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Testing Policies That Use Continuous Nutrient Sensing by Drinking Water Utilities to Reduce Non-Point Source Pollution under Climate Variability

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ABSTRACT

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More-frequent extreme weather events due to climate change are expected to increase operation costs for drinking water utilities, in part from increased non-point source (NPS) pollution from agricultural land. High-frequency, high-quality sensors can help utilities better monitor water quality and utilities could use this information in programs that subsidize upstream producers to improve the quality of water they receive. Such a subsidy could be based on ambient pollution—paying producers directly based on their pollution abatement—or targeted production—paying producers to implement specific practices that reduce pollution. This distinction has implications for the structure of contracts, distribution of payments, and, most notably, allocations of damage from extreme weather events to producers and the utility. Under an ambient-based subsidy, risks associated with weather are shared by producers. Under a production-targeted subsidy, the utility bears risk posed by severe weather. We use an economic experiment involving operational data from a municipal water utility to study producer responses to a theoretically equivalent ambient-based and targeted subsidy to improve water quality under various weather scenarios. We find that the level of risk associated with weather variability affects producers' behaviors in response to subsidies. The results suggest that both types of subsidies lead to improved social welfare and decreased pollution and that production-based subsidies, which can be implemented using real-time sensing technologies, minimize the utility's economic cost and the social cost of damage. We also find that both types of subsidies become more effective as weather variability and the likelihood of extreme events increase.

Key Points:

- By offering subsidies to upstream producers for watershed protection, drinking water utilities can decrease their costs.
- High-quality data from continuous water-quality sensors can increase the effectiveness of subsidies by targeting individual producers
- As the likelihood of extreme weather events increases, both ambient pollution and targeted production subsidies become more effective

Testing Policies That Use Continuous Nutrient Sensing by Drinking Water Utilities to Reduce Non-Point Source Pollution under Climate Variability

The primary function of drinking water utilities (DWUs) is taking raw water from a natural source, killing bacteria and removing impurities it contains, and distributing the resulting drinkable water to customers so that safe and appetizing water flows from their taps. A major determinant of the quality of raw water is the level of dissolved organic carbon associated with decomposed plant and animal material. High levels of dissolved organic carbon are problematic because they negatively affect the taste and smell of the water, are detrimental to the health of end-user consumers, and increase the cost of purification for the DWU. Furthermore, adding chlorine to kill bacteria in the water can increase the concentration of cancer-causing trihalomethanes such as chloroform in municipal drinking water supplies [*Delpa et al.,* 2009], requiring use of additional processing such as coagulation and filtration or pumping water from reserves, all of which are costly. According to the U.S. Environmental Protection Agency (EPA), one of the largest sources of contamination is agricultural and other non-point source (NPS) polluters [EPA, 2016] associated with heavy runoff from large storms, prompting concern among scientists that increases in extreme weather events related to climate change will lead to higher levels of dissolved organic carbon in raw water supplies and higher operation costs for DWUs.

Policy tools that address NPS pollution can target various outcomes. Output-based mechanisms focus on the amount of pollution an individual property produces while input-based mechanisms focus on decisions a property owner makes regarding intensity of production, fertilizer use, and agricultural management practices that affect how much pollution a property will produce. Currently, most programs meant to improve water quality rely on input-based subsidies to reduce pollution by altering owners' land uses and management practices (e.g., reducing use of chemical fertilizers and tillage). These are blunt instruments in that it is not always clear how much, if at all, the subsidized inputs result in the desired changes in output (of polluted runoff). Output-based mechanisms are attractive because they directly target pollution, but the expense and difficulty of directly monitoring NPS pollution from individual parcels have generally made output-based policies infeasible. That may change in the future, however, as (relatively) inexpensive, high-frequency water-quality sensing technologies are developed that can spatially differentiate pollution sources [*Miao et al.*, 2016].

Tax/subsidy mechanisms based on ambient levels of pollution are a proposed alternative to policies that target individual contributions. Such policies impose taxes and/or provide subsidies based on the observable total amount of pollution in a water source (determined by a sensor at a downstream location) to motivate agricultural producers whose properties contribute to that pollution to reduce their contributions to an exogenous target level that corresponds to a socially optimal overall level of pollution [e.g., *Xepapadeas*, 1992; *Cabe and Herriges*, 1992; *Xepapadeas*, 1995; *Horan et al.*, 1998; *Segerson*, 1988]. This type of group output-based policy avoids the need for information on individuals' production of pollution. Mechanisms of this type have attractive theoretical properties, and economic experiments have found them to be effective in achieving pollution-reduction targets under a 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 et al.*, 2009; *Vossler et al.*, 2013; *Suter et al*., 2008].

