

**TESTING POLICIES FOR DRINKING WATER UTILITIES TO REDUCE NON-
POINT SOURCE POLLUTION UNDER CLIMATE VARIABILITY**

by

Linda Grand

A thesis submitted to the Faculty of the University of Delaware in partial
fulfillment of the requirements for the degree of Master of Science in Agricultural &
Resources Economics

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ABSTRACT

This research will focus on the challenges faced by drinking water utilities due to extreme weather events. The higher occurrence of extreme weather events due to climate change is expected to lead to increased non-point source pollution from agricultural land. Using experiments with students we study behavioral responses towards various policies that can reduce non-point source pollution. Specifically, we study responses toward ambient (output-based) versus targeted (input-based) subsidies to improve water quality under various weather scenarios. We find behavior changes with the type of subsidy offered due to differences in risk allocation. Under ambient policy, the risk is shared with the entire group while targeted policies involve individual risk. People that are risk-averse tend to prefer input-based policies more because they are given perfect information. Our results suggest both ambient and targeted subsidies work to improve social welfare and decrease pollution. We find that input-based subsidies, that could be implemented with real time sensing technology, are best to minimize the economic and social cost to the drinking water utility. In addition, the results of the experiment show that as weather variability increases and there is a greater likelihood of extreme events, both policies become more effective, resulting in lesser pollution.

Key Words: Nonpoint source pollution, Laboratory economic experiment, Extreme Weather

Chapter 1

INTRODUCTION

According to the EPA, one of the largest sources of water quality impairment results from agricultural and other non-point source (NPS) pollutants (U.S. Environmental Protection Agency). To reach federal water quality standards in the Clean Water Act will require new policies that focus on mitigating non-point source pollution from agriculture and other sources. Scientists are concerned that a climate change-related increase in extreme weather events will result in higher levels of dissolved organic carbon (DOC) in water. Increased DOC combined with chlorine used to treat bacteria at drinking water utilities (DWUs) can lead to increased levels of cancer-causing trihalomethanes such as chloroform in municipal drinking water (Delpa et al. 2009).

The expense and difficulty of monitoring NPS pollution makes its regulation problematic. Early work in NPS pollution regulation focused on ambient tax/subsidy mechanisms to achieve an exogenous pollution target corresponding to socially optimal pollution levels (Xepapadeas 1992, Cabe & Herriges 1992, Xepapadeas 1995, Horan et al. 1998, Segerson 1988 etc.). Ambient policies are based on the total observed pollution concentration. These have attractive theoretical properties, and recent economic experiments have found them to be effective in achieving the target under a fairly broad variety of conditions (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; Suter et al. 2008). Ambient mechanisms are output-based mechanisms because the transfers (a tax or subsidy to the producer) are based on the observed concentration of a byproduct of producers' output decisions. In contrast, most current water quality programs used in practice are voluntary and offer input-based

mechanisms that subsidize land use and production practices. Such as conservation easements and best management practices (BMPs). Output-based mechanisms focus on the amount of pollution resulting from production. While input-based mechanisms focus on the amount of production or inputs such as fertilizer and practices used during production. This research focuses on how DWUs are impacted by extreme weather events and how the risk allocation implied by mechanism structure affect the efficiency of NPS pollution regulations. Under ambient policy, the risk of getting no subsidy or a lower subsidy is shared with the entire group while targeted policies involve individual risk. People that are risk-averse tend to like the input-based policies more because they are given perfect information. In addition, as extreme weather events increase, the risk of increasing pollution and getting a lower subsidy increases. Laboratory-based economic experiments test ambient output-based and targeted input-based policies in reducing NPS pollution under various weather scenarios. In the experiments we assume the regulator is risk neutral. We are studying the risk-aversion of the producers, and find that producers tend to be more risk-averse when there is a greater likelihood of extreme weather events.

We study the behavioral response towards output-based ambient versus input-based targeted subsidies to improve water quality at the point of intake at a DWU facility. Ambient subsidies are based on downstream damage, while targeted policies subsidize reductions in individual production. This research aims to learn how to best minimize potential social damages from NPS water quality impairment by examining the performance of institutional arrangements in the context of changes in weather variability. Extreme weather events increase the concentration of NPS contaminants leading to a significant decrease in water quality. Ultimately we are interested in classifying strategies to understand the interaction of mechanism structure, risk sharing, and strategic rent-seeking behavior to improve the design of NPS pollution regulations. This research will add to the literature by comparing the effectiveness of ambient subsidies versus targeted subsidies of NPS pollution under various weather scenarios. In

addition, this research adds to the literature on NPS pollution, by analyzing the increased risk when there is a greater likelihood of extreme weather events. Currently, better water sensor technology with real time sensing capabilities is being developed. This research shows how real time sensing could improve water quality and social welfare especially under extreme weather events. We find that as extreme weather events increase, targeted subsidies that could be implemented with real time sensing technology increases in effectiveness. Effectiveness is measured as the mechanism's ability to result in socially optimal pollution levels.

The experimental design involves six homogenous firms producing the same good in different locations along a river. However, there are no spatial differences influencing marginal damage. The experiments implement two subsidy policies: an ambient subsidy policy, and a targeted input-based subsidy under three different weather scenarios. The homogenous firms represent farmers and we are studying how weather is likely to impact farmers' decisions.

Based on the results of the experiments we find that having a policy (either ambient or targeted subsidy) increases social welfare by approximately 38% compared to a realm without any policies in place. Even though both policies are efficient, our research suggests targeted subsidies are significantly more effective than ambient subsidies at reducing pollution and increasing social welfare. Our research shows that targeted input subsidies become more effective as the likelihood of extreme events increase. Targeted policies could be implemented with sensors that detect the amount of pollution entering a stream from a farm.

Chapter 2

BACKGROUND/MOTIVATION

Human activities and climate change may decrease surface water quality (Delpa et al. 2009). As temperature increases, the amount of dissolved organic matter, and other pollutants will rise. Amounts of organic material such as DOC in water might increase from drought-rewetting cycles that enhance decomposition and flush the matter into local waterways (Evans et al. 2005). DOC increases have been seen in Northern Europe, Central Europe, and Northern America (Evans et al. 2005, Monteith et al. 2007, Worrall et al. 2004 and, Hejzlar et al. 2003). The combination of high levels of DOC in the water and chlorine used at DWUs can lead to the formation of cancer causing chemicals referred to as trihalomethanes. Heavy rains lead to high levels of turbidity and organic matter found in river waters which cause deterioration in treatment performance (Delpa et al. 2009). Heavy rainfalls will not only increase DOC but will also increase the amounts of pesticides that enter streams.

Due to climate change, DWUs will be financially affected by changes in quantity and timing of annual runoff, saltwater intrusion into groundwater sources, changes in temperature, increased sea levels, and increased extreme events. As warmer temperatures cause surface water to evaporate more readily, some regions will receive more annual runoff and others less (Rayburn et al. 2008). Precipitation variability will increase due to reduced in-stream flows, snowpack decreasing earlier in the season, more intense snowmelt, and reduced aquifer recharge. Due to these changes in runoff, DWUs need to pay for additional water supply and management options (AMWA-NACWA 2009). Changes in the timing of runoff increase variability in the amount of water DWUs can capture in current reservoirs. Seawater intrusion will lead to the contamination of

aquifers, decreasing the availability of drinking water in coastal regions. Changes in temperature could lead to increases in disinfection by-products (DBPs) and the probability of algal blooms. Climate change will lead to an increase in extreme events such as flooding, droughts, more intense tropical storms, and wildfires that greatly impact DWUs. Increased flooding could lead to water storage problems, and damage such as pipe breaks (Rayburn et al 2008). Lower dissolved oxygen levels during droughts lead to microbial growth that results in color and odor issues.

The EPA estimates costs of \$300- 500 billion for infrastructure upgrade, renewal, and replacement programs for DWU and wastewater for 2007-2027 (AMWA-NACWA 2009). The net present value costs of climate change adaption for drinking water systems through 2050 is estimated to be \$362-692 billion. This estimate includes capital and operation and maintenance costs. DWUs have been implementing short- and long-term water conservation policies to reduce water demand or to reallocate water resources for the past 30 years. (Hughes and Leurig 2013). An example of a conservation technique is offering farmers financial incentives to irrigate less or to install best management practices (BMPs) that reduce nutrient flow. For instance, the Watershed Agricultural Council (WAC) with funding from the DEP and USDA in NY worked to decrease nutrient eutrophication in the Catskills by helping farmers implement BMPs. In 2011 the WAC helped implement 102 new BMPs on small and large farms such as fencing, animal waste storage, and conservation crop rotation (New York State Department of Environmental Conservation 2016). In addition, the City of Syracuse Department of Water created the Skaneateles Lake Watershed Agricultural Program (SLWAP). SLWAP helps farmers create environmental protection plans and then helps pay farmers to install management practices that reduce runoff (Miner et al. 2015). The Skaneateles lake watershed is 59 square miles and 48% of the land use in the area is by agriculture. Thanks to the SLWAP program in 2011 the Skaneateles lake was named the cleanest of the Finger lakes (Miner et al. 2015).

This research will add to the literature on climate change impacts on DWU. It will also contribute to literature focused on identifying policy mechanisms that efficiently abate non-point source pollution. Segerson (1988) present a theoretically optimal ambient tax/subsidy incentive mechanism. Under an ambient tax/subsidy regime, every polluter pays the same amount that amount is equivalent to the full marginal benefit of reduced ambient pollutant levels. This ambient tax/subsidy transfer is a linear function calculated from estimates of ambient pollution, abatement costs, and it is dependent on each individual's abatement. If agents pollute over a target, a tax equal to marginal damage is used as a penalty. If agents pollute under a target, agents are rewarded with a subsidy equal to marginal damage. An ambient tax or subsidy decreases the cost for a regulator when there is asymmetric information, and it gives firms the freedom to choose the least cost pollution abatement technique that ensures a set level of abatement at minimized costs.

A large number of laboratory experiments focused on non-point source pollution instruments have been built off of Segerson's theoretical work. Spraggon (2002) uses a laboratory experiment that finds that both an ambient tax/subsidy and an ambient tax are more efficient than other mechanisms such as a group fine. Building off Spraggon's work, Cochard et al. (2005) studied a NPS pollution problem with endogenous externalities. The experiment compared an input tax, an ambient tax/subsidy, an ambient tax and a group fine. Cochard et al. (2005) concluded that an ambient tax/subsidy is not the best policy since it decreases social welfare and is very unreliable compared to other instruments. An alternative to an ambient tax/subsidy is an input tax which is effective, but is expensive.

