0 -$

$\gamma_1(\gamma_{2i} - x_i)^2 - \tau\gamma_{2i}a_i$, where $\tau\gamma_{2i}a_i$ takes into account whether the firm adopted the technology. Now the individual payoff function under the tax/subsidy scheme becomes: $\pi_i = PE_i(x_i, a_i) - (TD - \bar{D})$.

We find the Nash strategy by backward induction. Consider firm i , given the pollution level of others in the group D_{-i} , its profit function from producing x_i and adopting the technology is: $\pi_i^A = \gamma_0 - \frac{(\beta_i\alpha)^2}{4\gamma_1} - \left(D_{-i} - \bar{D} + \beta_i\alpha\gamma_{2i} - \frac{\beta_i^2\alpha^2}{2\gamma_1}\right) - \tau\gamma_{2i}$, taking first order condition, the maximum is reached at $x_i^A = \gamma_{2i} - \frac{\beta_i\alpha}{2\gamma_1}$. The profit for not adopting the technology is $\pi_i^N = \gamma_0 - \frac{\beta_i^2}{4\gamma_1} - \left(D_{-i} - \bar{D} + \beta_i\gamma_{2i} - \frac{\beta_i^2}{2\gamma_1}\right)$, and the maximum can be reached by producing $x_i^N = \gamma_{2i} - \frac{\beta_i}{2\gamma_1}$. The condition for a farmer to prefer to adopt compared with not adopt is therefore $C = \pi_i^N - \pi_i^A = \frac{\beta_i^2}{4\gamma_1}(1 - \alpha^2) - \beta_i\gamma_{2i}(1 - \alpha) + \tau\gamma_{2i} < 0$. Thus, a unique dominant Nash strategy for a farm is defined as $\{C < 0: x_i = \gamma_{2i} - \frac{\beta_i\alpha}{2\gamma_1}, a_i = 1; C \geq 0: x_i = \gamma_{2i} - \frac{\beta_i}{2\gamma_1}, a_i = 0\}$. This dominant Nash strategy is also the same as the social planner's optimal strategy.

2.2 Treatments

We consider two dimensions of treatments. On the within-subject level, we varied whether the tax/subsidy policy is in place and also the complexity of heterogeneity that is in the experiment. For each of the policy treatment, we conducted four heterogeneity treatments, namely,

- (1) A homogeneous treatment where the locational impact on water quality and size of each farm is the same (Homo);

- (2) A first heterogeneous treatment where the locational impact on water quality vary, but the size of each farm is the same (Hetero1)
- (3) A second heterogeneous treatment where the size of the farms vary, but locational impact on water quality is the same (Hetero2);
- (4) A third heterogeneous treatment where both size and locational impact on water quality of farms vary (Hetero3).

To control for potential order effects, we randomly varied the order of the within-subject treatments that are presented. On the between-subject level, we provided participants with three information treatments. No Info serves as the baseline. In the Info1 treatment, we provide testimonial information on what production and technology adoption decisions people “like them” have made in the past. The information comes from the “no information” treatments. We find true decisions participants made that are closest to the Nash optimal strategies conditioning on their size and location. Therefore, this information differs by the location and the size of the firm and approximates the actual Nash optimal strategies. This resembles some policy recommendation on what people should consider doing based on their location and size.

In the information treatment 2, we give participants information on the technology adoption rate and average production in their group in the last decision. This is similar to a policy that provides information on what others in the neighborhood are doing and has a self-evolving nature. Since each decision is independent and each participant has a unique dominant Nash strategy, theoretically the information treatments should not change participants’ decisions. However, as noted before, human decisions often demonstrate bounded rationality and may follow simple heuristics or *ad hoc* rules.

2.3 Experiment procedure

The economic experiment consisted of twelve sessions conducted in late 2016, involving a total of 192 participants recruited at a large public university in the northeastern United States.

3. Agent-Based Model Setup

In this part, we discuss the ABM setup and initialization. We design the ABM to capture key elements of the economic experiment and an actual watershed while avoiding including unnecessary assumptions and processes. We first set the ABM to a spatially explicit context based on the Murderkill¹ watershed located in the southeast part of Kent County, Delaware (Figure 1). The Murderkill watershed is chosen mainly because it consists of primarily agricultural land use and it is a typical coastal plain. Besides, it has promulgated TMDL regulations and has research efforts on the estuarine portion of the watershed. Moreover, the watershed is comprised of 68,000 acres of land, which is large enough to generate meaningful conclusions, but not too large to create computational obstacles.

[Figure 1 here]

3.1 GIS Environment Setup

In our model, the agents are farmers operating farms in the watershed. However, since farm level data is not publicly available, we develop a method to simulate farm level agents from

¹ Note that the origin of the name, Murderkill, has a Dutch origin as “moeder” means mother and “kill” means river or creek in Dutch. Thus, the rough translation of the name is “Mother River”, and not a reference to a bloody past.

parcel level data. We obtain three sources of geographic information system (GIS) data for the Murderkill River watershed: (1) Parcel level size and location data for Delaware; (2) Watershed boundary data for Murderkill watershed; and (3) National Land Cover Database (NLCD, 2011). We combine these three data sources together to generate an estimate of the agricultural land for each parcel in the watershed.

3.2 Agent Initialization

By combining parcel-level GIS information with data on land cover for this watershed, we can estimate the amount of land used for agriculture within each parcel and the X-Y coordinates of the parcels. Since farms often consist of a constellation of parcels and we do not have data on the actual allocation of parcels to specific landowners, we initialize the size of each farm based on the probability density function from data from the 2012 Census of Agriculture (U.S. Department of Agriculture, 2012) for Kent County, Delaware. Using that information and the GIS information, we match a simulated landowner agent to various numbers of parcels. In this process, we first calculate a “distance matrix” that contains information on the geographic distance between the individual parcels and every other parcel in the watershed. We then create landowner agents by grouping the nearest neighboring parcels until they meet criteria identified by the probability density and average size of each category of farms in the Census of Agriculture. The result is that our agents constructed from neighboring parcels closely mimic the census data on farm size distributions. Figure 2 displays the farm size distribution of Kent County, Delaware, and Figure 3 shows our simulated farm size distribution.

[Figure 2 and Figure 3 here]

3.3 Network and Layout

An agent is assumed to operate a farm that consists of a number of parcels. The agents are placed at the center points of their farms, which are determined using GIS data. Each agent is connected to a number of neighbors based on geographic proximity and influences those neighbors. The number of agents in one neighbor group is determined by the modeler at the beginning of each simulation.

3.4 ABM Model Framework

In the ABM, we adopt the modification of the classic model in environmental and resource economics as documented in our previous section. Each agent operates a farm and generates income by producing an agricultural product (e.g., corn) and simultaneously generate byproducts that cause NPS pollution. The agents may choose to adopt a technology at a cost proportional to its size that could reduce byproducts. As explained before, an underlying dominant Nash strategy could be solved for every agent in the watershed. Since the dominant Nash strategy is the same as the optimal strategy for the social planner's problem, we can treat the Nash strategy as the "Theoretical Target" level of participants' response. A pollution monitor (i.e., sensor) is placed at the downstream end of the watershed, and amount of pollution contributed by each farm is based on the farm's distance from the monitoring point (our experiment measured individual contributions of pollution in the same way). Different policy and regulatory scenarios influence the agents' production and technology-adoption decisions based on results drawn from the experiment. Table 1 summarizes the variables used in the ABM.

[Table 1 here]

3.5 ABM Model Process Flow

Figure 4 demonstrates the process flow of our ABM. Each agent makes two decisions, a production decision and a technology decision. Both decisions influence the income received and the pollution generated by the agent. Combined with pollution generated by other agents, the total pollution is calculated. Depending on whether an ambient based policy is in place, the agent's income may be affected by a tax or subsidy based on the target level and the total environmental damage. This influence on income further affects agent decisions in the next year. An agent's production and adoption decisions are modeled based on the production and adoption deviations from the target levels. These deviations are modeled in two phases as demonstrated in the next section.

[Figure 4 here]

4. Experimental Data Analysis

We conducted statistical data analysis on data from the experiment as documented in Wu, Palm-Forster, and Messer (2017). The analysis was done in two phases. First, we are interested in classifying people into different behavior groups. The idea is to capture the inherent behavioral difference among people (e.g., some people are more environmentally friendly, some are more self-oriented, etc.) Second, after we classify participants into behavior groups, we estimate how agent production and adoption decisions are influenced by their location, size, information treatment and type. We use the results to calibrate agent decision rules in the ABM model.

4.1 Cluster Analysis

Since we do not have any pre-defined knowledge or want to impose any assumption on how many groups participant behavior should be clustered into, the goal of this analysis is to identify

the number of behavior types and cluster agents into that number of groups. With no pre-determined grouping structure, meaning that we do not observe the response variables, cluster analysis is suitable for this purpose. As a popular unsupervised statistical learning method, cluster analysis could generate grouping structures based on patterns in predictors. The first key question is to determine how many clusters the agents should be grouped into.

4.1.1 Clustering Metric

To account for the fixed effects of different treatments, the difference between an agent's actual pollution level and the Nash optimal strategy level in that treatment was considered as a measure of the agent's behavior at each round. Therefore, clustering analysis was implemented based on five variables (diff1, diff2, diff3, diff4, diff5), the agents' differences to Nash over five rounds. These variables are defined as:

$$\text{Diff}_{ijt} = \text{Pollution}_{ijt} - \text{TargetPollution}_{ijt}.$$

Where Diff_{ijt} denotes the difference of participant i 's pollution level to the target pollution level in treatment j , round t .

There are a number of clustering methods available, the most popular ones include K-means clustering, hierarchical clustering and Gaussian mixture models. There is no definite right or wrong for each of the clustering methods. We selected to use K-means clustering because it generated the most informative grouping structure.