Group-output mechanisms are also strategically complex since the amount of pollution overall depends on individual landowners' actions and on factors such as the number and intensity of storms that generate runoff. Tax-based policies, for example, can potentially punish landowners who incurred additional expense to significantly reduce their contributions of pollution while neighboring landowners made no such effort and further punish landowners for weather-related contributions beyond their control. Consequently, subsidies that provide incentives to reduce pollution are generally preferred.

The basis for such subsidies determines how risk is shared by landowners and the DWU. Under a targeted subsidy mechanism, the water utility, which is assumed to be risk-neutral, bases subsidy payments on each landowners' level of agricultural production and bears the risk associated with weather that would otherwise be borne by risk-averse producers. Under a subsidy based on the ambient level of pollution downstream, behavior by the landowners collectively determines whether they individually earn a subsidy, and they bear the risk associated with weather-related pollution.

Extreme weather events increase the concentration of NPS contaminants and thus degrade water quality. In this study, we use a laboratory-based economic experiment to compare the effects of a subsidy based on the ambient level of pollution to the effects of a targeted subsidy based on individuals' agricultural production in reducing NPS pollution at the point of intake of a DWU facility under various weather scenarios, thereby reducing the utility's costs in the face of more-frequent and more-extreme weather events, and how the subsidies' relative effectiveness changes as the level of risk posed by weather conditions changes. Producers who are risk-averse should tend to prefer a targeted subsidy because they would have less exposure to the risk of others' decisions decreasing or eliminating their subsidy. And if the subsidy is tied to their production, they would be less vulnerable to the effects of weather in terms of severe storms. The experiment incorporates data from an existing municipal DWU and predictions of weather conditions under several climate-change scenarios.

We aim to understand how to best minimize potential social damage associated with NPS contamination of water by examining the performance of two institutional arrangements in the context of changes in weather variability. Ultimately, we are interested in understanding the interaction of strategic rent-seeking behavior with the mechanism's structure and assignment of risk-sharing to identify ways to improve the design of NPS pollution regulations. This research contributes to the literature by comparing the effectiveness of ambient-pollution and targeted-production subsidies under various weather scenarios and by analyzing the effect of increased risk associated with a greater likelihood of extreme weather events—long-lasting droughts and floods—due to climate change. We also evaluate the ability of real-time water-quality sensors currently being developed to improve water quality and social welfare, especially in the presence of extreme weather events. We find that the effectiveness of targeted subsidies, which could be implemented with affordable real-time sensors, increases as extreme weather events increase. The measure of effectiveness is the mechanism's ability to generate the socially optimal levels of agricultural production and pollution.

The experiment involves six homogeneous firms producing the same good at different locations along a river. However, the spatial differences do not influence the marginal damage produced by each firm. We apply one subsidy that is based on the ambient level of total pollution at the DWU intake and one that is based on targeted levels of production by the firms and compare the results for three levels of weather variability. The homogeneous firms represent agricultural producers, and we study how variability of weather affects their decisions.

Our results suggest that both types of subsidy increase social welfare by approximately 38% over no subsidy. Though both types are effective, we find that the targeted subsidy is significantly more effective than the ambient-pollution subsidy in reducing pollution and increasing social welfare. Furthermore, the effectiveness of the targeted subsidy increases with the likelihood of extreme weather events. Using multiple real-time sensors, a targeted subsidy could address actual emissions of pollution (rather than using the amount of production as a proxy) by detecting the amount of pollution entering the river from each farm.

1. Background and Motivation

Both human activities and climate change can decrease the quality of surface water [*Delpa et al.*, 2009]. As average temperatures rise, the amount of dissolved organic matter and other pollutants in the water can increase through mechanisms such as drought-rewetting cycles that enhance decomposition and flush matter into local waterways [*Evans et al.*, 2005]. In recent years, increases in dissolved organic carbon have been noted in Northern Europe, Central Europe, and North America [*Evans et al*., 2005; *Monteith et al*., 2007; *Worrall et al*., 2004; *Hejzlar et al*., 2003]. When water containing a high level of dissolved organic carbon is treated with chlorine by DWUs, cancer-causing chemicals referred to as trihalomethanes can form, further degrading the water. In terms of weather, heavy rains lead to high levels of turbidity and organic matter [*Delpa et al.*, 2009] and increase the amount of dissolved carbon and pesticides in rivers and streams, making treatment of the water for drinking more challenging and expensive.

The broader effects of climate change also affect DWUs financially through a cascade of effects associated with changes in precipitation patterns, air and water temperatures, sea levels, and the frequency of severe storms. Flooding is a likely consequence of all of these changes, presenting the potential for physical damage to drinking water infrastructures [Rayburn et al., 2008], breaching of dams, intrusions of seawater into aquifers, and widespread deposition of sediment, debris, and pollution in various waterways used to provide drinking water. In addition, climate change can potentially affect the timing of runoff from rain and snowmelt [Rayburn et al., 2008] collected in existing reservoirs as well as increase the cost of treating water due to increases in disinfection by-products and microbial growth (e.g., algal blooms) and decreases in dissolved oxygen that cause noxious odors and discolor the water. Another effect of drought is a greater frequency of wildfires that denude hillsides; the resulting erosion, ash, and plant debris are deposited in rivers and streams. All of these consequences of climate change require significant investments by DWUs to repair, upgrade, and expand their facilities and infrastructures [*AMWA-NACWA, 2009]*.