Suter et al. (2008) compared linear vs. non-linear ambient taxes and concluded that when communication is not allowed both mechanisms reach the social optimum. A linear tax follows Segerson's theoretical work where each firm is charged a constant marginal tax that is equal to marginal damages at the social optimum, while a non-linear

tax requires that each polluter pay a tax equal to total economic damages. Suter et al. (2009) compares homogenous and heterogeneous groups and concluded that an ambient tax mechanism lowers emissions levels significantly in both the homogeneous and heterogeneous settings. The homogenous pollution setting was composed of six firms with identical profit and emission functions (Suter et al. 2009). While the heterogeneous pollution setting was composed of three small firms, two medium firms, and one large firm. In the heterogeneous setting each firm had different profit and emission functions depending on their size. Suter shows that the distribution of firm sizes does have a significant impact on observed group decision-making, and that heterogeneity can generate both some relatively desirable outcomes as well as some undesirable outcomes. One undesirable outcome was that small firms can go bankrupt due to predatory actions by large firms.

Miao et al. (2016) shows that when there are spatial differences, increasing the frequency of ambient monitoring improves emissions reductions. Fooks et al. (2016) ran an economic experiment using “estimated” pollution source policy, an ambient exogenous targeted tax policy, and an exact information policy. Fooks et al. (2016) found that an increase in information under estimated and exact information actually lead to higher levels of pollution than under ambient information. This study used student and farmer participants and found no significant difference in the emissions decisions between the two groups. Our study uses a similar framework based on the work by Miao et al. (2016) and Fooks et al. (2016). We based the number of firms and parcels off the work by Miao et al. (2016) and Fooks et al. (2016). Palm-Forster et al. (2016) ran an economic experiment using ambient tax, and ambient subsidy mechanisms with and without individual assurances. Palm-Forster et al. (2016) found that both subsidy reduction mechanisms were as effective as an ambient tax mechanism in reducing emissions. Butler et al. (2016) used mascots and data visualizations in an economic experiment and found that when there is attachment to a mascot participants are more

likely to have “green behavior” and reduce pollution. Based on past studies, the regulator implements both ambient and targeted policies based on information from high-tech sensors in our experiment (Miao et al., 2016; Fooks et al. 2016; Butler et al. 2016.). The regulator finds the amount of ambient damage from a downstream sensor and implements ambient policies. Similarly, the regulator implements targeted input-based subsidies based off data from sensors near each parcel reporting pollution from that particular parcel. Many 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).

Chapter 3

EXPERIMENTAL DESIGN

In this experiment, participants assume the role of business owners making production decisions on parcels along a river. Firms produce a good which generates income. Firms' production generates pollution proportional to production which enters the river. In our research, firms represent farmers' decisions', however participants were only told they are business owners. University of Delaware undergraduate students were recruited to participate in the experiment. Participants had the opportunity to earn more money based on the decisions that they made in the experiment. Experimental earnings were \$30, on average. Past studies have used students and farmers as participants and found there were no significant differences between pollution decisions (Fooks et al. 2016). The experiment was framed in a way in which the pollution does not affect the participants, however it may cause damage to a hypothetical downstream user external to the experiment. The amount of downstream damage depends on the pollution released by all six parcels and the weather. The firms receive a subsidy from a regulator either based on the measured ambient pollution or how much they individually produced. In our research, the regulator knows the amount of individual production from a sensor near the parcel; however, we did not include any language about sensors in the experiment. In our experiment, there are no spatial differences among firms; therefore, we believed adding language about sensors could increase confusion. Instead, participants were told that targeted subsidies were based on their amount of individual production. The experiment has six treatments that vary weather variability and type of subsidy. To discover what would happen under a no policy regime we ran one session with weather variability, but there was no subsidy policy. This session was used as a baseline. The experimental

design is further explained in Table 1. To best understand the setting, we first describe the model followed by the details of the treatments and experiment set up.

3.1 Model

In each round, participants make individual production decisions that generate private income and damage. Based off the model used in Spraggon (2002), our research assumes we have N producers and each individual i who produces output x_i and receives income $I_i(x_i)$. The private income function takes the form

$$I_i(x_i) = \gamma_0 - \gamma_1(\gamma_2 - x_i)^2 \quad (1)$$

Total output from production across all producers is the sum of all individual production:

$$X = \sum_{i=1}^N x_i, \quad (2)$$

Total Income is the sum of all individual income:

$$I = \sum_{i=1}^N I_i(x_i). \quad (3)$$

Since producers are identical, production will be symmetric at the equilibrium so we can use total production in the income function to express total income as a function of total production. Then, the total cost of abatement borne by the producer is:

$$TC(x) = I(x_{max}) - I(x) = I(x_{max}) - \gamma_0 + \gamma_1(\gamma_2 - x_i)^2. \quad (4)$$

The producers' marginal cost of abatement is:

$$MC(X) = -2\gamma_1\gamma_2 + 2\gamma_1X \quad (5)$$

In addition to income to the producers, production also imposes a cost on downstream external users. This damage is a quadratic function of total production:

$$TD(X) = \delta(\beta_0 + \beta_1X + \beta_2X^2) \quad (6)$$

The parameterization of this function is based on predicted weather scenarios and cost data from DWUs. We vary these across treatments, as discussed in depth in section 3.3.

The total benefit to the downstream users of abatement below the producers' maximum production at the unregulated optimum is:

$$TB(X) = TD(X_{max}) - TD(X) \quad (7)$$

The corresponding marginal benefit of abatement is

$$MB(X) = -\beta_1 - 2\beta_2X \quad (8)$$

We assume the regulator is risk neutral and wants to maximize net social welfare by equating marginal costs and benefits, which leads to optimal total production across all six firms.

$$X^* = \frac{\gamma_1\gamma_2 - \beta_1/2}{\gamma_1 + \beta_1} \quad (9)$$

Each individual producer's share of production is:

$$x_i^* = X^*/N \quad (10)$$

Under this form on the instrument, X^* is an equilibrium if producers believe that total production will be less than or equal to the subsidy, however X_{max} will be the equilibrium if producers think that X^* is unobtainable.

3.2 Treatments

Through this experiment we ran six treatments that vary weather variability and type of subsidy (Table 3). This experiment only looks at subsidies there are no tax policies tested. We will define weather variability based on the probability of weather conditions. There are four levels of weather variability: 1) no weather variation 2) standard, 3) high, and 4) very high. Each level of variability is associated with probability of three types of weather conditions: a) normal, b) severe, and c) extreme. The amount of damage that reaches the downstream user differs depending on weather condition. Damage functions were created for each type of weather condition. These functions were created based off models depicting costs to DWUs under various weather conditions (AMWA-NACWA 2009). In addition, to simplify the design we made the marginal damage at the target equal across treatments. The parameters for these functions are shown in Table 4. The Downstream damage functions are quadratic functions of total production and the impact of total production on damage is shown in Figure 1. As production increases past the social optimal additional production significantly increases downstream damage.

Extreme Weather Damage Function:

$$TD = \delta * (\beta_{0H} + \beta_{1H} * Total Production + \beta_{2H} * Total Production^2) \quad (11)$$

Severe Weather Damage Function:

$$TD = \delta * (\beta_{0M} + \beta_{1M} * Total Production + \beta_{2M} * Total Production^2) \quad (12)$$

Normal Weather Damage Function:

$$TD = \delta * (\beta_{0L} + \beta_{1L} * Total Production + \beta_{2L} * Total Production^2) \quad (13)$$

Standard weather variability has an 80% chance of normal weather, 10% chance of more severe weather, and 10% chance of extreme weather. High weather variability is associated with a 50% chance of normal weather, 40% chance of severe weather, and 10% chance of extreme weather. Very high weather variability is associated with a 50% chance of normal weather, 10% chance of severe weather, and 40% chance of extreme weather. The weather variabilities are depicted in Figure 2.

Ambient subsidies are calculated using the total downstream damage from all users. With an ambient subsidy everyone in the same group receives the same payment. If the measured damage level is greater than or equal to the target, there will be no payment. The target damages TD_j^* are calculated for total group production, $X^* = 144$. This total group production target is derived from equating MD with MC across weather conditions (j) shown in Figure 3. For instance, under normal weather conditions, if total group production is 120 which results in damage of \$44.35 which is less than the target damage of \$53.54, then everyone will receive a subsidy of \$22.55.

Below is the calculation used to determine the ambient subsidy parameters for the equation can be found in Table 4.

From Spraggon (2002), an ambient subsidy for each individual takes the form of:

$$S(X) = \begin{cases} 0 & \text{if } TD > TD_j^* \\ MD(TD) * (TD - TD_j^*) + b_j & \text{if } TD \leq TD_j^* \end{cases} \quad (14)$$

Where MD is marginal damage, TD is total damage and b is a bonus. Following, Spraggon (2002) a bonus is included to induce compliance to produce at the target instead of at the maximum.

3.2.1 Calculating Targeted Input-based Subsidies

Targeted input-based subsidies are calculated based on the amount of individual production levels. Individual production is known by a regulator due to a sensor next to each parcel. The payment could be different for different members of the group. If individual production is greater than or equal to the target, there will be no payment. The individual target production is $x^* = 24$. The individual target production is calculated from the total group production target, $X^* = 144$. This is derived from equating MD with MC across weather conditions as shown in Figure 3.

Below is the calculation used to determine the targeted subsidy. Parameters for the equation can be found in Table 4:

$$S_i(X) = \begin{cases} 0 & \text{if } x > x^* \\ MD(TD) * (x - x^*) + b_i & \text{if } x \leq x^* \end{cases} \quad (15)$$

Where MD is marginal damage x is individual production and b is a bonus. Following, Spraggon (2002) a bonus is included to induce compliance to produce at the target instead of at the maximum.

Profits will be calculated as individual income plus the subsidy

$$P_i(x_i) = \gamma_0 - \gamma_1(\gamma_2 - x_i)^2 + S_i(X) \quad (16)$$

Participants choose a level of production between 0 and 50. Based on the parameters in Table 4, this would correspond to income ranging from \$16.25 to \$35.

3.3 Experiment Protocol

Six sessions of the experiment were run using 120 participants at the University of Delaware Center for Experimental and Applied Economics. Undergraduate students were recruited to participate in the experiment through an email announcement. The experiment was run on computers using the computer interface Willow, and a python framework. Earnings were made as experimental dollars, then converted into US dollars. Experimental dollars were converted into actual US dollars at a rate of one US dollar per 40 experimental dollars. Session length was between 1.5 to 2 hours. Communication was not allowed in these experiments.