For K-means clustering, the most important task is to determine how many groups to cluster into. This depends on both statistical criterion and knowledge on what a sensible grouping structure is. We perform various statistical procedures to determine the number of clusters.

4.1.2 The Elbow Method

The most intuitive way to determine the number of groups is the “Elbow Method”. Figure 5 depicts the within groups sum of squares versus the number of clusters. We can see that there is a sharp turn when the number of cluster is equal to three. Therefore, three appeared to be a reasonable number of clusters to divide the agent types into.

[Figure 5 here]

4.1.3 Calinski Criterion

Another popular method for this purpose is the Calinski Criterion (also known as the Pseudo F statistics). Figure 6 shows the results of applying Calinski Criterion to our data. The Calinski Criterion suggests that we should also use three clusters.

[Figure 6 here]

4.1.4 Majority Rule

Third, we applied 26 other indices on the same problem and use the majority rule to select the number of clusters. We consider up to ten clusters as the possible number of clusters that we could group into. As shown in Figure 7, the Y-axis means the frequency that a number is selected as the best number of clusters chosen by the indices, and the X-axis is the possible best number of clusters. Eleven out of the 26 indices selected three as the best number of clusters. Therefore, according to the majority rule, we will assume three is the number of clusters we should use in the K-means clustering.

[Figure 7 here]

4.1.5 Separation Examination

We examine if the three clusters generated by K-means clustering provide reasonable separation for the data. We perform K means clustering, assigning three as the number of clusters, and setting the seed to 20 to ensure reproducibility.

[Table 2 about here]

The results of the K-means clustering are summarized in Table 2. As we can see, the median values for Group 3 in all five rounds are equal to zero, meaning that group 3 is the group that tend to behave in accordance with the theoretical prediction. Group 1 and Group 2 have median values that are lower and higher than the target pollution, respectively. This means that Group 1 is the group that tend to generate less pollution than theoretically predicted and Group 2 is the group that tend to generate more pollution than theoretically predicted. We do not see obvious skewness or scarcity of any groups and the magnitude of the separation seems reasonable. Next, we assign agents in the ABM into behavior groups using a multinomial logit model.

4.1.6 Mixed-effects Multinomial Logit model to assign group probabilities

Based on cluster analysis, agents' behavior could be clustered into three categories. Cluster 3 corresponds to agents that tend to agree with theoretical predictions, and cluster 1 and 2 correspond to agents that tend to under and over pollute, respectively. In this part, we use a mixed effects multinomial logit model to estimate the cluster distributions among agents conditioning on the policy, heterogeneity and information treatments.

The multinomial logit model could be formulated as follows:

$$\begin{aligned}
& \log \left(\frac{Pr(cluster = 1)}{Pr(cluster = 3)} \right) \Big| (Policy = j) \\
& = f(u_{1,i}, HeteroTreatments, InfoTreatments, HeteroInfo_Interactions) \\
& = X_i B_{1i}
\end{aligned}$$

$$\begin{aligned}
& \log \left(\frac{Pr(cluster = 2)}{Pr(cluster = 3)} \right) \Big| (Policy = j) \\
& = f(u_{2,i}, HeteroTreatments, InfoTreatments, HeteroInfo_Interactions) \\
& = X_i B_{2i}
\end{aligned}$$

where $u_{1,i}, u_{2,i}$ are the random effects on the intercept and are assumed to follow a normal distribution. J equals 1 or 0 and denotes whether the policy treatment is in place or not, respectively.

Therefore, the predicted probabilities for the three clusters could be calculated as:

$$\begin{aligned}
Pr(cluster_i = 1) &= \frac{\exp(X_i B_{1i})}{1 + \exp(X_i B_{1i}) + \exp(X_i B_{2i})} \\
Pr(cluster_i = 2) &= \frac{\exp(X_i B_{2i})}{1 + \exp(X_i B_{1i}) + \exp(X_i B_{2i})} \\
Pr(cluster_i = 3) &= \frac{1}{1 + \exp(X_i B_{1i}) + \exp(X_i B_{2i})}
\end{aligned}$$

The results of the mixed effects multinomial logit model for both policy and no policy treatments are presented in Table 3.

[Table 3 here]

In the no policy treatments, it is always in the agents' best interest to produce at the maximum and not adopt the technology, therefore, the theoretical optimal strategy is the upper bound of the pollution level. As a result, only two clusters exist in the no policy treatments, as

reflected by having one intercept value in Table 3. Based on the above regressions, we calculate the cluster probabilities for each of the treatment cases to initialize the model.

4.2 Modeling agent production and adoption behavior.

For production decisions, we calculate the percentage deviations from the target production decisions, taking into account the size of the farm. The metric is defined as:

$$PerProdDiff = \frac{Production - TargetProd}{Size}.$$

In this case, we run a random-effects OLS model for each policy and information segment of data with standard errors clustered at the individual level.

[Table 4 here]

For adoption decisions, we calculate the probability that an agent deviates from its target adoption decision, which means the probability that an agent changes its adoption decision away from the theoretical prediction. The metric is defined as the absolute difference of the actual adoption decision and the target adoption decision:

$$AdoptChange = |ActualAdopt - TargetAdopt|$$

Since the variable AdoptChange is binary, we run a random effects logit model for each policy and information treatment segments with individual clustered standard errors. The result of the model is shown below:

[Table 5 here]

Based on the above regressions, we parameterize the agent's actual production and adoption decisions relative to their Nash optimal strategy levels.

5. Calibration

5.1 Prices

Agents are assumed to produce an agricultural good (corn) and act as price-takers. Given the constant fluctuation of corn prices in the US, we conduct an OLS regression for the mean corn price from 1996 to 2016 on logarithm of year to capture the general price trend, and use a triangular distribution with maximum and minimum defined by the predicted mean and standard deviation of the prices to reflect the fluctuation.

5.2 Yield

In order to determine how much agricultural product (corn) is produced by each agent, we calculate the average yield of each unit of land. Similarly, we conduct an OLS regression for mean corn yield from 1996 to 2016 on logarithm of year to capture the general trend in corn production, and use a triangular distribution to reflect the fluctuation, with maximum and minimum defined by the standard deviation of the average yield.

5.3 Pollution

Following Zia et al. (2016a), we provide an estimate for the average Phosphorus leakage of corn fields based on the maximum and minimum Phosphorus loss estimates. During each simulation, the modeler has the option to modify the mean and standard deviation of average Phosphorus leakage. However, this value affects all simulation cases equally and therefore does not influence any relative comparison conclusions we draw.

6. Simulation Results

We present the results of the simulation experiment, and discuss the sensitivity of the results.

6.1 The Effect of Information Treatments

We compare how different information treatments would affect the performance of the ambient based policy. Both location and size heterogeneity are included in this simulation. In Figure 8, the red line indicates the target level of pollution, and the blue line indicates the experiment simulation results. From left to right, the three subfigures indicate the results for the no information case, individual level information case, and group level information case. As shown in Figure 8, a gap exists between the simulated pollution level (blue line) and the target pollution level (red line) in the no information case; however, the gap is much smaller in either of the information treatments. This suggests that under this simulation scenario, both information treatments decrease the deviation between the target pollution level and the simulated level, which indicates that the effect of policy is stronger when ambient based policy is coupled with information ‘nudges’.

[Figure 8 here]

6.2 Comparing Individual Decisions

In this section, we break up pollution by production decisions, adoption decisions and size of the farms. We look at each information treatment separately.

6.2.1 No Information

Recall that under no information baseline, the aggregate simulated pollution level is mostly over the target level, but the deviation does not appear to be large. However, when we break up pollution into production and adoption decisions by farm size, we observe huge deviations in these decisions (Figure 9). The small farms are significantly over adopting the technology (blue lines), and the large farms are widely under adopting, even though it is not in their best interest to do so (as depicted by the blue lines). Similarly, the small farms are also over producing and large farms are under producing.

[Figure 9 here]

6.2.2 Individual Level Information

When we provide participants with individual level information on what people like them have done in the past, we observe that the deviations from participants' behavior to the target levels are much smaller (Figure 10). This clearly demonstrates that the individual level information induces participants to make better decisions, and improves policy efficiency.

[Figure 10 here]

6.2.3 Group Level Information

When participants are informed with group level information on average adoption and production decisions in their group in the last round, we find that this information helps participants make better decisions than the no information baseline, but the policy efficiency is lower compared to individual level information scenario (Figure 11). Furthermore, small farms tend to over adopt and over produce, and the large farms tend to under adopt and under produce. However, compared to the target levels, the deviations between the target and the simulated results are smaller compared to the no information scenario, but larger than when people were given individual level information. Therefore, group level information helps the policy performance and efficiency on an aggregate level, but the policy efficiency is lower than if people were given individual level information.

6.2.4 Possible Explanations

Finally, we want to provide some discussion of the potential reasons for the patterns that were demonstrated in the simulation results. Under the no information treatment, the adoption of the technology is largely negatively related to the size of the farm. A possible explanation for this observation is that since the cost of adopting the technology is proportionally related to the size of the farm, participants may follow some heuristic decision rules that attribute significant weight to the cost of adopting in the processes. This clearly demonstrates that as opposed to always following profit maximizing decision rules, human behavior is often limited in their calculating ability and may be affected by various cognitive reasons and therefore demonstrate bounded rationality in terms of forming some rather heuristic decision rules. Furthermore, both information treatments seem to provide anchors for the participants. Knowing what people like them have done in the past and what others in their group have done provide people with a

reference point in their decision process. Since individual level information provides people with tailored information, it helps people make better decisions compared to the myopic baseline case. Under the group level information where a group average is provided, we can observe that the absolute adoption and production decisions for farms with different sizes tend to be very close. This suggests that people might be anchored to the group level averages, or peer actions, even though it might not be in their best interest to do so.