The EPA estimated the cost of needed infrastructure upgrade, renewal, and replacement programs for drinking water and wastewater for 2007–2027 at $300 billion to $500 billion and estimated the net present value cost of climate-change adaptions for drinking water systems through 2050 at $362 billion to $692 billion, which includes the cost of capital and operation and maintenance [*AMWA-NACWA, 2009*]. DWUs have been implementing short-term and long-term water conservation policies to reduce the demand for water and/or reallocate their water resources for the past 30 years [*Hughes and Leurig*, 2013]. One such conservation technique involves offering farmers financial incentives to irrigate less and to adopt best management practices (BMPs) such as restricting fertilizers and tillage that reduce the flow of nutrients into waterways. For instance, the New York Watershed Agricultural Council (WAC) with funding from the New York State Department of Environmental Protection (NY-DEC) and the U.S. Department of Agriculture (USDA) worked to decrease nutrient eutrophication (lack of dissolved oxygen in waterbodies) in the Catskills by assisting farmers in implementing BMPs. In 2011, 102 BMPs, such as fencing, animal waste storage facilities, and conservation crop rotation were implemented on small and large farms with WAC support [NY-DEC, 2016]. In addition, the City of Syracuse's Department of Water created the Skaneateles Lake Watershed Agricultural Program (SLWAP), which assists farmers in creating individual environmental protection plans and then subsidizes their adoption of management practices that reduce runoff [*Miner and Somers*, 2015]. The Skaneateles Lake watershed covers 59 square miles, and 48% of the land uses in the watershed are agricultural. Thanks to SLWAP, Skaneateles Lake was named the cleanest of the Finger Lakes in 2011 [*Miner and Somers*, 2015].

This research contributes to the literature on the economic effects of climate change for DWUs and to the literature related to policy mechanisms that efficiently abate NPS pollution. In an early work, *Segerson* [1988] presented a theoretically optimal tax/subsidy incentive mechanism based on ambient levels of pollution in which every polluter pays the same amount. The tax (or reduction in subsidy) is equivalent to the full marginal benefit of a reduced level of ambient pollution The ambient tax/subsidy transfer is a linear function calculated from estimates of the level of ambient pollution and the cost of abating that pollution and is based on the degree to which an individual agents abates its pollution emissions. Agents that fail to meet the pollution abatement target are subject to a tax penalty equal to the marginal damage of their excess pollution, and agents that exceed the pollution abatement target are rewarded with a subsidy equal to the marginal damage avoided. This mechanism decreases the cost for a regulator when there is asymmetric information and gives firms the freedom to choose the least costly pollution-abatement technique that ensures the necessary level of abatement.

Numerous laboratory experiments focused on mechanisms for reducing NPS pollution have been based on Segerson's [1988] theoretical work. *Spraggon* [2002], for example, found that ambient-based tax/subsidies and taxes were more effective than other mechanisms such as group fines. Building on Spraggon's work, *Cochard et al*. [2005] studied an NPS pollution problem with endogenous externalities, comparing an input tax, an ambient-based tax/subsidy, an ambient-based tax, and a group fine, and concluded that the ambient-based tax/subsidy was not the best policy because it decreased social welfare and was highly unreliable in reducing pollution compared to other instruments. *Miao et al.* [2016] showed that increasing the frequency of ambient monitoring improved emission reductions when firms were differentiated spatially. A number of studies [e.g., *Spraggon*, 2002; *Vossler et al.*, 2006] also included error terms that were symmetric to the measured concentration of pollution to mimic uncertainty caused by stochastic environmental factors such as weather.

Suter et al. [2008] compared linear and non-linear ambient-based taxes and concluded that both mechanisms achieved the social optimum when communication was not allowed. The linear tax followed Segerson [1988]; each firm was charged a constant marginal tax that was equal to the marginal damage at the social optimum. The non-linear tax required each polluter to pay a tax equal to the total economic damage. In a follow-up study, *Suter et al.* [2009] compared homogeneous and heterogeneous groups. The homogeneous pollution setting consisted of six firms that had identical profit and emission functions. The heterogeneous pollution setting consisted of three small firms, two medium firms, and one large firm, and each firm had different profit and emission functions based on their size. The results showed that an ambient-based tax mechanism reduced emission levels significantly in both settings. Furthermore, the distribution of firm sizes had a significant impact on observed group decision-making and heterogeneity generated some relatively desirable outcomes and some undesirable outcomes. One particularly undesirable outcome was that small firms could go bankrupt due to predatory actions by large firms.