Each participant sat a desk with dividers in groups of six around the room. The dividers ensured that participants' decisions were confidential. The room was set up with 24 desks, separated in four groups of six desks. Participants were randomly assigned to a computer by drawing a number out of a bag before entering the laboratory.

Each session had 12-24 participants randomly organized into independent stream groups composed of six participants. Participants were unaware of who were the members of their stream group. In each treatment, each individual participant was assigned to one of the six parcels. Parcel locations and stream groups were randomly mixed between treatments. However, all the parcels are homogeneous and damages do not vary by spatial location. We controlled for potential order effects by varying the treatment orders in each session. Each treatment consisted of five decision rounds. In each round, participants make a confidential production decision and learn the subsidy they face, the weather condition and their total profit from the round. Rounds are independent, meaning that production decisions and downstream damage during one round do not affect future rounds. The session begins with participants reading and signing the consent form and then spending approximately 15 minutes reading the

instructions that explain how production decisions impact their profit, the types of subsidies, and the different weather variation scenarios (see Appendix A). To help participants understand how the subsidies vary dependent on weather scenario they are given time to use a special calculator on the computer which allows them to enter hypothetical production decisions for each parcel and then see potential subsidies under each weather scenario. The calculations change with each treatment. The written instructions include a training on the use of the calculator and require that participants use the calculator to identify the possible subsidies for different levels of production. The experiment administrators make sure that participants know how to correctly operate and understand the calculator. There are two sets of practice rounds which follow the no weather variation treatment. The first three practice rounds have the ambient subsidy treatment and the last three practice rounds have the targeted subsidy treatment. Additional written instructions and an oral presentation are provided to the participants before each new treatment to explain the weather variation and policy type.

3.4 Testable Hypotheses

The series of hypotheses tested in this research are summarized in Table 2. The first hypothesis is that climate variability does not impact the effectiveness of the subsidy mechanism. Effectiveness is measured as the mechanism's ability to result in socially optimal damage levels. As mentioned above, the weather conditions affect the damage functions. We want to see if the mechanisms work differently under varying weather conditions.

The second hypothesis is that changes in risk do not impact production under targeted subsidies. As weather variation increases, the firm takes on added risk in the case of an ambient output-based policy; however, with a targeted input-based policy the regulator takes on this risk. Under a targeted policy, there is perfect information. The

regulator knows how much the firm is producing from a sensor near the parcel, and the firm knows the target production. We expect to see only ambient interactions with weather significantly impacting damage production and welfare.

The third hypothesis is that ambient output-based and targeted input-based policies have the same impact on total downstream damage. We want to test to see which mechanism is more effective in reducing total damage to the social optimal level.

The fourth hypothesis is that total production from a stream group does not change in response to normal weather, severe weather events, and extreme weather events. Extreme weather events are long lasting droughts or floods, while severe weather events are more short term impacts. Each weather condition has a different damage equation based off of real weather data. We are testing to see if participant's behavior is influenced by these varying damage functions. We want to see if severe and extreme weather have a different impact on total production then normal weather.

The fifth hypothesis is that ambient output-based and targeted input-based policies have the same impact on total production. We want to test to see which mechanism is more effective in reducing total production to the social optimal level.

The sixth hypothesis is that ambient and targeted subsidies have the same impact on social welfare. We want to test to see which mechanism is more effective in increasing social welfare close to the social optimal level. Social welfare is measured as total income of all firms minus downstream damage.

Chapter 4

RESULTS

We find that well-designed policy can dramatically improve water quality and increase social welfare levels closer to the optimal level. Our first hypothesis asks if the effectiveness of the subsidy mechanism changes under different weather conditions. To test this hypothesis, we estimate the equation below:

$$\begin{aligned} \text{Damage} = & c + \partial_1 \text{Standard} + \partial_2 \text{High} + \partial_3 \text{Very High} + \partial_4 \text{Ambient} + \partial_5 \text{Ambient} \\ & * \text{Standard} + \partial_6 \text{Ambient} * \text{High} + \partial_7 \text{Ambient} * \text{Very High} + \partial_8 \text{Targeted} \\ & + \partial_9 \text{Targeted} * \text{Standard} + \partial_{10} \text{Targeted} * \text{High} + \partial_{11} \text{Targeted} \\ & * \text{Very High} + \epsilon \end{aligned} \quad (17)$$

We are testing the null hypothesis:

$$H_0: \partial_4 = \partial_5 = \partial_6 = \partial_7 = \partial_8 = \partial_9 = \partial_{10} = \partial_{11}$$

In equation 17, standard, high, and very high refer to the weather variability. We expect both ambient and targeted policies to decrease damage compared to the baseline of no policy and no weather variation. We are interested in seeing if the effectiveness of the policy changes under different weather variations. Therefore, we include in our equation the interacting terms of policy and weather variation.

Results show that either policy works to decrease damage compared to no policy in place. Table 5 shows that with a targeted policy, average damage across all weather variations was \$35.89, and with an ambient policy, the average damage was \$49.21. Having no policy in place results in an average damage of \$123.84. With a policy in place, either ambient or targeted, downstream damage decreased as weather variation

increased. In Table 6, data is pooled from both policies, ambient and targeted, to examine downstream damage when a policy is in place. Table 6 shows how damage under very high weather variation is \$29.88 which is 41% lower than if there is no weather variation where damage is \$50.67. The average subsidy for very high weather variation was \$23.90 while the average subsidy for no weather variation was \$16.37.

Supporting our first hypothesis we find that as weather variation increases, subsidy policies, either ambient or targeted, become more effective at decreasing damage. Figure 4 shows how downstream damage is 33% less when we have very high weather variation versus standard weather variation under a policy regime. Remember, very high weather variability is associated with 40% chance of extreme weather. To clarify under a policy regime means there was either a targeted or ambient subsidy policy. Since we have many observations from the same individuals a random-effects models was appropriate to analyze damage, production, and welfare. Table 7 shows three log-linear models we estimated all of which have a baseline of no policy and no weather variation. Log-linear models were used so as to be able to compare the impacts by percentage amounts. Model A₁ has the dependent variable $\log(\text{damage})$, explaining how the independent variables impact the log of the amount of measured downstream damage. We look at the independent variables: standard weather variation, higher weather variation, policy, and the interactions of policy with different weather variations. The independent variable policy represents if there was a policy in place either ambient or targeted, and the variable higher weather variation represents if there was high weather variation or very high weather variation. In Model A₁ we see that having a policy (either ambient or targeted) in place significantly reduces downstream damage by approximately 63%. We also see that when we have the interaction of policy and higher weather variation the amount of downstream damage, which is a function of production, decreases significantly.

Table 8 shows three additional models that include targeted and ambient policies as independent variables and their interaction with weather variations. All three models

have a baseline of no policy and no weather variation. Model A₂ has the dependent variable $\log(\text{damage})$, explaining how the independent variables impact the log of the amount of measured downstream damage. In Model A₂ we see that both ambient and targeted policies significantly reduce damage compared to the baseline of no policy and no weather variation. Model A₂ also shows that downstream damage decreases with an increase in the likelihood of extreme events. High weather variation significantly reduces damage compared to no weather variation. In addition, results show that when we have the interaction of targeted subsidies and increased weather variation, the subsidy becomes more effective in decreasing downstream damage.

Our second hypothesis is that changes in risk due to increase in extreme weather does not impact downstream damage under targeted policies. As weather variation increases with an ambient policy, the firm takes on the added risk of more damage due to extreme weather events; however, with a targeted policy the regulator takes on this risk. We expect to see only ambient interactions with weather significantly impacting damage. However, we reject this null hypothesis and see significant interactions with weather impacting damage for both targeted and ambient policies (See Table 8 Model A₂).

Our third hypothesis is that ambient and targeted subsidies have the same impact on reducing downstream damage. To test this, we use equation 17 and focus on the null hypothesis:

$$H_0: \partial_4 = \partial_5$$

We reject the null hypothesis and find that there is a significant difference between the impact of the two policies. The average damage from targeted policies is \$35.89 while the average downstream damage when there is an ambient policy is \$49.21. We performed a two-tailed paired t-test and found significant differences between targeted and ambient policies mean damage ($p=0.000$). In addition, we performed a chi-squared

test and found that the coefficients for targeted and ambient in Table 8 Model A₂ are significantly different. Both policies work to decrease downstream damage, however targeted input-based policies are more effective at decreasing pollution compared to ambient output-based policies. Targeted policies are probably more effective because firms know how much they are producing and the possible subsidies offered to them for that level of production for various weather scenarios. In addition, firms know the regulator has exact information on their production due to a sensor near their parcel. This knowledge that the regulator can pin-point pollution directly to them influences the firms to reduce production resulting in less downstream damage.

Our fourth hypothesis looks to see if total production decisions change in response to different weather conditions. To test this, we estimate the equation below:

$$Total\ Production = c + \partial_0 None + \partial_1 Standard + \partial_2 High + \partial_3 Very\ High + \epsilon \quad (18)$$

We are testing the null hypothesis:

$$H_0: \partial_0 = \partial_1 = \partial_2 = \partial_3 = 0$$

In Table 7 model B₁ we see that having a policy in place either ambient or targeted significantly reduces total production. On average, having an ambient or targeted subsidy policy reduces total production approximately 52% compared to the baseline of no policy and no weather variation. Model B₁ has the dependent variable log(total production) explaining how the independent variables impact the log of the amount of total production from all six parcels.

In Table 8 model B₂, we see that both ambient and targeted policies significantly reduce total production compared to the baseline of no policy and no weather variation. Model B₂ has the dependent variable log(total production) explaining how the independent variables impact the log of the amount of total production. Model B₂ shows how both policies are effective in reducing total production.

Supporting our fourth hypothesis we find that weather does not impact total production. Generally, we find that total production levels decrease as weather variability increase but it is not significant. As shown in model B₂ standard, high and very high weather variations are not significant in reducing production compared to the baseline of no weather variation.

We reject our fifth hypothesis that targeted and ambient policies have the same impact on total production. We find that targeted policies that focus on inputs are more effective than ambient policies that are output-based. Ambient policies result in individuals on average producing 23 and an average total production of 143.28, while targeted policies result in an average individual production of 19 and an average total production of 114. Recall that the social optimal level is reached when total production equals 144. We performed a two-tailed paired t-test and found that the results showed statistically significant differences in average total production between having an ambient policy and a targeted policy ($p=0.000$). Targeted policies are able to be implemented by having a sensor near each parcel. Targeted policies work better because there is no asymmetric information.