7. Sensitivity Analysis

In this section, we discuss how our results would be affected by uncertain parameters in our ABM. Ideally, the result of an ABM should come from complex agent interactions and adaptations in a concise model rather than from complex assumptions about individual behavior and free parameters (Axelrod, 1997). Most of the parameters that influence the observed results in the ABM are calibrated and validated based on experimental data. Therefore, the uncertainty only results from realization of the randomness in each simulation experiment, which is stochastic in nature and should not generate any systematic biases. Meanwhile, if an uncertain variable affects each scenario of the simulation in an equal magnitude, the relative comparisons between the scenarios will not be affected. Therefore, one uncertain parameter that would possibly affect the result is how many farms the participants consider part of their group. This parameter affects the grouping structure and the group level information that is shown to the participants. In our baseline scenario presented before, we assume five people are considered to be in one group. We increase this parameter to ten, fifteen and twenty in this part and the result is shown in Figure 12.

[Figure 12 here]

As shown in Figure 12, as the number of people that the participants consider themselves to be in the same group with increase, the deviation from the target pollution level and the simulated pollution level is not largely affected under individual level information treatment, but increases under the group level information treatment. This suggests that individual level information not only generates highest policy efficiency, but also is more robust to participant perceptions on their group size.

8. Conclusions and Discussions

Our study is one of the first that integrates economic experiments with agent based modeling in a nonpoint source pollution setting. The ABM extends and scales up the findings from the economic experiment by providing a spatially explicit simulation environment based on an actual watershed. Instead of assuming full rationality, the economic experiment calibrates and validates the ABM by defining human-based bounded rational decision rules for the agents. We apply a modification of a classic game theoretical model from the environmental economics literature to the ABM and the experiment as the core underlying model in both scenarios. We define the target level (fully rational theoretical level) by solving for unique dominant Nash strategy. Using experimental data, we first identify the number of behavioral groups using exploratory cluster analysis and then group agents into the three identified groups by multinomial logistic model; second, we define agent decision rules by estimating adoption and production deviations from the target levels based on the information treatment, type, size and location of each agent.

The result of our simulation experiment demonstrates that both information ‘nudges’ help the performance of the ambient-based policy. Individual level information induces higher policy efficiency compared to group level information, where the individual decisions tend to be

anchored to the group averages, even though it may not be in their best interest. Our results show in a spatially explicit watershed setting that ambient-based policies, coupled with information ‘nudges’ to provide guidance to people’s behavior, have the ability to induce group level compliance, and the policy efficiency is higher when individual level information is being provided. Therefore, it is important to use informational ‘nudges’ to help people make better decisions, especially under complex heterogeneous scenarios.

There are a number of limitations and directions of future work based on our research. First, a more complicated hydrological model may be developed and incorporated in the ABM and the experiment. Examples of such models include the WWACShed model by Tesfation (2017) and the SWAT model used in Ng et al., (2011). However, if one attempts to also include bounded rationality in the agent decision processes and use economic experiments to capture these irrationalities, it is crucial to ensure that the conclusions from the experiment could be safely carried over to the ABM. In our experiment, this link was built by adopting the same underlying model and therefore the same incentives around the dominant Nash strategies. If a more complicated model is in place, it would be hard to solve for a perfect rational utility maximization prediction, and therefore would be difficult to have a baseline to compare with actual human behavior. Additionally, the more complicated a model is, the more information burden is introduced to the participants and the harder for the participants to generate informed decisions.

Second, another extension of this research is to use farmer sample instead of a sample from university students in the experiment, aiming to increase externality validity of the experiment. The majority of research comparing samples from students and professionals generally find the two samples demonstrate similar responses in both agricultural (e.g.,

Cummings, Holt, and Laury, 2004; Messer et al. 2008; Fooks et al. 2016) and non-agricultural (Vossler et al., 2009) contexts, it may still be a valid extension since the decision process of farmers is likely different from that of students. However, one also needs to note that the farmers may treat the experiment as a pre-policy evaluation and therefore behave strategically in hopes to potentially influence policy makers (Suter and Vossler, 2013).

There has been very few articles in the literature trying to integrate experiments and agent-based modeling even though the integration would benefit both fields. This could probably largely be attributed to the interdisciplinary nature of the field, and the challenge to build a credible link between the two. In our exploratory work, we hope to have established a framework on how these two fields could be combined and helped motivate future research in this area.

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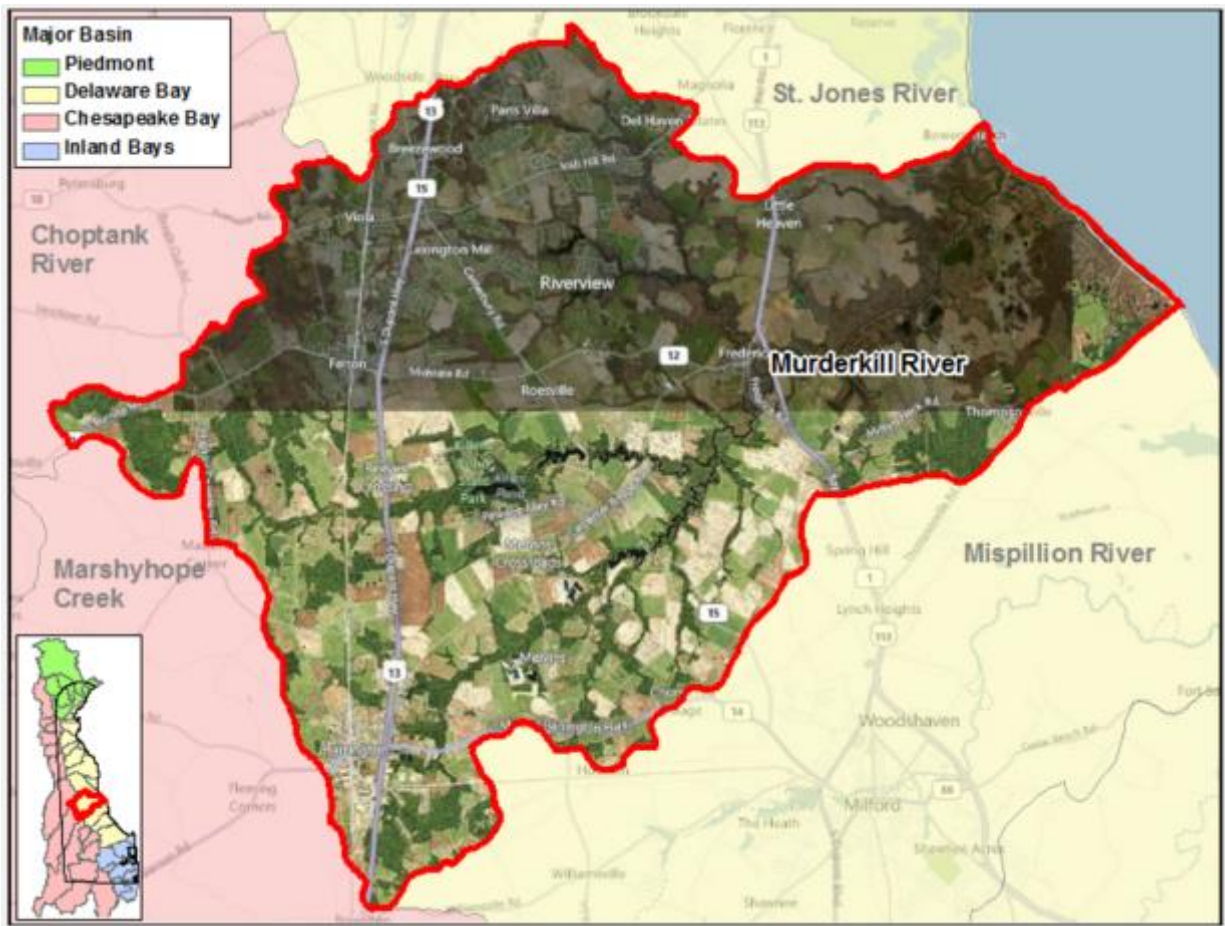


Figure 1. Murderkill River Watershed, Delaware, United States. Figure source: delawarewatersheds.org

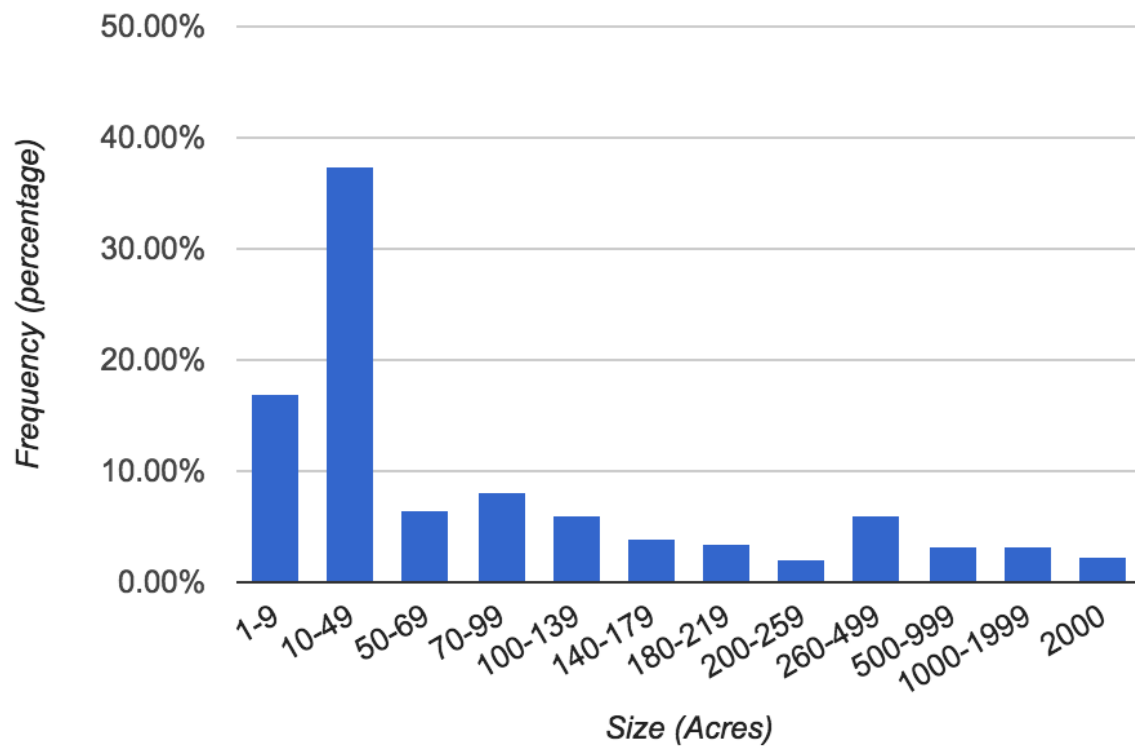


Figure 2. 2012 Ag Census Farm Size Distribution of Kent County, Delaware, United States