Given the results of prior studies, we chose to apply both ambient-based and production-targeted policies that use information from high-tech sensors in our experiment. Under the ambient-based policy, the regulator uses a downstream sensor to determine the collective ambient damage (pollution); under the production-targeted policy, the regulator identifies individual parcels' contributions of pollution using sensors located near each parcel and bases the provision of a subsidy on that data.

2. Experimental Design

In the experiment, participants assumed the role of business owners making production decisions regarding parcels along a river. Each firm produced a good that generated income, and the production process generated a proportional amount of pollution that entered the river. The participants, who were undergraduate students at a large public university on the east coast of the United States, represented agricultural producers but were told only that they were business owners. In the experiment, the participants had the opportunity to earn money based on the decisions they made, and the average amount earned during an experiment session was $30. *Fooks et al.* [2016] involved both students and agricultural producers in a similar experiment and found no significant differences in their production decisions.

The experiment was framed such that the pollution did not affect the participants but could cause damage to a hypothetical downstream user external to the experiment. The amount of downstream damage depended on the amount of the good produced by each business owner and weather conditions, and the firms received a subsidy from a DWU that was based on either the measured ambient level of water pollution downstream or on the quantity of the good the firm produced (we did not address tax policies in the experiment). In the model, the utility could determine each firm's production of pollution by way of nearby sensors.

Six treatments were used in the experiment to examine the effects of weather variability and type of subsidy on the effectiveness of an NPS pollution abatement policy. A single session involving a weather-variability treatment and no provision of a subsidy provided a baseline for comparison.

2.1. Experiment Protocol

Six sessions of the experiment were conducted each involving either 12 or 24 of the 120 undergraduate student participants recruited through an email announcement. See Table 1 for a summary of the experiment characteristics.

Table 1. Summary of the Experiment 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
Subsidies	i. Ambient Subsidy ii. Targeted Subsidy (perfect information)
Time Structure	7 Parts, 5 Rounds/Part
Average Time	2 hours
Average Earnings	$30

The experiment was conducted using computers running a Willow interface and a Python framework. Each desk in the laboratory was equipped with a computer and a privacy divider that ensured that the participants' decisions remained confidential. The room was set up with desks arranged into four groups of six. Sessions lasted 90 to 120 minutes, and no communication was allowed between participants, who were randomly assigned to a desk by drawing a number from a bag before entering the room.

The participants were also assigned separately (unrelated to the desk assigned) to six-member stream groups that collectively emitted pollution to a waterbody. They were not aware of the identities of the other members of their stream group. The participants made production decisions that determined the amount of pollution emitted into their group's stream and thus determined whether they would earn a subsidy provided as experimental dollars that would be converted to U.S. dollars at a rate of 40 experimental dollars per U.S. dollar.

The session began with participants reading and signing the consent form and then spending approximately 15 minutes reading instructions that explained how production decisions affected their earnings, the types of subsidies provided, and how the weather scenarios varied (see Appendix A). To further assist the participants in understanding how the subsidies varied in response to the weather scenarios, they were given time to use a special calculator presented on the computer that allowed them to enter hypothetical production decisions for each parcel and see the amount of the subsidy under each weather scenario. The calculations changed with the weather treatment. The written instructions included training in how to use the calculator and required participants to use it to identify the amount of subsidy provided for different levels of production. The experiment administrators also made certain that participants knew how to correctly operate and understood the calculator.

Table 2 shows the order of the treatments. In all cases, the experiments started with two sets of practice rounds that did not include weather variation (one with ambient subsidies and one with targeted subsidies. The treatments were represented in a varied order to control for potential order effects. Between treatments, the experiment administrators provided a set of additional written instructions and an oral presentation that explained the weather variation and type of subsidy used in that treatment for the next set of rounds.

Table 2. Treatment Conditions

Treatment	Subsidy	Weather Variation
P	Ambient	None
P	Targeted	None
A	Ambient	Standard
B	Targeted	Standard
C	Ambient	High
D	Targeted	High
E	Ambient	Very High
F	Targeted	Very High
G	Ambient	None
H	Targeted	None
Treatment Order	PPABCDEFGH	
	PPBADCFEHG	
	PPHGFEDCBA	
	PPGHEFCDAB	

In each treatment, the administrator computer randomly assigned each participant to a six-member stream group and then to a parcel located at a unique location along the group stream. However, the parcels were homogeneous and the amount of damage caused was not affected by their location. Each treatment consisted of five decision rounds in which the participants made a confidential production decision and were then informed of the amount of the potential subsidy, the degree of weather variability, the amount of any subsidy they earned in the round, and their total net profit for that round. The instructions informed the participants what the pollution target was in each scenario and how the subsidies would be calculated. The rounds were independent so production decisions and downstream damage in one round did not affect future rounds.