Table 9 shows that when using a subsidy mechanism (either targeted or ambient) average welfare is 38% higher than if there is no policy in place. Welfare is measured as income minus downstream damage. Figure 5 shows how with a policy in place the regulator can get much closer to the social optimal level of welfare under various weather variations. We performed a two-tailed paired t-test for differences in the mean welfare with and without policy interventions. The results showed statistically significant differences between having a policy in place and no policy ($p=0.000$). Model C₁ in Table 7 has the dependent variable $\log(\text{welfare})$ explaining how the independent variables impact the log of the amount of total social welfare. In Model C₁ we see that both ambient and targeted policies significantly increase social welfare compared to the baseline of no policy and no weather variation.

We reject our sixth hypothesis that ambient and targeted policies have the same impact on social welfare and find that targeted policies are more effective at increasing social welfare. We ran a chi-squared test comparing the coefficients for ambient (.546) and targeted (.577) and find a significant difference between the two ($p=.05$). We also see the similar trend where high weather variation results in significantly better outcomes.

Chapter 5

CONCLUSION

In this paper, we use an economic experiment to test participants' behavioral responses towards various incentives to reduce nonpoint source pollution. We specifically investigate the effectiveness of ambient (output-based) and targeted (input-based) subsidies under various weather scenarios. The results from our experiment show that both ambient and targeted policies work to reduce pollution and improve social welfare. We also find that when there is a greater likelihood of extreme weather events, targeted policies become more effective in reducing pollution. As the probability of extreme and severe weather increases, the risk of not receiving a subsidy due to high levels of pollution increases. We find that under high weather variability situations, participants are risk-averse. Participants react to this additional weather risk by reducing production in order to increase the amount of subsidy rewarded.

Drinking water utilities can subsidize upstream users to improve water quality. The results suggest that DWUs may prefer to implement targeted (input-based) policies to reduce pollution. Our research found that targeted subsidies are more effective than ambient subsidies at reducing production, reducing pollution, and increasing social welfare compared to ambient subsidies. Under ambient policies the risk of getting no subsidy is shared with the entire group while targeted policies involve individual risk. Currently targeted subsidies are difficult to implement. To measure individual contribution to total pollution, one would need advanced sensor technology. Targeted subsidies make NPS pollution more similar to point-source pollution. Our research shows it will be easier to reach pollution targets with more advanced sensors that predict

individual activity. There is a political need for more research and development to be done to achieve real time sensing at a micro level.

In addition, the results offer the regulator insight that both types of subsidies work to reduce pollution, reduce production, and increase social welfare especially under extreme weather conditions. To enhance our ability to reach general conclusions related to the relationship between policy type and water quality improvements, several of our assumptions could be modified in future research. For instance, future research could add a dimension where there are spatial differences in the relationship between production and ambient damage. Further research could also be done with farmers as participants. In addition, research could be done to examine subsidies on a watershed scale by increasing the number of firms and amount of land. In our study, we assume all firms are homogenous. Future research can relax this assumption and study heterogeneous agents by differentiating the size and capacity of firms. Another element that could be examined is to include communication between participants.

TABLES

Table 1. Drinking Water Utility Game Experimental Design

Participants	120 student participants
Session Setup	12-24 participants split into groups of 6
Participant Decision	Production level on their parcel (within a given range).
Key Behavioral Measures	i. Individual production by treatment relative to a baseline
Policies	i. Ambient Subsidy ii. Targeted Subsidy (perfect information)
Time Structure	7 Parts, 5 Rounds/Part
Average Time	2-hours
Average Earnings	\$30

Table 2. Hypotheses

Hypotheses	Result
1) Climate variability does not impact the effectiveness of the subsidy.	Reject - As weather variation increases subsidies become more effective (Table 7 Model A ₁ ; Table 8 Model A ₂)
2) Changes in risk do not impact damage under targeted policies.	Reject- Downstream damage decreases when there is interaction between weather variability and targeted policies (Table 8 Model A ₂)
3) Ambient and targeted subsidies have the same impact downstream damage.	Reject- Downstream damage is higher on average if there is a ambient policy instead of an targeted policy (Table 8 Model A ₂)
4) Total production does not change in response to different weather conditions.	Unable to Reject - Production decreases as weather variability increases but it is not statistically significant. (Table 7 Model B ₁ ; Table 8 Model B ₂)
5) Ambient and targeted subsidies have the same impact on total production.	Reject- Production decreases more on average from ambient policies instead of a targeted policy (Table 8 Model B ₂)
6) Ambient and targeted subsidies have the same impact on social welfare.	Reject- Social Welfare is higher on average if there is a targeted policy instead of an ambient policy (Table 8 Model C ₂)

Table 3. Treatment Conditions

Treatment	Policy	Weather Variation
<i>P</i>	Ambient	None
<i>P</i>	Targeted	None
<i>A</i>	Ambient	Standard
<i>B</i>	Targeted	Standard
<i>C</i>	Ambient	High
<i>D</i>	Targeted	High
<i>E</i>	Ambient	Very High
<i>F</i>	Targeted	Very High
<i>G</i>	Ambient	None
<i>H</i>	Targeted	None
<i>Treatment Order</i>	PPABCDEFHG PPBADCFEHG PPHGFEDCBA PPGHEFCBAB	

Table 4. Parameters for Equations

Parameters			
Weather Condition	β_{1L}	-1	
	β_{2L}	0.0018	
	β_{0L}	30	
	β_{1M}	-.5	
	β_{2M}	0.0032	
	β_{0M}	40	
	β_{1H}	-1	
	β_{2H}	0.0051	
	β_{0H}	50	
	δ	1	
Ambient Subsidies	b_N	Normal	18.52
	b_S	Severe	24.85
	b_E	Extreme	32.76
	$MD(TD^*)$		-.44
	TD^*_N	Normal	53.54
	TD^*_S	Severe	35.99
	TD^*_E	Extreme	11.56
Targeted Subsidies	b_N	Normal	18.52
	b_S	Severe	24.85
	b_E	Extreme	32.76
	$MD(TD^*)$		-.44
	x^*		24
Income	γ_0	35	
	γ_1	.0075	
	γ_2	50	

Table 5. Mean Production, Damage, and Welfare

	No Policy	Targeted	Ambient
Average Damage	\$123.84	\$35.89	\$49.21
Average Total Production	253.11	114.00	143.28
Average Welfare	78.75	130.44	124.10

Table 6. Mean Production and Damage and Subsidy under Policy Regimes

Weather Variation	None	Standard	High	Very High
Average Individual Production	22.15	21.91	21.27	20.69
Average Total Production	131.08	131.48	127.65	124.14
Average Damage	\$50.67	\$45.33	\$39.21	\$29.88
Average Subsidy Payment	\$16.37	\$18.73	\$20.97	\$23.90

Table 7. Random Effects Models on Downstream Damage, Total Production, and Social Welfare

	Model A₁	Model B₁	Model C₁
Dependent Variable	Log(Damage)	Log(Total Production)	Log(Welfare)
Standard Weather Variation	-.139 (.088)	-.084* (.050)	.152 (.081)
Higher Weather Variation	-.106 (.072)	-.062 (.041)	.141 (.100)
Policy	-1.00*** (.070)	-.728*** (.048)	.561*** (.081)
Policy X Standard Weather Variation	-1.64 (.134)	.081 (.068)	-.129 (.117)
Policy X Higher Weather Variation	-.699*** (.128)	.011 (.003)	-.047 (.094)
Treatment Round	.006 (4.87)	.011*** (.003)	-.013*** (.004)
Constant	4.87*** (.083)	5.55*** (.040)	4.26*** (.082)
Number of Observations	794	794	794
R ²	.3331	.6441	.5923
Shows significance at p<0.05 level *Shows significance at p<0.01, Standard errors in parenthesis			

Table 8. Extended Random Effects Models on Downstream Damage, Total Production, and Social Welfare

	Model A₂	Model B₂	Model C₂
Dependent Variable	Log(Damage)	Log(Total Production)	Log(Welfare)
Standard Weather Variation	-.140 (.088)	-.085 (.050)	.152 (.115)
High Weather Variation	-.154** (.077)	-.082 (.043)	.197** (.100)
Very High Weather Variation	-.060 (.077)	-.043 (.043)	.087 (.103)
Ambient Policy	-.905*** (.078)	-.627*** (.054)	.546*** (.082)
Targeted Policy	-1.11*** (.067)	-.828*** (.048)	.577*** (.082)
Ambient Policy X Standard Weather Variation	-.052 (.151)	.083 (.085)	-.162 (.122)
Ambient Policy X High Weather Variation	-.228 (.159)	.040 (.085)	-.139 (.105)
Ambient Policy X Very High Weather Variation	-.830*** (.251)	.001 (.077)	.023 (.112)
Targeted Policy X Standard Weather Variation	-.273 (.164)	.080 (.060)	-.096 (.116)
Targeted Policy X High Weather Variation	-.329** (.144)	.054 (.058)	-.124 (.101)
Targeted Policy X Very High Weather Variation	-1.40*** (.167)	-.048 (.072)	.049 (.105)
Treatment Round	.006 (4.87)	.012 (.003)	-.013** (.004)
Constant	4.87*** (.083)	5.55*** (.040)	4.26*** (.082)
Number of Observations	794	794	794
R ²	.4181	.7201	.6122

Shows significance at p<0.05 level *Shows significance at p<0.01, Standard errors in parenthesis

Table 9. Average Social Welfare

Average Social Welfare			
	Social Optimal	With Policy	No Policy
Average Welfare	134.97	127.29	78.75
No Weather Variation	126.04	119.77	99.52
Standard Weather Variation	131.99	123.81	101.57
High Weather Variation	137.26	128.66	104.02
Very High Weather Variation	144.59	137.00	108.06

FIGURES

Figure 1. Downstream Damage vs. Group Production under Different Weather Conditions