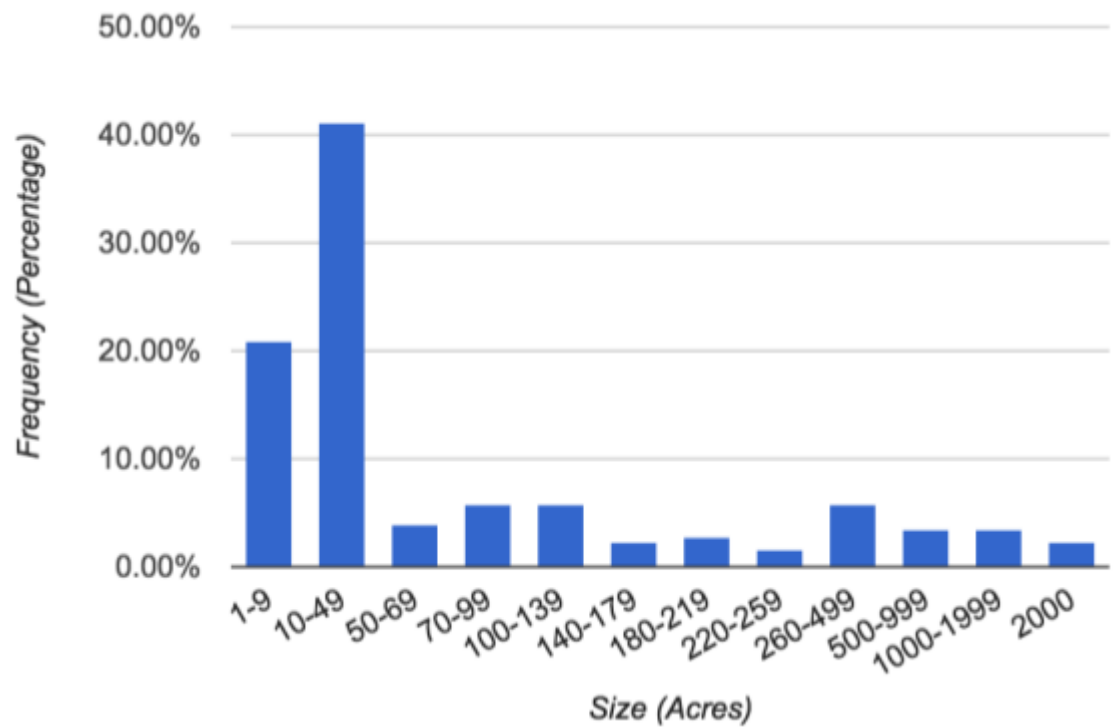


Figure 3. Simulated Farm Size Distribution

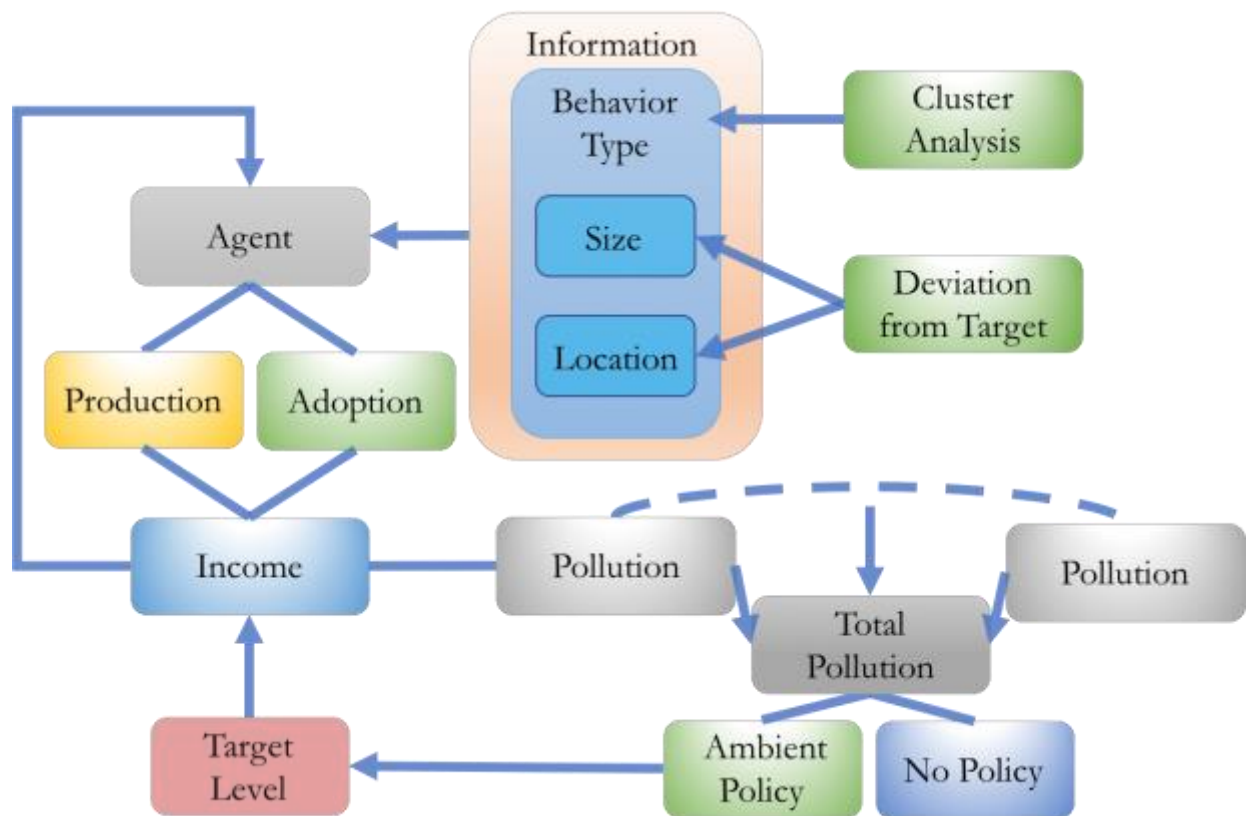


Figure 4. ABM Model Process Flow.

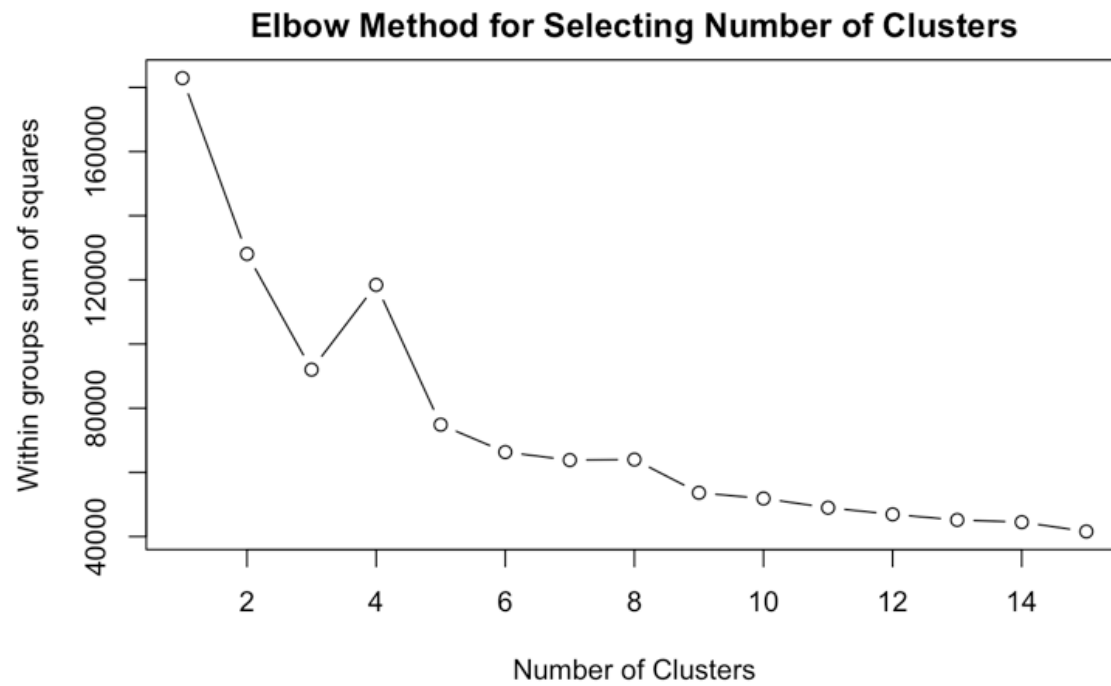


Figure 5. Within Groups Sum of Squares Versus the Number of Clusters.