2.2. Model

In each round of the experiment, participants made individual production decisions that generated private incomes and damage (to the water resource). Following *Spraggon* [2002], we assume that there are N producers i that each produce output x_i and receive income $I_i(x_i)$. The private income function takes the form

$$I_i(x_i) = \gamma_0 - \gamma_1(\gamma_2 - x_i)^2. \tag{1}$$

Total output from production by all producers is the sum of all individuals' production:

$$X = \sum_{i=1}^{N} x_i \tag{2}$$

and total income is the sum of all individuals' incomes:

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

Since the producers are identical, production will be symmetric at the equilibrium. Therefore, 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 an individual producer is

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

and the producer's marginal cost of abatement is

$$MC(X) = -2\gamma_1\gamma_2 + 2\gamma_1 X. \tag{5}$$

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

$$TD(X) = \delta(\beta_0 + \beta_1 X + \beta_2 X^2). \tag{6}$$

The parameterization of this function is based on real predicted weather scenarios and cost data from the water utility serving Wilmington, Delaware, in the United States. The weather scenarios are varied in the treatments as discussed in more detail later.

The total benefits from pollution abatement at the unregulated optimum is

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

The corresponding marginal benefit of abatement is

$$MB(X) = -\beta_1 - 2\beta_2 X. \tag{8}$$

We assume that the utility is risk-neutral and that, as a public entity, the utility wants to maximize net social welfare by equating the marginal cost and benefit, which leads to optimal total production by all six firms:

$$X^* = \frac{\gamma_1\gamma_2 - \beta_1/2}{\gamma_1 + \beta_1}. \tag{9}$$

Each individual producer's share of production is

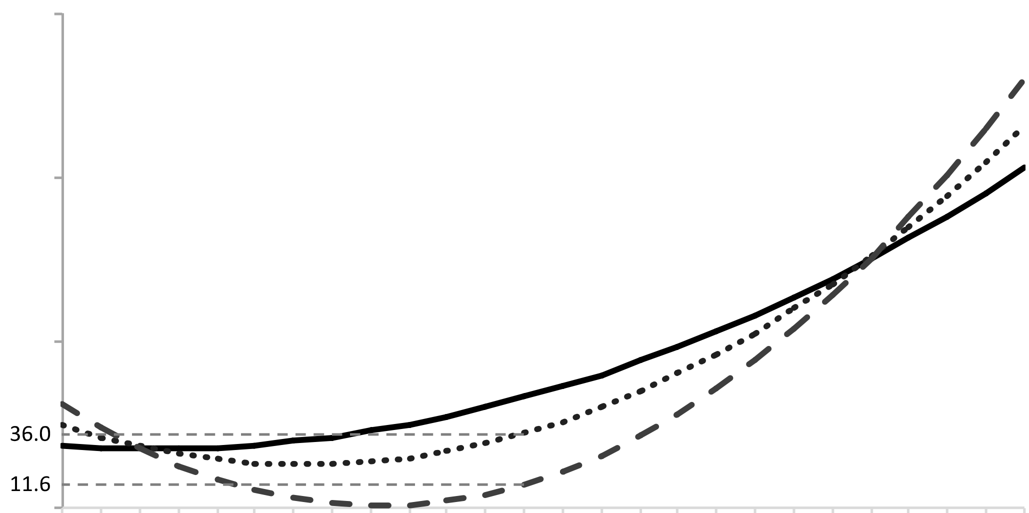
$$x_i{}^* = {}^{X^*}\!/_{N}. \tag{10}$$

Under this form of the instrument, X^* is the equilibrium when producers believe that total production will be less than or equal to the subsidy; X_{max} is the equilibrium when producers believe that X^* is unobtainable.

2.3. Treatments

The six treatments in the experiment combined the ambient-based and production-targeted subsidies with four levels of probability of variability in the weather: (1) none, (2) standard, (3) high, and (4) very high (see Table 2) associated with the probability of (a) normal, (b) severe, and (c) extreme weather conditions. Extreme weather events are long-lasting droughts and floods; the impacts of severe weather have a relatively brief duration. The amount of damage done to the downstream user varied with the weather condition in the treatment. We created a damage function for each type of weather condition using models that predicted the DWU's cost [AMWA-NACWA, 2009]. In addition, to simplify both the policies (subsidies) and the participants' decisions, we made the marginal damage incurred at the pollution-reduction target equal for all treatments. The parameters for these functions are shown in Table 3. Downstream damage is a quadratic function of total production, and the impact of total production on damage is shown in Figure 1. Once production exceeds the socially optimal amount, the amount of downstream damage increases significantly.