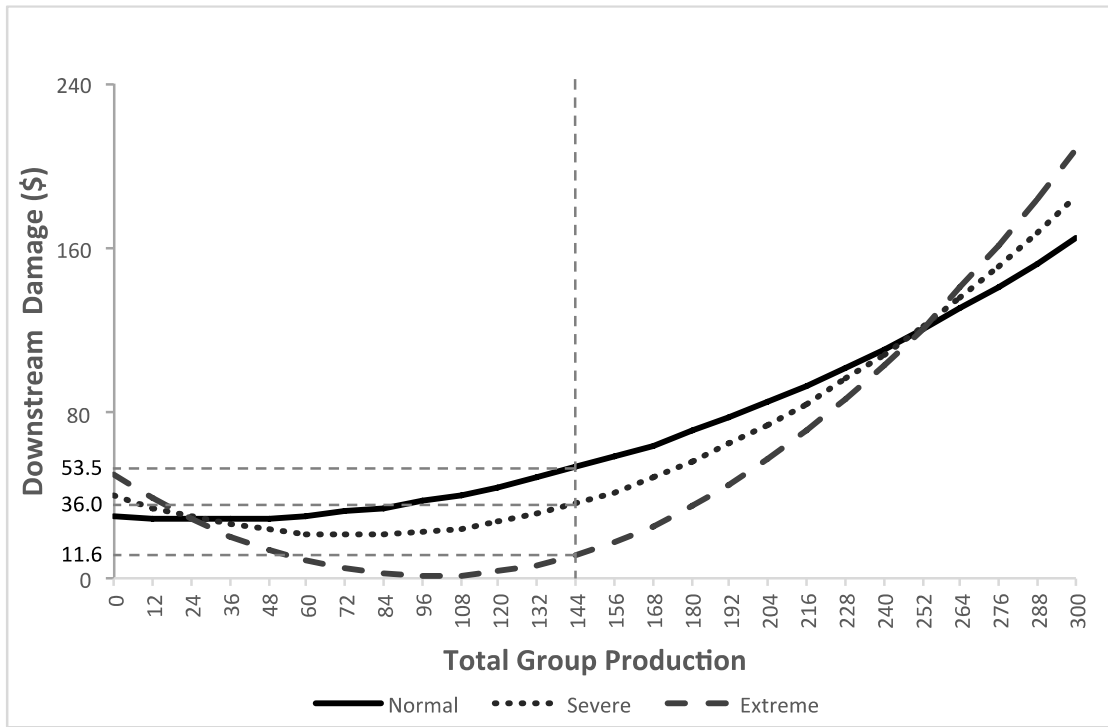


Figure 2:

Weather Variations

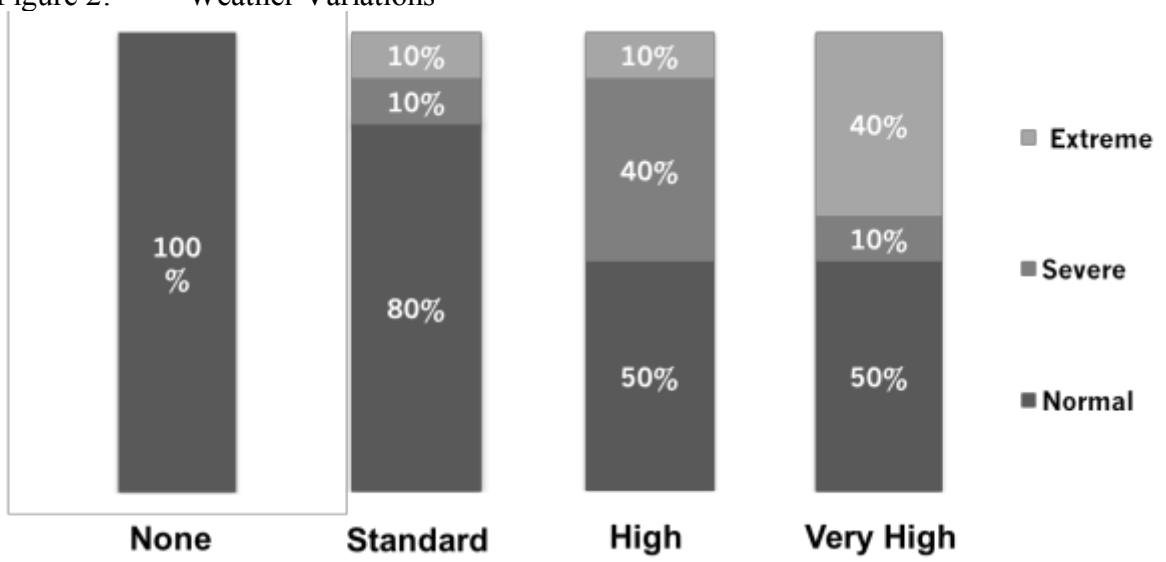


Figure 3. Marginal Benefit vs. Marginal Cost

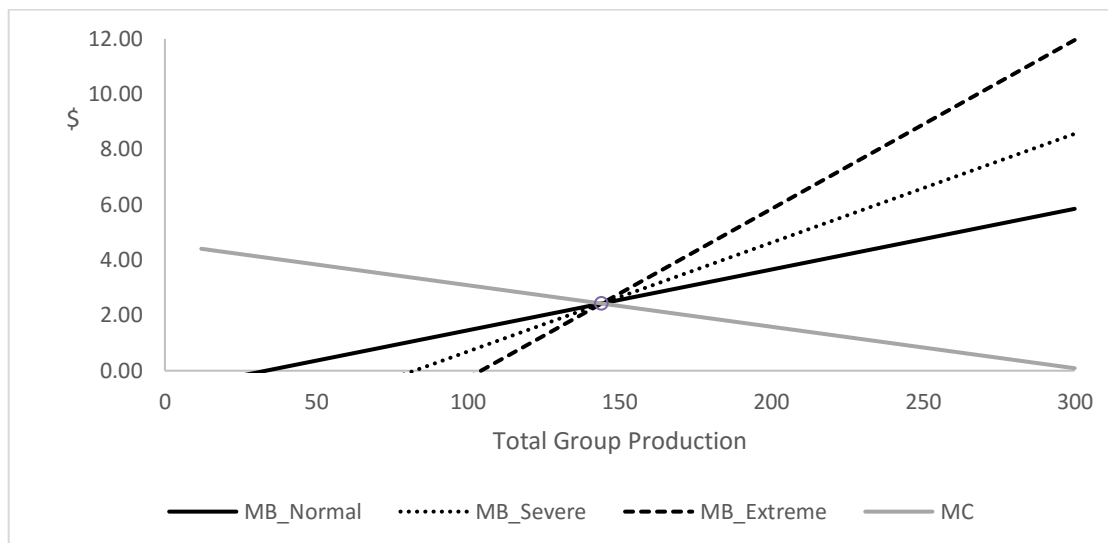


Figure 4. Downstream Damage under various Weather Variations under a Policy Regime

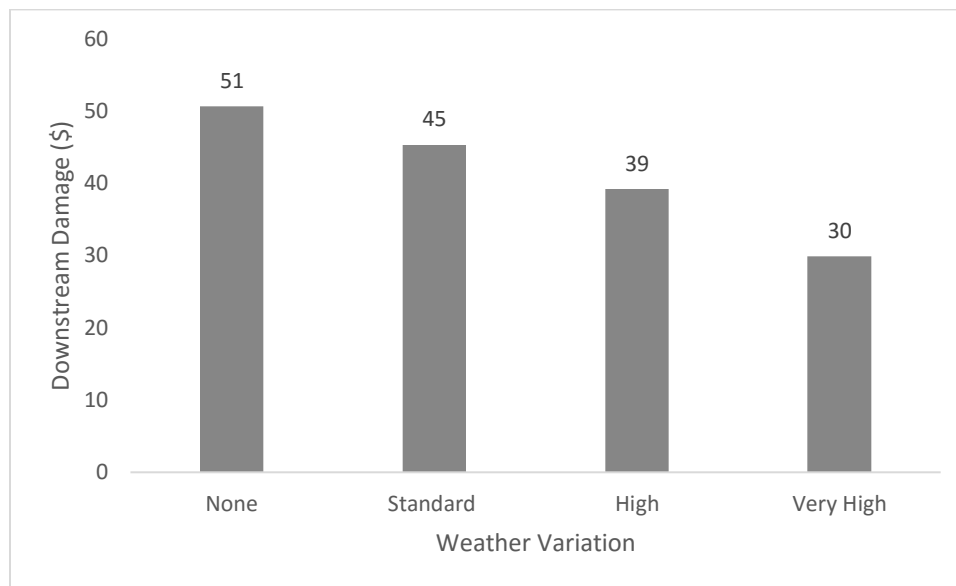
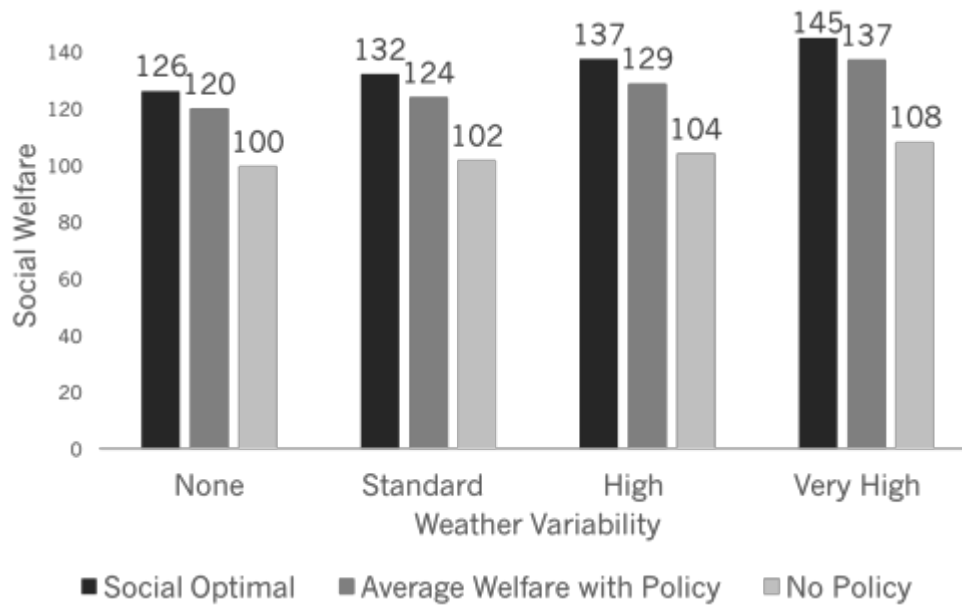


Figure 5: Average Social Welfare under different Weather Variations



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Appendix A

INSTRUCTIONS

Welcome to an experiment in decision-making. In the course of the experiment, you will have several opportunities to earn cash. Throughout the experiment, your earnings will be recorded as **experimental dollars**. At the end of this experiment, we will convert your experimental dollars into actual **US dollars** at a rate of one US dollar per 40 experimental dollars. This money will be given to you as you leave and it is yours to keep. The more experimental dollars you earn the more US dollars you will receive at the end of the experiment.

Please read these instructions carefully and do not communicate with any other participants during the experiment.

What you need to know to make decisions:

There are a number of parts in today's experiment. Each part will have five rounds. Each round is independent, meaning that decisions during one round do not affect future rounds. The only value that gets carried across rounds is your cumulative **profit**, which will be used to calculate your cash earnings at the end of the experiment.

In each part, you will be assigned to a group with five other people.