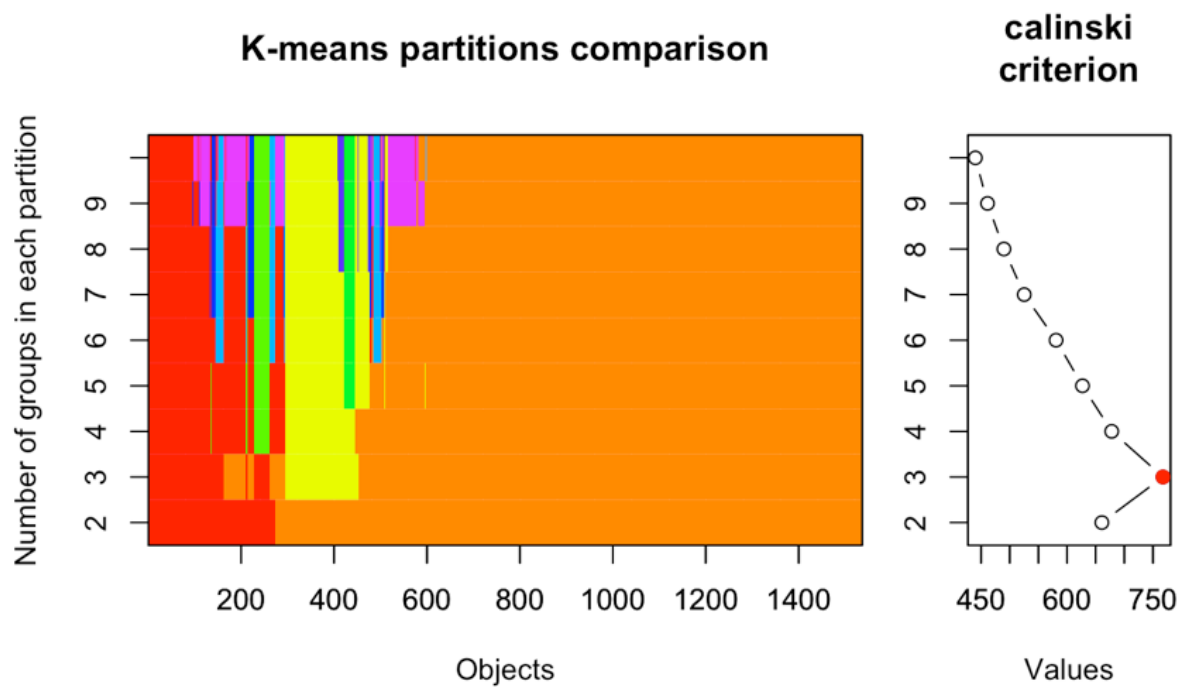


Figure 6. Calinski Criterion Results.

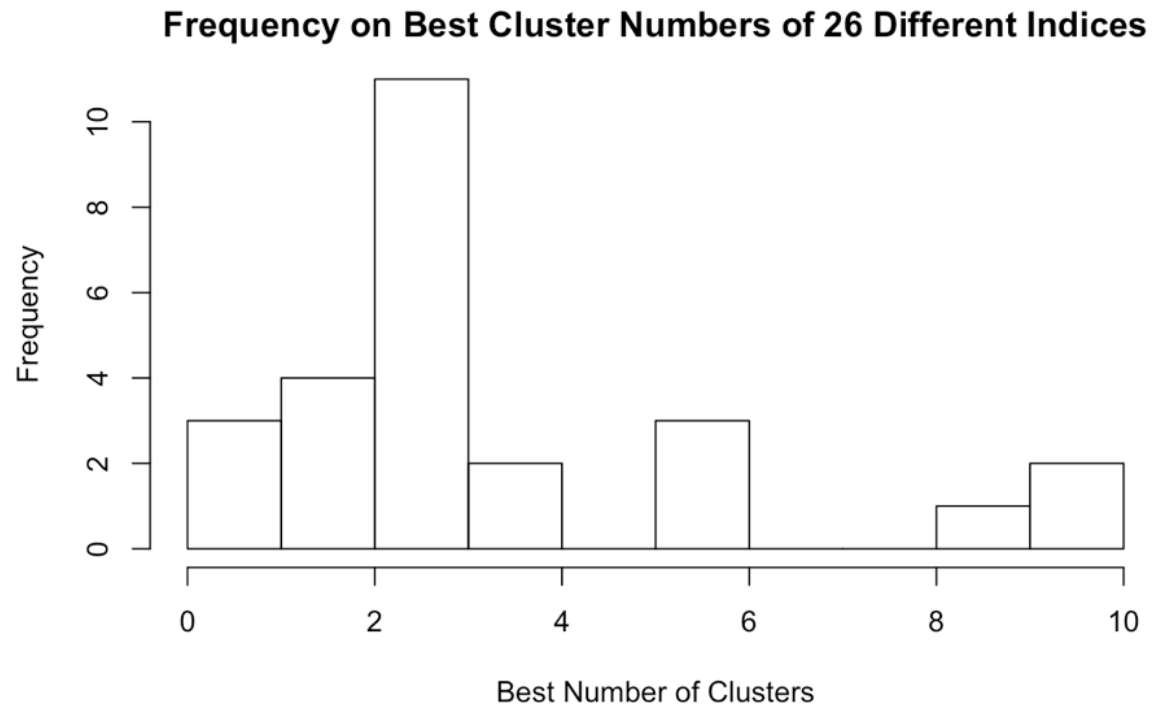


Figure 7. Results of Using a Majority Rule with 26 Grouping Indices.

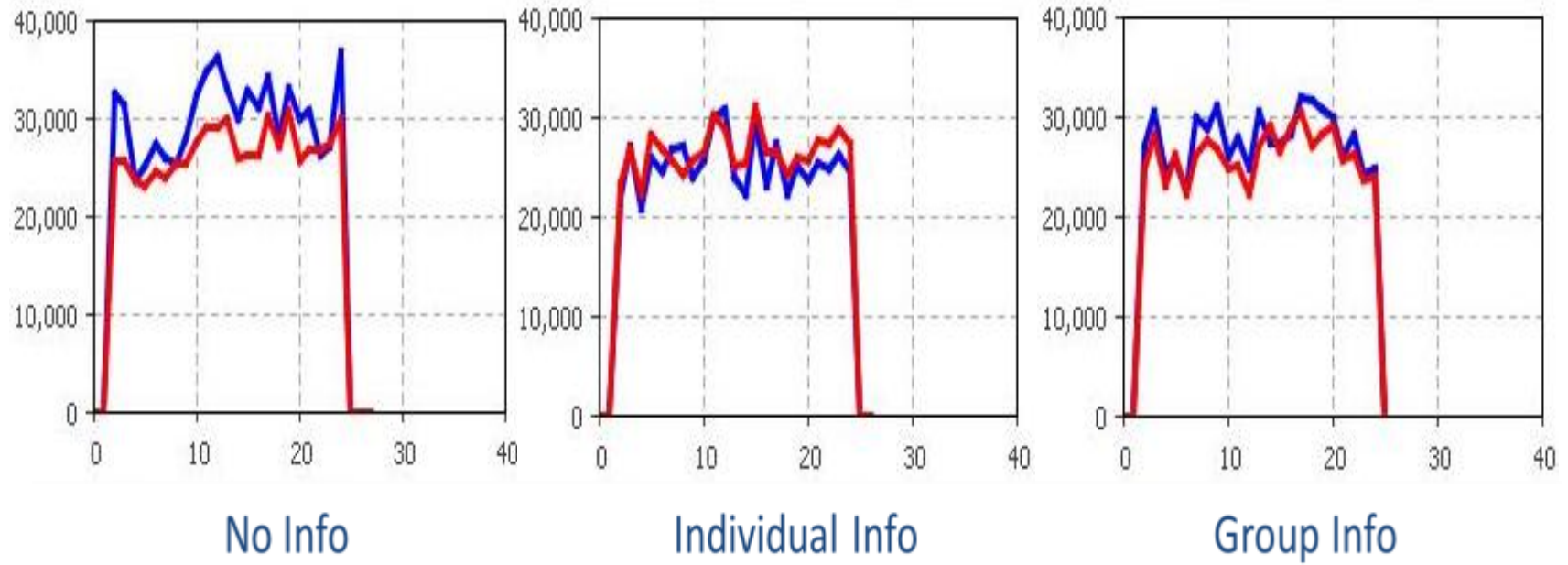
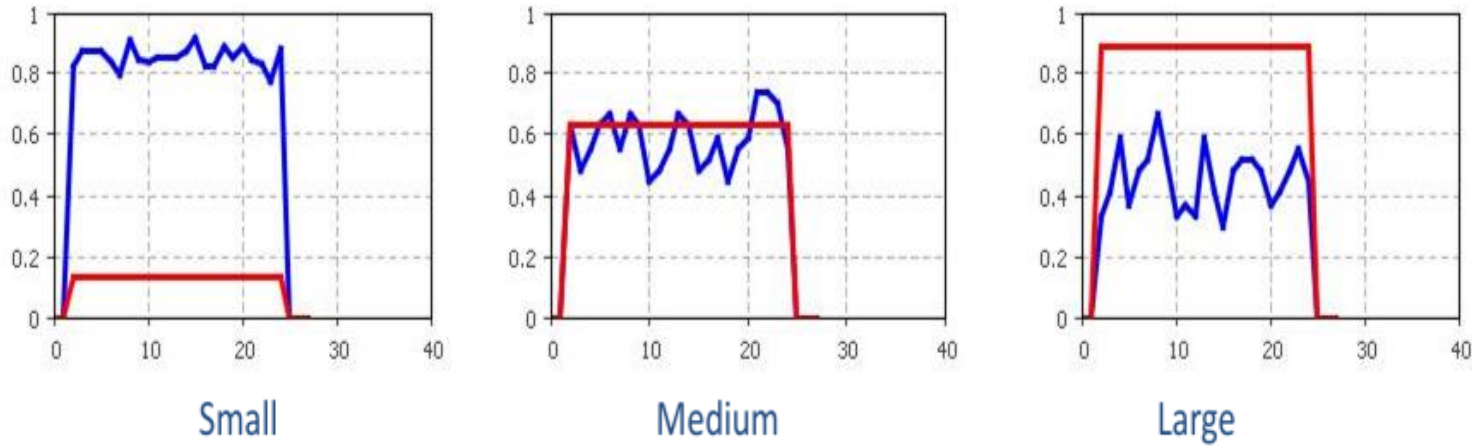
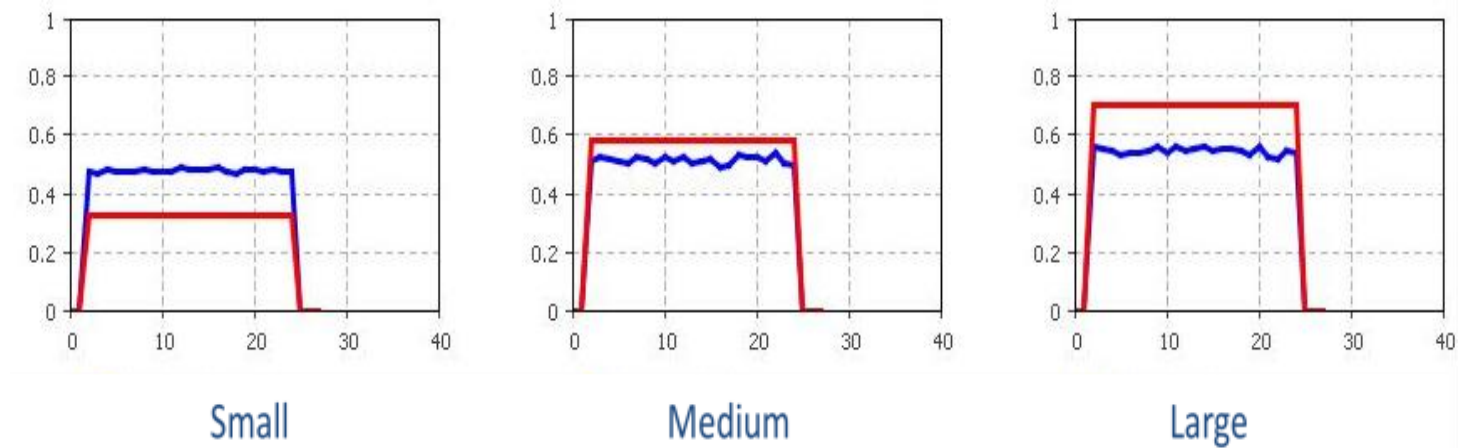