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



Damage Function: Extreme Weather

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

Damage Function: Severe Weather

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

Damage Function: Normal Weather

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

As shown in Figure 2, standard variability is composed of an 80% chance of normal weather, a 10% chance of severe weather, and a 10% chance of extreme weather. High variability is composed of a 50% chance of normal weather, a 40% chance of severe weather, and a 10% chance of extreme weather. Very high variability is composed of a 50% chance of normal weather, a 10% chance of severe weather, and a 40% chance of extreme weather.

Figure 2: Weather Variations

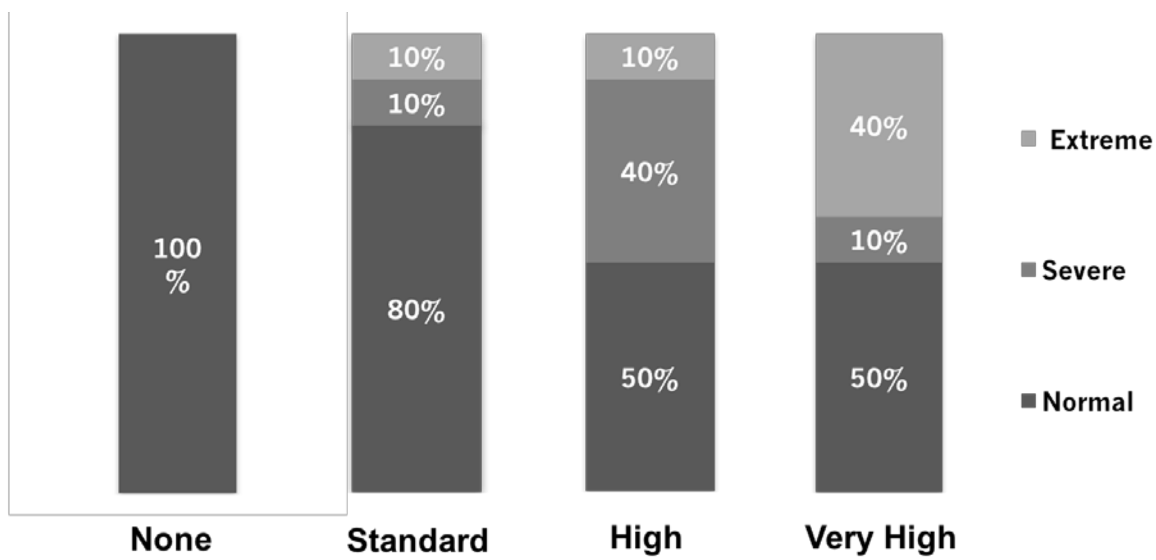


Table 3. Equation Parameters

Parameter			
Weather condition	β_{1L}	–0.1	
	β_{2L}	0.0018	
	β_{0L}	30	
	β_{1M}	–0.5	
	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
	$MD(TD^*)$		–0.44
	$TD^*{}_N$	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
	$MD(TD^*)$		–0.44
	x^*		24
Income	γ_0	35	
	γ_1	0.0075	

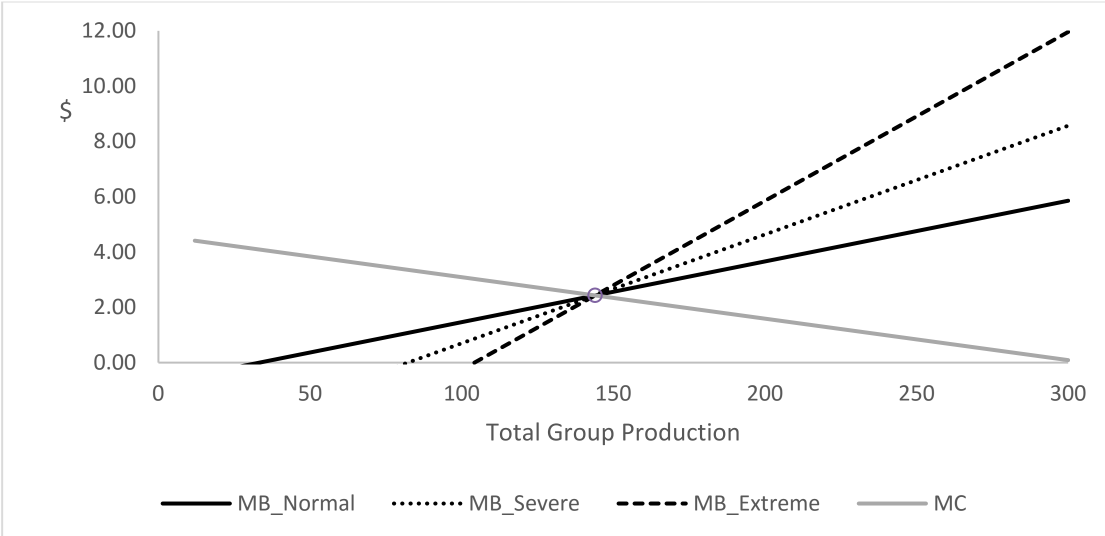
γ_2	50

2.3.1. Calculating the Ambient-based Subsidies

The ambient-based subsidies in the treatments are calculated using the total amount of downstream damage collectively contributed by the six firms, and each firm receives the same amount of subsidy, which is based on the amount of damage relative to the socially optimal target level, $TD_j{}^*$. When the measured level of damage equals or exceeds the target, the participants do not receive a subsidy.