Each member of your group will be playing the role of a business owner who operates on a parcel of land along a river. The parcels are labeled Parcel 1 through 6, as displayed on the map in Figure 1.

Parcel 1 is the furthest upstream and Parcel 6 is the furthest downstream in the group. The parcel that you operate during each part will be indicated to you on your computer screen.

Your parcel and group will remain the same for each part of the experiment, but may change for different parts.

How to make decisions:

Each round, you must choose how much you want to produce on your parcel. This **production** level must be between 0 and 50 units. The more you produce the more revenue your business makes. **Revenue** can be as low

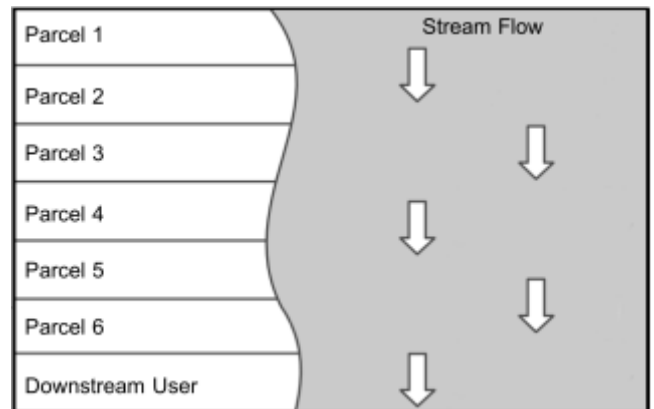
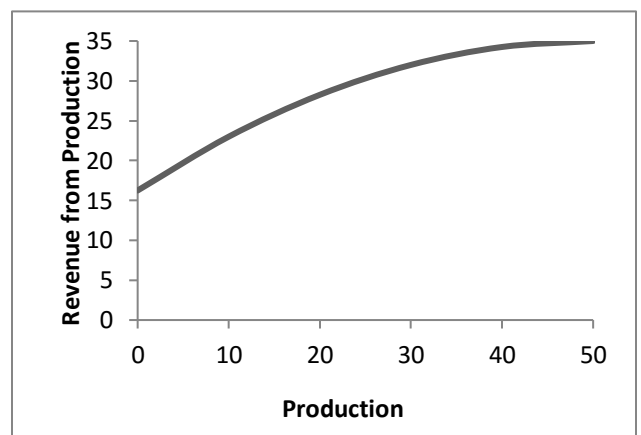


Figure 1. Stream Flow



as \$16.25 and as high as \$35.00, as shown in Figure 2 to the right.

At the same time, the more you produce on your parcel the more **byproduct** you create.

This byproduct does not affect you or others in your group, however, too much byproduct causes damage to the downstream user. The amount of downstream damage depends on the byproduct released by all six parcels, and varies between \$0.91 and \$208.2.

The amount of damage that reaches the downstream user also depends on the weather condition as shown in Figure 3.

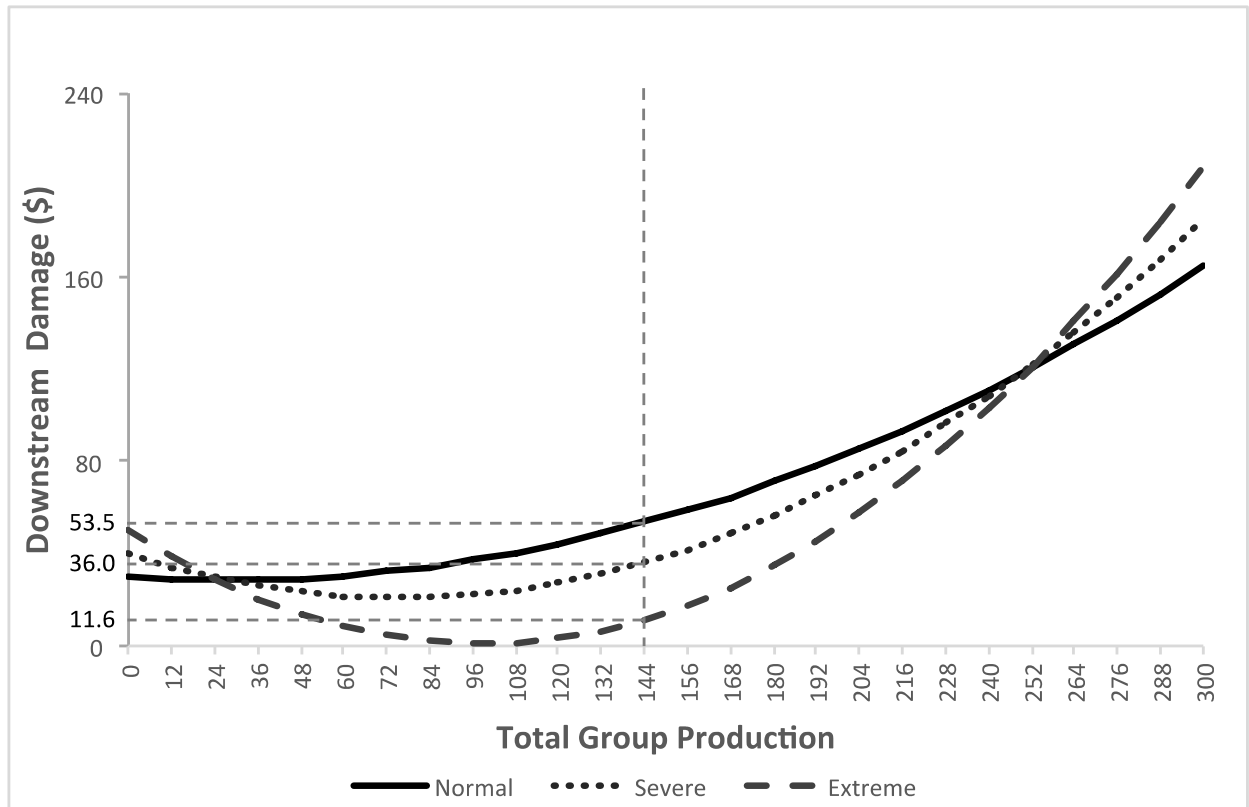


Figure 3. Production and Downstream Damage

There are three weather types: normal, severe, or extreme.

- The downstream damage depends on the weather type and total group production as shown in figure 3.
- In each part, you will be told the weather variation. This weather variation explains the likelihood of experiencing each weather type.

There are Four Weather Variations:

- With no weather variation you will experience normal weather.
- With standard weather variation you will likely experience normal weather.

- With high weather variation you have a higher chance of experiencing severe weather.
- With very high weather variation you have a higher chance of experiencing extreme weather.

Other than location, all business owners are identical, meaning that each individual faces the same decisions. In some parts of today's experiment, your **profit** will be equal to your revenue plus a **subsidy**. This subsidy will be paid to you by the downstream user who is willing to pay you to decrease production and, therefore, downstream damage. This subsidy is determined based on either the group damage created from all business owners relative to a **target** or the damage created from your parcel alone relative to a **target**.

Group Damage:

- Group damage is the average amount of damage that reaches the downstream user from all six parcels.
- If the group damage is greater than or equal to the target, there will be no subsidy.
- The target for group damage is achieved when total group production is 144.

Example 1: If total group production is greater than 144. There will be no subsidy because group damage is equal to the target.

Example 2: If total group production adds up less than 144. In this case a subsidy will be paid to everyone in the group. The size of the subsidy depends on the weather condition.

Your Individual Production:

- Your individual production is how much you produce on your parcel.
- If your individual production is greater than or equal to the target, there will be no subsidy.
- The target for individual production is 24.

Example 3: If your individual production is 24, There will be no subsidy because individual production is equal to the target.

Example 4: If your individual production is less than 24, There will be a subsidy regardless of what everyone else in your group produces.

Summary

- Each Round you will make a production decision between 0 and 50.
- The more you produce the more revenue you will generate.
- The more you produce the more byproduct you will create.
- Byproduct impacts downstream users negatively and varies depending on the weather conditions.
- Downstream users may pay you a subsidy to reduce the byproduct.
- The subsidy will either be determined by group damage or individual production.

- In each round, Profit = Revenue + Subsidy.
- Your cash earnings at the end of the experiments equal the combination of profits from each round.

Practice

A calculator is provided on your computer that will allow you to determine the average subsidy for any set of production decisions for the six parcels. Subsidies will defer depending on the weather type.

The calculator will be available to you throughout the experiment and will update throughout the parts so that you can try out different strategies. You can enter production decisions for each parcel by typing it directly into the column labeled “Production”, you can also change production by using the slider for each parcel, or the one slider for all of the parcels.

Please use the calculator to fill out the table below.

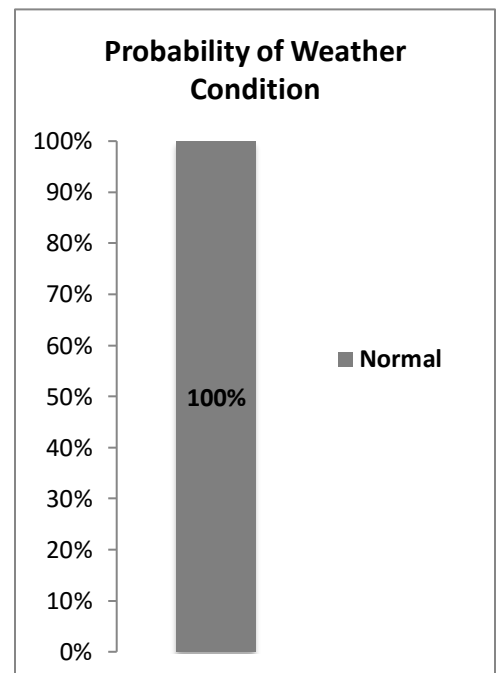
		Subsidy		
Example	If every parcel produces:	Normal Weather	Severe Weather	Extreme Weather
A	0	\$	\$	\$
B	15	\$	\$	\$
C	35	\$	\$	\$
D	50	\$	\$	\$

There are six practice rounds that will give you an opportunity to familiarize yourself with the software. **These first six rounds are for practice only and will not result in any earnings.**

In the first three practice rounds, there is a subsidy that will be offered based on the average amount of damage that reaches the downstream user from all six parcels. Everyone in your group will receive the **same** subsidy. There will be a large subsidy for minimal damage, but the subsidy gets smaller as average group damage increases. If the group damage level is greater than the target, there will be no subsidy.

Your group of six parcels is experiencing no weather variation. With no weather variation, you have a 100% experiencing normal weather.

Example 1: If everyone produces 20 then your normal weather subsidy will be \$22.55.