Figure 8. Effects of Information on Pollution Level. The red lines indicate target levels and the blue lines indicate experiment simulated results.

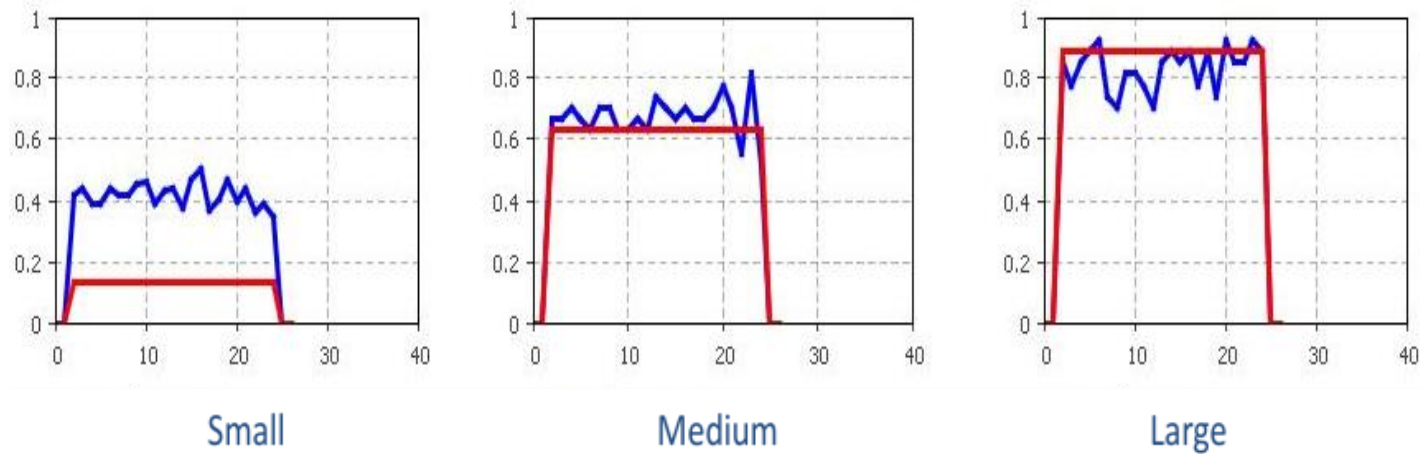


Panel a. Adoption Decisions

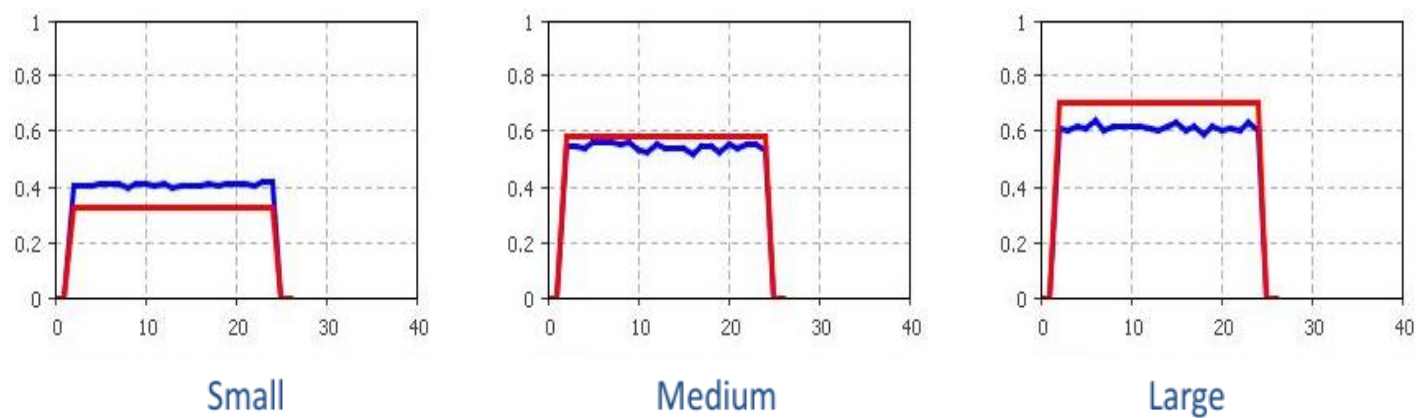


Panel b. Production Decisions

Figure 9. Adoption and Production Decisions by Size under No Information Treatment. The red lines indicate target levels and the blue lines indicate experiment simulated results.