The target level of damage, $TD_j{}^*$, is calculated based on the group's total production, and $X^* = 144$. The group production target is derived from equating the marginal benefit (*MB*) with the marginal cost (*MC*) across weather conditions (*j*) as shown in Figure 3. Therefore, under normal weather conditions, total group production of 120 units results in $44.35 of damage (see Figure 1), which is less than the target damage of $53.54. Therefore, the producers receive subsidies of $22.55.

Figure 3. Marginal Benefit vs. Marginal Cost



12.00
10.00
8.00
6.00
4.00
2.00
0.00
$
0
50
100
150
200
250
300
Total Group Production
MB_Normal
MB_Severe
MB_Extreme
MC

Following *Spraggon* [2002], we calculate the ambient-based subsidy as

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

where *MD* is marginal damage, *TD* is total damage, and *b* is a bonus included to induce production at the target level rather than at the maximum level. The parameters for the equation are presented in Table 3.

2.3.2. Calculating the Production-targeted Subsidies

The production-targeted subsidies are calculated using the individual firms' production, which is observed by the utility via a water-quality sensor next to each parcel. Therefore, the amount of any subsidy paid varies according to the firm's production decision. A firm that chooses to produce at or above the target level receives no payment. In our model, the individual target level of production is $x^* = 24$, which corresponds to the total group production target of $X^* = 144$ and is derived from equating *MD* with *MC* across weather conditions as shown in Figure 3.

The targeted subsidy is determined by

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

where *MD* is marginal damage, *x* is the individual's production, and *b* is a bonus. The parameters for the equation are provided in Table 3. Again following *Spraggon* [2002], we include a bonus to induce the firm to produce the target level rather than the maximum.

The individual firm's profit is calculated as the firm's income plus the subsidy:

$$P_i(x_i) = \gamma_0 - \gamma_1(\gamma_2 - x_i)^2 + S_i(X). \tag{16}$$

Participants chose to produce 0 to 50, which generated income of \$16.25 to \$35.00 (see Table 3).

2.4. Testable Hypotheses

The hypotheses tested in this research are summarized in Table 4. The first hypothesis is that the degree of variability of weather does not have an impact on the effectiveness of the subsidy mechanisms. Effectiveness is measured as the mechanism's ability to generate the socially optimal level of damage. As previously mentioned, weather conditions, which are expected to be more severe in the future due to climate change, affect the damage functions in our model. We assess how the subsidy mechanisms might perform as weather patterns change.

The second hypothesis is that changes in risk do not affect production under the targeted subsidy. As weather variability increases, the firm is subjected to greater risk under a policy based on the level of ambient pollution—it can be penalized for weather-related increases in pollution. Under a production-targeted subsidy policy, the level of pollution, which can increase due to severe weather events, does not control the firm's receipt of a subsidy; instead, the utility bears the weather-variability risk. Under the targeted subsidy, there is perfect information; the utility knows how much the firm is producing from a sensor near the parcel and the firm knows the target number of units of production. We expect to find that only the ambient-based subsidy's interactions with weather will significantly affect the production of damage and social welfare.

The third hypothesis is that the ambient-based and production-targeted subsidies will have the same impact on total downstream damage. We want to determine whether one of the mechanisms is more effective than the other at reducing total damage to the socially optimal level.

The fourth hypothesis is that the total amount of production from a stream group does not change in response to the degree of weather variability. As previously noted, the effects of extreme weather events are protracted (droughts, wide-scale flooding) while the effects of severe weather events last days to weeks. Each weather condition is represented by a unique damage function that is based on actual weather data. We are testing to determine whether the firm/participants' behaviors are influenced by the various damage functions and thus whether severe and extreme weather conditions have different impacts on total production relative to normal weather.

The fifth hypothesis is that ambient-based and production-targeted subsidies have the same impacts on total production. We want to determine whether one of the mechanisms is more effective than the other in reducing total production to the socially optimal level.

The sixth hypothesis is that the ambient-based and production-targeted subsidies have the same impact on social welfare. We want to determine whether one mechanism is more effective than the other at increasing social welfare to close to the socially optimal level. In the model, social welfare is measured as the stream group's total income minus the total amount of downstream damage from the group.