Example 2: If five parcels produce 20 and one parcel produces 50, your normal weather subsidy is \$0.

Note how, in this part, your production decision will influence the profits of everyone in your group and the production decisions of others affect your profit.

No Weather Variation

Practice

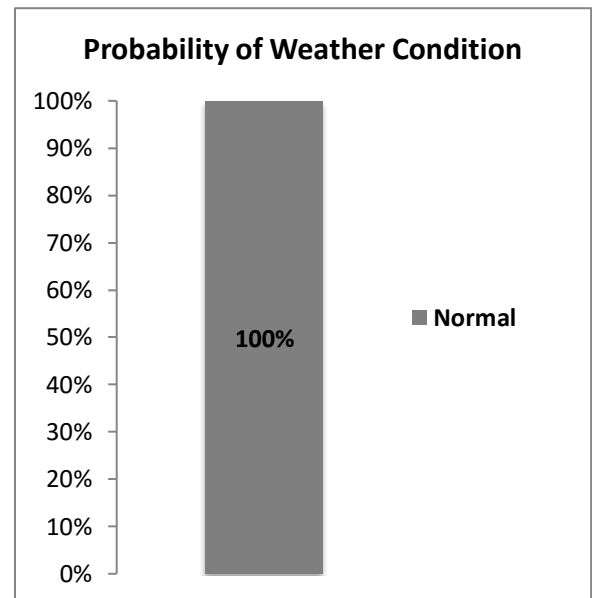
There are three practice rounds that will give you an opportunity to familiarize yourself with the software. **These next three rounds are for practice only and will not result in any earnings.**

In these practice rounds, there is a subsidy that will be offered based on **individual production**. The subsidy may be **different** for different members of your group. If your production is greater than the target production for individuals, there will be no subsidy. The target for individual production is 24.

Your group of six parcels is no weather variation. With very no variation, you have a 100% chance of experiencing normal weather.

Example 1: If everyone else produces 35, but you produce 15 then your normal weather subsidy will be \$22.47. Everyone else will have a normal weather subsidy of \$0. Your subsidy is more than everyone else because you produced less.

Example 2: If everyone else produces 20, but you produce 35 then your normal weather subsidy will be \$0. Everyone else will have a normal weather subsidy of \$20.28. Your subsidy is less than everyone else because you produced more.



No Weather Variation

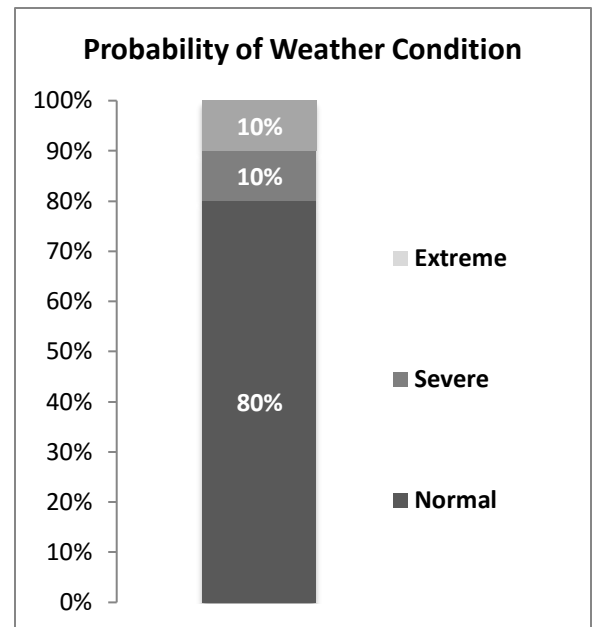
You can test these scenarios on the calculator. Note how, in this part, others' production does not influence your profit. Your subsidy is more than everyone else because you produced less.

In this part, there is a subsidy that will be offered based on the **average amount of damage** that reaches the downstream user from all six parcels. Everyone in your group will receive the **same** subsidy. There will be a large subsidy for minimal damage, but the subsidy gets smaller as average group damage increases. If the measured group damage level is greater than the target, there will be no subsidy. The target for group damage is achieved when total group production is 144.

Your group of six parcels is experiencing standard weather variation. With standard weather variation, you have a 10% chance of experiencing extreme weather, a 10% chance of experiencing severe weather, and an 80% chance of experiencing normal weather.

Example 1: If everyone produces 20 then your normal weather subsidy will be \$22.55.

Example 2: If five parcels produce 20 and one parcel produces 50, your normal weather subsidy is \$0.



Standard Weather Variation

You can test these scenarios on the calculator. Note how, in this part, your production decision will influence the profits of everyone in your group and the production decisions of others affect your profit.

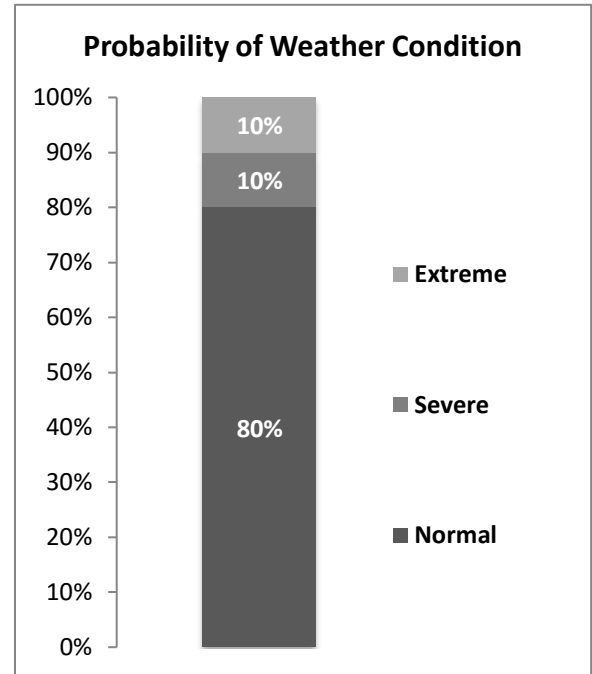
In this part, the subsidy will be based on **individual production**. The subsidy may be **different** for different members of your group. If your production is greater than the target production for individuals, there will be no subsidy. The target for individual production is 24.

Your group of six parcels is experiencing standard weather variation. With standard weather variation, you have a 10% chance of experiencing extreme weather, a 10% chance of experiencing severe weather, and an 80% chance of experiencing normal weather.

Example 1: If everyone else produces 35, but you produce 15 then your normal weather subsidy will be \$22.47. Everyone else will have a normal weather subsidy of \$0. Your subsidy is more than everyone else because you produced less.

Example 2: If everyone else produces 20, but you produce 35 then your normal weather subsidy will

be \$0. Everyone else will have a normal weather subsidy of \$20.28. Your subsidy is less than everyone else because you produced more.



Standard Weather Variation

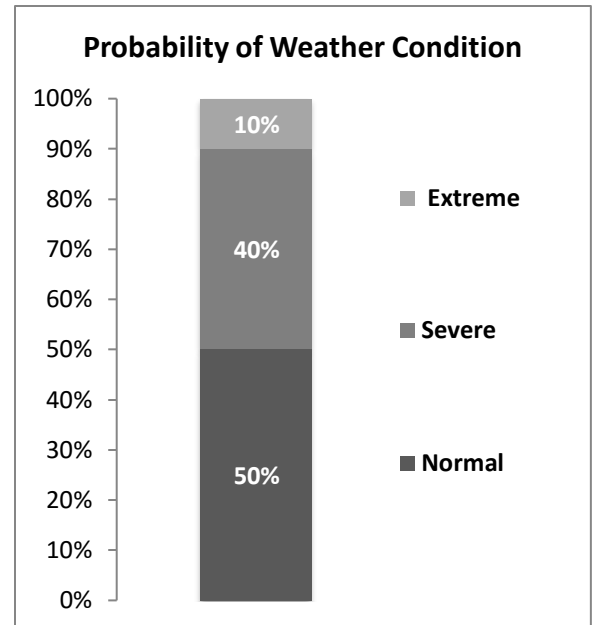
You can test these scenarios on the calculator. Note how, in this part, others' production does not influence your subsidy.

In this part, there is a subsidy that will be offered based on the **average amount of damage** that reaches the downstream user from all six parcels. Everyone in your group will receive the **same** subsidy. There will be a large subsidy for minimal damage, but the subsidy gets smaller as average group damage increases. If the measured group damage level is greater than the target, there will be no subsidy. The target for group damage is achieved when total group production is 144.

Your group of six parcels is experiencing high weather variation. With high weather variation, you have a 10% chance of experiencing extreme weather, a 40% chance of experiencing severe weather, and a 50% chance of experiencing normal weather.

Example 1: If everyone produces 20 then your severe weather subsidy will be \$28.70.

Example 2: If five parcels produce 20 and one parcel produces 50, your severe weather subsidy is \$0.



High Weather Variation

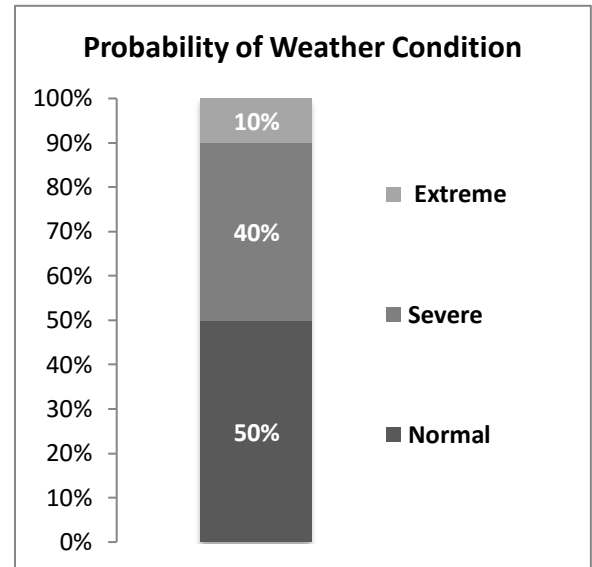
You can test these scenarios on the calculator. Note how, in this part, your production decision will influence the profits of everyone in your group and the production decisions of others affect your profit.

In this part, the subsidy will be based on **individual production**. The subsidy may be **different** for different members of your group. If your production is greater than the target production for individuals, there will be no subsidy. The target for individual production is 24.

Your group of six parcels is experiencing high weather variation. With high weather variation, you have a 10% chance of experiencing extreme weather, a 40% chance of experiencing severe weather, and a 50% chance of experiencing normal weather.

Example 1: If everyone else produces 35, but you produce 15 then your severe weather subsidy will be \$28.80. Everyone else will have a severe weather subsidy of \$0. Your subsidy is more than everyone else because you produced less.