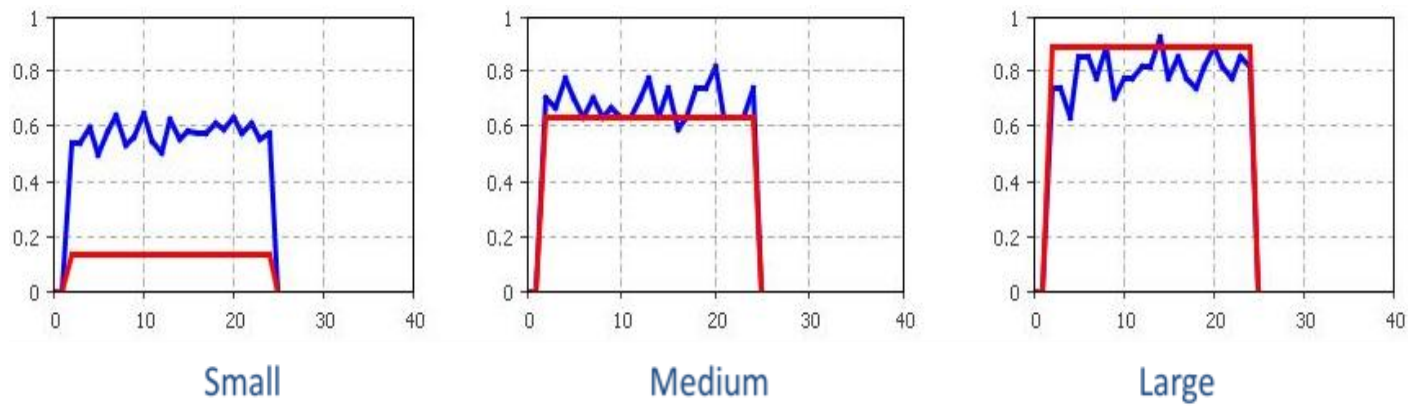


Panel a. Adoption Decisions

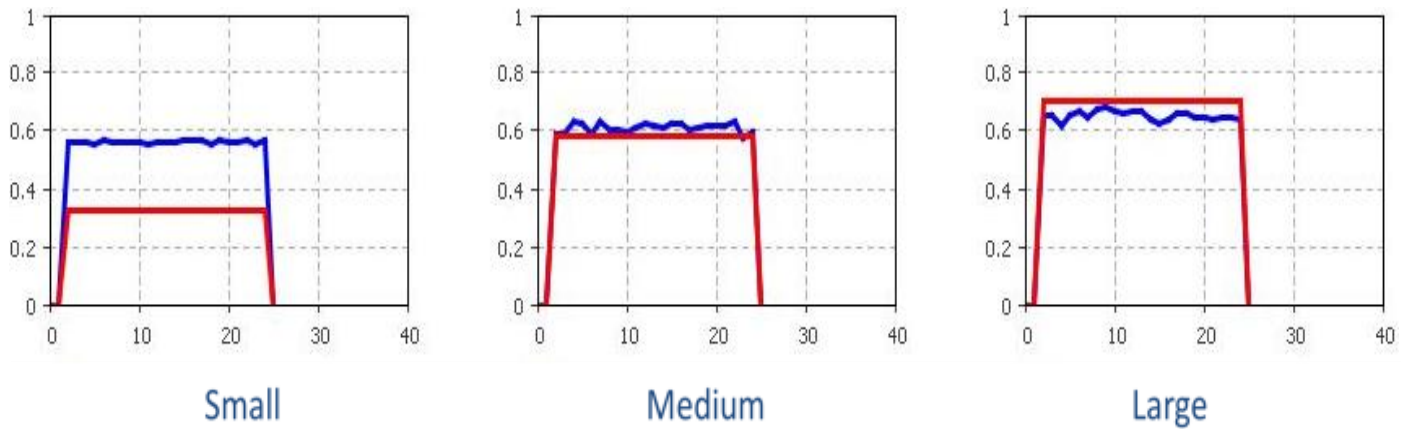


Panel b. Production Decisions

Figure 10. Adoption and Production Decisions by Size under Individual Level Information. The red lines indicate target levels and the blue lines indicate experiment simulated results.



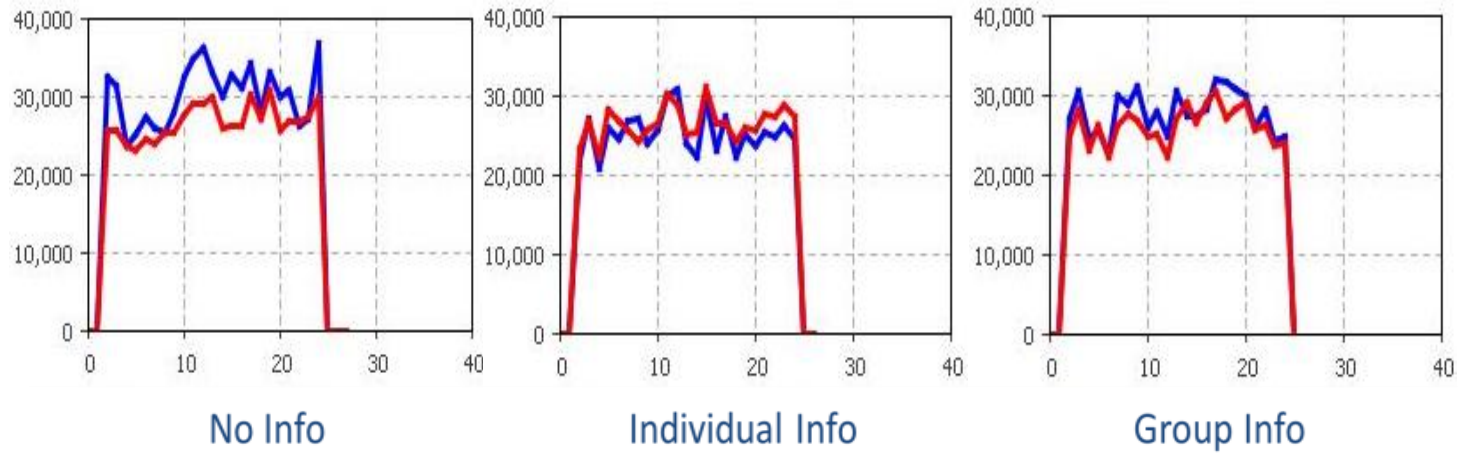
Panel a. Adoption Decisions



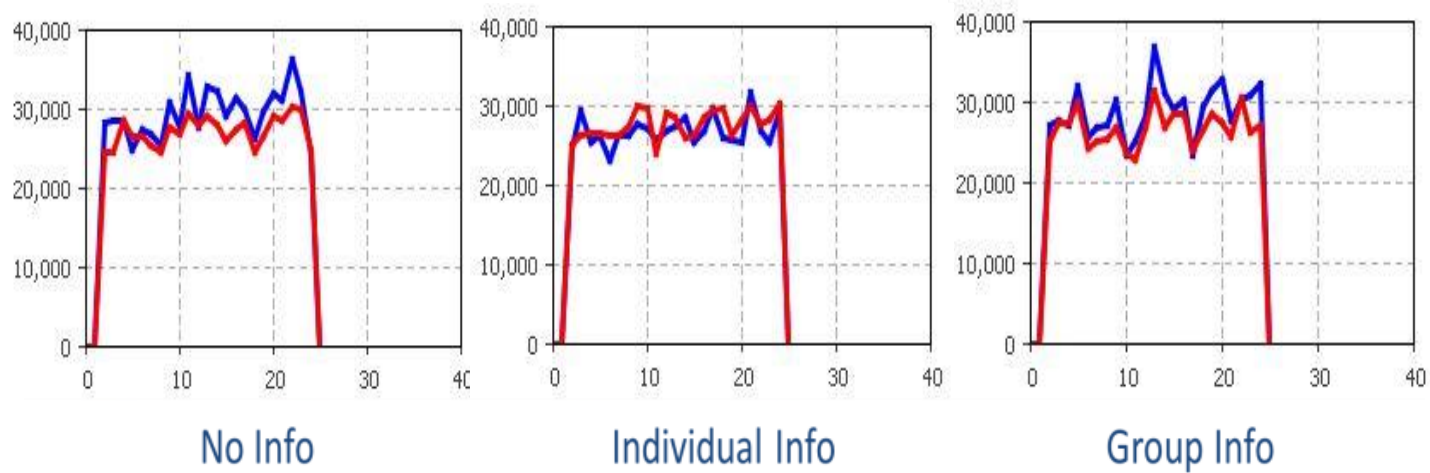
Panel b. Production Decisions

Figure 11. Adoption and Production Decisions by Size under Group Level Information. The red lines indicate target levels and the blue lines indicate experiment simulated results.

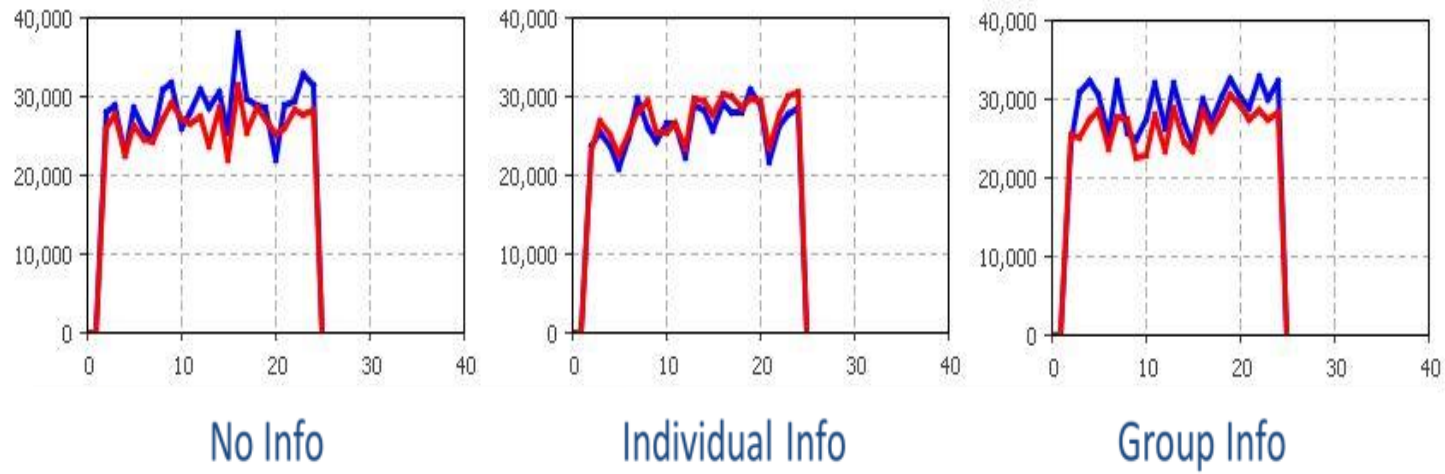
$N = 5$



$N = 10$



N = 15



N = 20

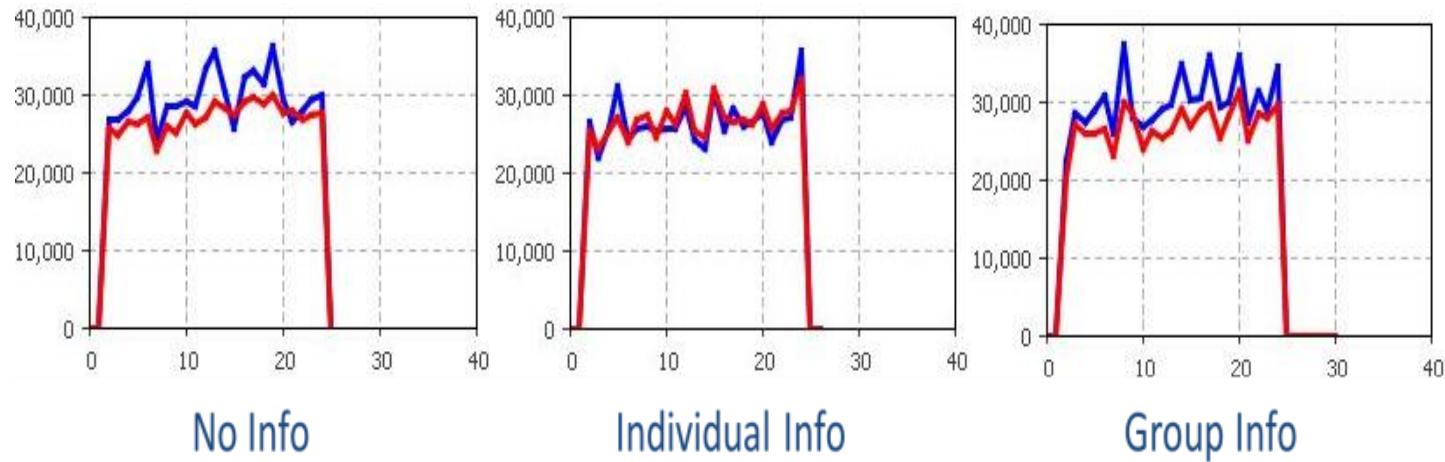


Figure 12. Sensitivity Test on Group Size. The red lines indicate target levels and the blue lines indicate experiment simulated results.