Example 2: If everyone else produces 20, but you produce 35 then your severe weather subsidy will be \$0. Everyone else will have a severe weather subsidy of \$26.61. Your subsidy is less than everyone else because you produced more.



High Weather Variation

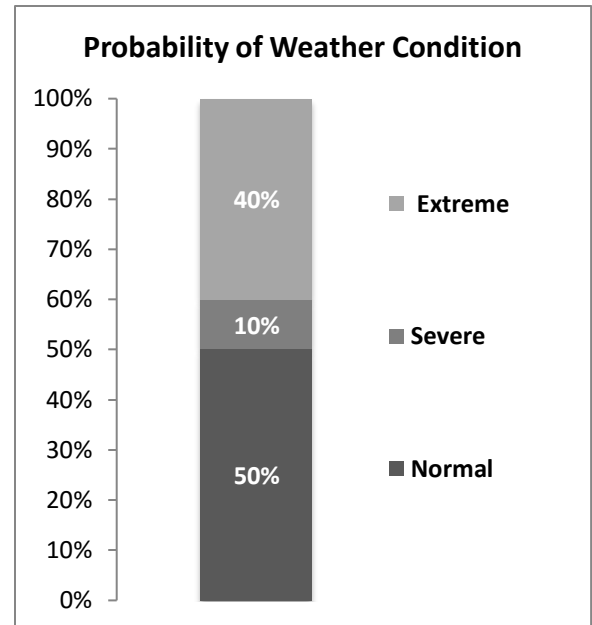
You can test these scenarios on the calculator. Note how, in this part, others' production does not influence your profit.

In this part, there is a subsidy that will be offered based on the **average amount of damage** that reaches the downstream user from all six parcels. Everyone in your group will receive the **same** subsidy. There will be a large subsidy for minimal damage, but the subsidy gets smaller as average group damage increases. If the measured group damage level is greater than the target, there will be no subsidy. The target for group damage is achieved when total group production is 144.

Your group of six parcels is experiencing very high weather variation. With very high weather variation, you have a 40% chance of experiencing extreme weather, a 10% chance of experiencing severe weather, and a 50% chance of experiencing normal weather.

Example 1: If everyone produces 20 then your extreme weather subsidy will be \$36.38.

Example 2: If five parcels produce 20 and one parcel produces 50, your extreme weather subsidy is \$0.



Very High Weather Variation

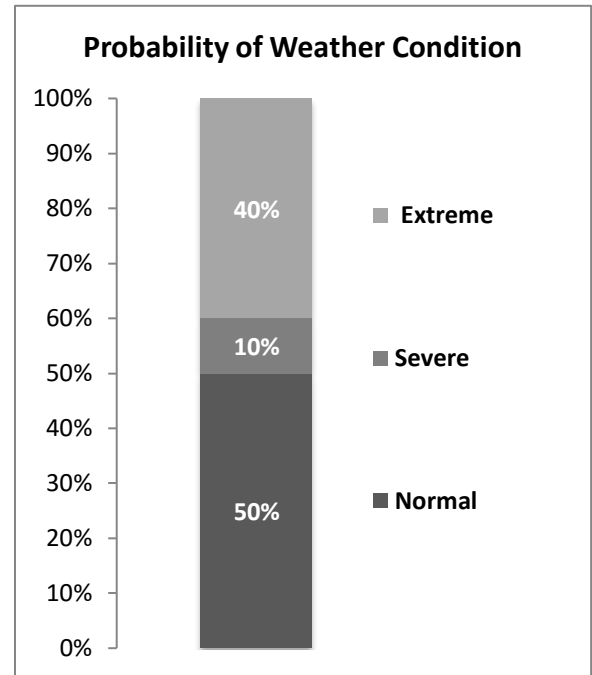
You can test these scenarios on the calculator. Note how, in this part, your production decision will influence the profits of everyone in your group and the production decisions of others affect your profit.

In this part, the subsidy will be based on **individual production**. The subsidy may be **different** for different members of your group. If your production is greater than the target production for individuals, there will be no subsidy. The target for individual production is 24.

Your group of six parcels is experiencing very high weather variation. With very high weather variation, you have a 40% chance of experiencing extreme weather, a 10% chance of experiencing severe weather, and a 50% chance of experiencing normal weather.

Example 1: If everyone else produces 35, but you produce 15 then your extreme weather subsidy will be \$36.71. Everyone else will have an extreme weather subsidy of \$0. Your subsidy is more than everyone else because you produced less.

Example 2: If everyone else produces 20, but you produce 35 then your extreme weather subsidy will be \$0. Everyone else will have an extreme weather subsidy of \$34.52. Your subsidy is less than everyone else because you produced more.



Very High Weather Variation

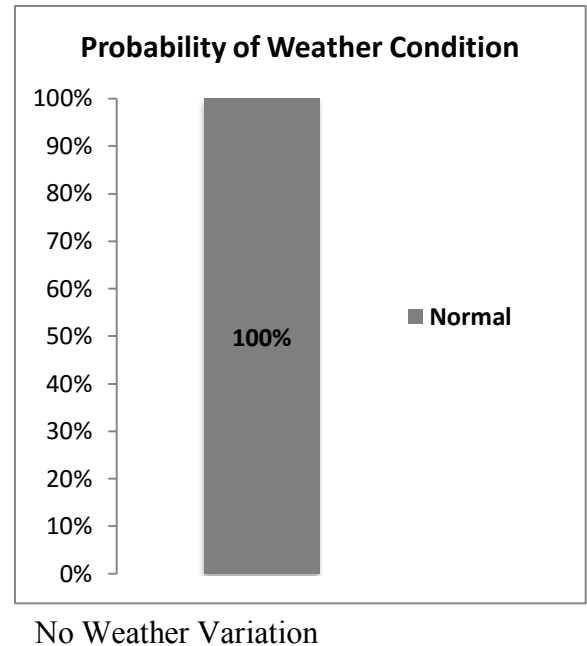
You can test these scenarios on the calculator. Note how, in this part, others' production does not influence your profit. Your subsidy is more than everyone else because you produced less.

In this part, there is a subsidy that will be offered based on the **average amount of damage** that reaches the downstream user from all six parcels. Everyone in your group will receive the **same** subsidy. There will be a large subsidy for minimal damage, but the subsidy gets smaller as average group damage increases. If the measured group damage level is greater than the target, there will be no subsidy. The target for group damage is achieved when total group production is 144.

Your group of six parcels is experiencing no weather variation. With no weather variation, you have a 100% experiencing normal weather.

Example 1: If everyone produces 20 then your normal weather subsidy will be \$22.55.

Example 2: If five parcels produce 20 and one parcel produces 50, your normal weather subsidy is \$0.



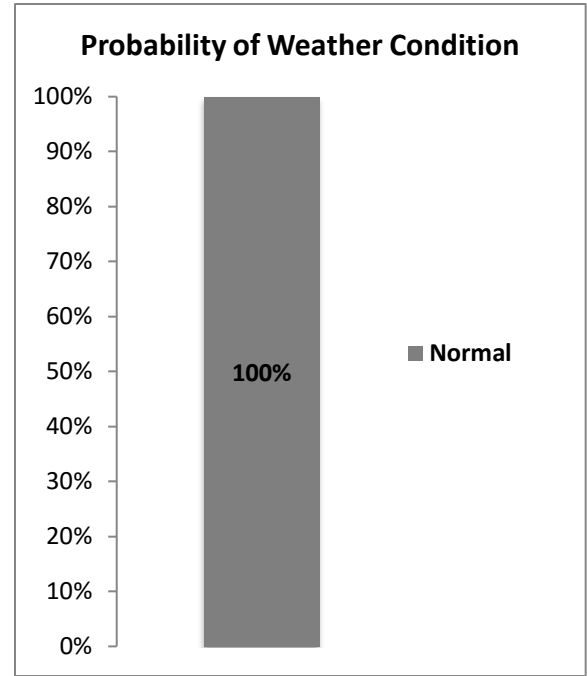
You can test these scenarios on the calculator. Note how, in this part, your production decision will influence the profits of everyone in your group and the production decisions of others affect your profit.

In this part, the subsidy will be based on **individual production**. The subsidy may be **different** for different members of your group. If your production is greater than the target production for individuals, there will be no subsidy. The target for individual production is 24.

Your group of six parcels is no weather variation. With very no variation, you have a 100% chance of experiencing normal weather.

Example 1: If everyone else produces 35, but you produce 15 then your normal weather subsidy will be \$22.47. Everyone else will have a normal weather subsidy of \$0. Your subsidy is more than everyone else because you produced less.

Example 2: If everyone else produces 20, but you produce 35 then your normal weather subsidy will be \$0. Everyone else will have a normal weather subsidy of \$20.28. Your subsidy is less than everyone else because you produced more.



No Weather Variation

You can test these scenarios on the calculator. Note how, in this part, others' production does not influence your profit. Your subsidy is more than everyone else because you produced less.

Appendix B

IRB APPROVAL LETTER



RESEARCH OFFICE

210 Hullihen Hall
University of Delaware
Newark, Delaware 19716-1551
Ph: 302/831-2136
Fax: 302/831-2828

DATE: March 11, 2014

TO: Kent Messer
FROM: University of Delaware IRB

STUDY TITLE: [573740-1] NEWNet Water Quality Sensing Resolution

SUBMISSION TYPE: New Project

ACTION: APPROVED

APPROVAL DATE: March 11, 2014

EXPIRATION DATE: March 10, 2015

REVIEW TYPE: Expedited Review

REVIEW CATEGORY: Expedited review category # 7

Thank you for your submission of New Project materials for this research study. The University of Delaware IRB has APPROVED your submission. This approval is based on an appropriate risk/benefit ratio and a study design wherein the risks have been minimized. All research must be conducted in accordance with this approved submission.

This submission has received Expedited Review based on the applicable federal regulation.

Please remember that informed consent is a process beginning with a description of the study and insurance of participant understanding followed by a signed consent form. Informed consent must continue throughout the study via a dialogue between the researcher and research participant. Federal regulations require each participant receive a copy of the signed consent document.

Please note that any revision to previously approved materials must be approved by this office prior to initiation. Please use the appropriate revision forms for this procedure.

All SERIOUS and UNEXPECTED adverse events must be reported to this office. Please use the appropriate adverse event forms for this procedure. All sponsor reporting requirements should also be followed.

Please report all NON-COMPLIANCE issues or COMPLAINTS regarding this study to this office.

Please note that all research records must be retained for a minimum of three years.

Based on the risks, this project requires Continuing Review by this office on an annual basis. Please use the appropriate renewal forms for this procedure.