Table 1. Summary of Fixed, Variable, and Uncertain Parameters

Parameter Name	Value	Description
<i>Fixed Parameters</i>		
Number_of_agents	About 174, depending on each realization	Number of agents in simulation
Simulation_horizon	25	Length of each simulation in years
Probability_of_farm_type	Based on cluster analysis and multinomial logistic regression	The probability that each agent will fall into each behavioral type
Target_adoption_rate	Depends on farm grouping results	The target probability that each agent will adopt the technology
Target_production_rate	Depends on farm grouping results	The target production rate for each agent
Number_of_connections	User defined	Number of neighbors of each agent
Factor_technology	0.5	Percent of pollution relative to original level if technology is adopted
<i>Variable Parameters</i>		
Unit_corn_production	User defined	Weight of corn produced on one unit of farm size
Unit_pollution_generated	User defined	Average phosphorus generated by one unit of production
<i>Uncertain Parameters</i>		
Percent_prod_deviation	Depends on experiment data	Adjusts amount of corn produced per unit of land based on agent type
Adoption_change_prob	Depends on experiment data	Adjusts amount of pollution per unit of production based on agent type
Adopted	Binary, value depends on each realization	Indicates whether the farm adopted the technology
Agent Type	One of several types depending on the cluster analysis of the experiment data	Different types of agents determine different production, pollution, and adoption probabilities

Table 2. Group Frequencies and Median Value by Grouping Variables and Groups.

Cluster	Frequency	Diff1	Diff2	Diff3	Diff4	Diff5
1	171	-7.500	-5.60	-6.00	-6.16	-5.44
2	150	6.615	5.28	5.11	5.94	5.25
3	1215	0.000	0.00	0.00	0.00	0.00

Table 3. Mixed Effects Multinomial Logit Model to Assign Agent Behavioral Types.

	Policy		No Policy	
	Coefficient	Std. Err.	Coefficient	Std. Err.
intercept 1	-2.0416***	0.1119	-10.5036***	1.3820
intercept 2	-0.8200***	0.1127		
hetero1	0.3183*	0.1691	0.5156	0.4567
hetero2	0.5703***	0.1562	0.5156	0.4567
hetero3	0.4495***	0.1688	-0.5666	0.4796
info1	-1.2637***	0.2073	0.8735	1.3800
info2	-1.1185***	0.2123	-1.3688	1.4154
info1_hetero1	0.7143***	0.2746	-1.5310***	0.6499
info1_hetero2	0.6048**	0.2647	-4.2738***	0.8099
info1_hetero3	1.2097***	0.2745	-4.4023***	0.9440
info2_hetero1	0.3696	0.2631	0.1780	0.7027
info2_hetero2	1.3090***	0.2661	0.7511	0.6957
info2_hetero3	1.4883***	0.2566	2.8191***	0.7137
Number of Observations	3840		3840	
Number of groups	192		192	

***, **, * denote significant as 1%, 5% and 10% level. All standard errors are clustered as individual level.

Table 4. Deviations from Target Production Levels

	With Policy			Without Policy		
	No Info	Info1	Info2	No Info	Info1	Info2
constant	1.32*** (0.11)	0.16 (0.16)	1.41*** (0.13)	0.0015 (0.051)	-0.0039 (0.015)	-0.11 (0.14)
size	-0.0095*** (0.00067)	-0.00086 (0.0031)	-0.0089*** (0.00081)	-0.00019 (0.00016)	-0.000073 (0.000074)	0.000083 (0.00012)
region	-1.19*** (0.30)	0.25 (0.42)	-1.41*** (0.30)	0.032 (0.15)	0.023 (0.038)	-0.015 (0.026)
cluster1	-0.20*** (0.040)	-0.19*** (0.04)	-0.13*** (0.038)	-0.12*** (0.042)	-0.068** (0.032)	-0.057** (0.024)
cluster2	0.26*** (0.031)	0.21*** (0.039)	0.19*** (0.036)			
info1_adopt		-0.21** (0.085)				
info1_prod		-0.000028 (0.0029)				
info2_adopt			0.064 (0.063)			0.00040 (0.013)
info2_prod			-0.0020* (0.0011)			0.00098 (0.0014)

***, **, * denote significant as 1%, 5% and 10% level. All standard errors are clustered as individual level.

Table 5. Deviations from Target Adoption Decisions

	With Policy			Without Policy		
	No Info	Info1	Info2	No Info	Info1	Info2
constant	6.76*** (2.17)	5.69** (2.33)	9.67 *** (2.50)	-2.86 (2.05)	-5.17*** (1.09)	-14.96 (10.73)
size	-0.051*** (0.012)	-0.018 (0.042)	-0.050*** (0.013)	-.0096 (0.012)	-0.0041 (0.011)	-0.016 (0.017)
region	-7.09 (4.66)	-18.09*** (6.73)	-18.44*** (5.85)	-6.90 (5.96)	3.48 (3.35)	11.01* (6.61)
cluster1	-0.39 (0.44)	0.63 (0.57)	-0.27 (0.59)	2.13** (0.91)	3.48*** (0.54)	3.79*** (0.71)
cluster2	0.74** (0.33)	1.22*** (0.44)	1.10*** (0.38)			
info1_adopt		-2.29* (1.23)				
info1_prod		0.013 (0.040)				
info2_adopt			-0.59 (0.90)			4.48** (2.07)
info2_prod			-0.0012 (0.018)			0.079 (0.11)

***, **, * denote significant as 1%, 5% and 10% level. All standard errors are clustered as individual level.

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.

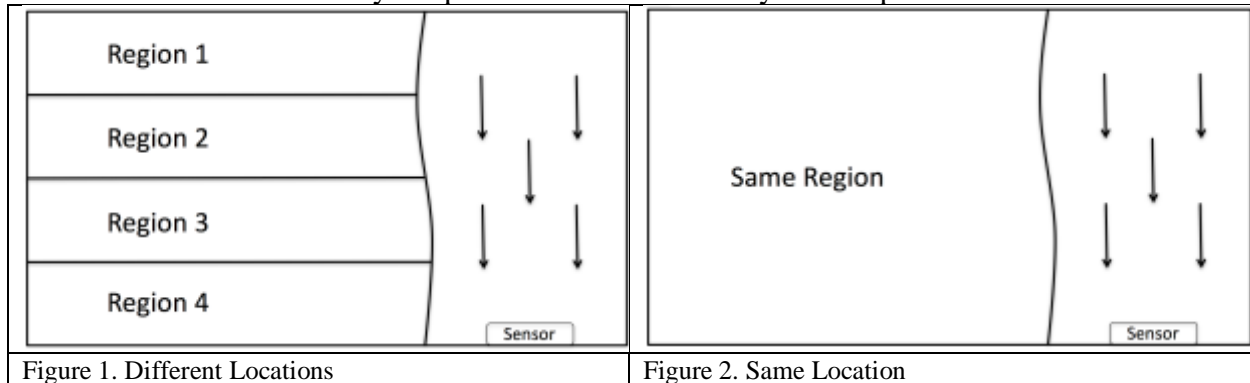
Production and Production Income: Each business owner produces output that creates **Production Income**. Production income only depends on how much is produced. The more a firm produces, the more production income the firm will get.

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.

Location: The firms may either be located in the same location or at different locations along a river. As shown in Figure 1, 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 Figure 2, 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.

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.

Medium

Not Adopt Adopt

0 /100

Medium

Not Adopt Adopt

0 /100

Medium

Not Adopt Adopt

0 /100

Medium

Not Adopt Adopt

0 /100

Medium

Not Adopt Adopt

0 /100

Medium

Not Adopt Adopt

0 /100

Medium

Not Adopt Adopt

0 /100

Medium

Not Adopt Adopt

0 /100

Note: Firms' sizes are the same;
Firms' locations are the same.

Sensor

Calculate

	Not Adopt	Adopt
Your Pollution	0	0
Total Pollution	0	0
Your Firm Profit	0	0

Now Make Your Actual Decisions

Your Firm

Medium

Location: Same Capacity: 100

Not Adopt Adopt

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.

Production	Your Firm Pollution									
	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.

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 Technology	Everyone else Production	Your Production	Your Technology	Your Profit
Not Adopt	80	50	Not Adopt	
Not Adopt	80	50	Adopt	
Not Adopt	80	80	Not Adopt	
Not Adopt	80	80	Adopt	
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 \leq 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 \leq 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.

The Department of Applied Economics and Statistics
College of Agriculture and Natural Resources
University of Delaware

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