Table 4. Hypotheses

Hypotheses	Result
1) Climate variability does not affect 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 affect damage under targeted subsidies.	Reject – Downstream damage decreases when there is interaction between weather variability and targeted subsidy (Table 8 Model A_2)
3) Ambient and targeted subsidies have the same impact on downstream damage.	Reject – Downstream damage is higher on average when there is a ambient-based subsidy instead of a targeted subsidy (Table 8 Model A_2)
4) Total production does not change in response to different degrees of weather variability.	Fail to Reject – The change in production as weather variability increases 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 an ambient subsidy relative to a targeted subsidy (Table 8 Model B_2)
6) Ambient and targeted subsidies have the same impact on social welfare.	Reject – Social welfare is higher on average with a targeted subsidy than with an ambient subsidy (Table 8 Model C_2)

3. Results

Overall, we find that a well-designed subsidy can dramatically improve water quality and increase social welfare to a level that is closer to optimal. Our first hypothesis asks whether the effectiveness of the subsidy mechanisms changes under different weather conditions. Since we are interested in seeing if the effectiveness of the subsidies changes in response to weather, we include interacting terms for the subsidy structure and weather variation:

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

where standard, high, and very high refer to the degree of weather variability. The null hypothesis is

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

We expected that both subsidies would lead to less damage than the baseline case of no subsidy and no weather variation. Our results, presented in Table 5, support that hypothesis. With a production-targeted subsidy, the average damage across the weather variability levels is

$35.89; with the ambient-based subsidy, the average damage is $49.21. These values are significantly less than average damage in the absence of a subsidy of $123.84. Furthermore, as the degree of weather variability increases, the degree of damage under both subsidy mechanisms decreases.

Table 5. Outcomes by Subsidy Type

	No Subsidy	Targeted Subsidy	Ambient Subsidy
Mean Damage	$123.84	$35.89	$49.21
Mean Total Production	253.11	114.00	143.28
Mean Welfare	78.75	130.44	124.10

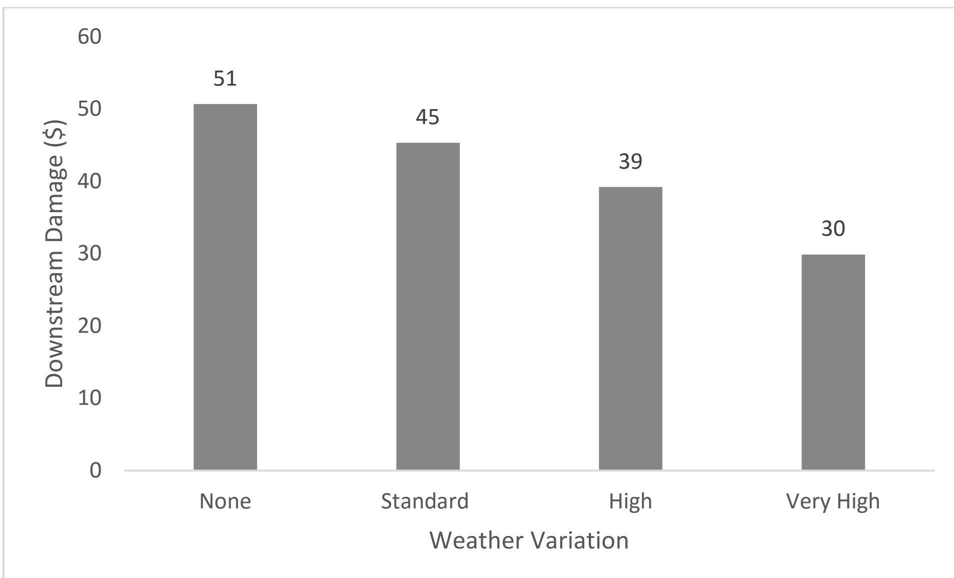
In Table 6, the data for the two subsidies are pooled, allowing us to examine downstream damage with a subsidy in place. Damage under very high weather variability is $29.88, which is 41% lower than when there is no weather variability ($50.67). The average subsidy received in the very high variability scenarios is $23.90 while the average subsidy for no variability is $16.37.

Table 6. Mean Production and Damage and Subsidy under Subsidy Types

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

Thus, we find that, as weather variation increases, both the ambient-based and the production-targeted subsidies become more effective at decreasing damage. As shown in Figure 4, downstream damage is 33% less for very high weather variability (involving a 40% chance of extreme weather) relative to standard weather variability.

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



Since our data set provides multiple observations from each individual, a random effects model is appropriate for analyzing damage, production, and welfare. Table 7 shows the results of the three log-linear (random-effects) models we estimated, which have a baseline of no subsidy and no weather variation and allow us to compare percent impacts in the presence of either type of subsidy. In model A_1, the dependent variable is log(*damage*); it explains how the independent variables—standard weather variability, high or very high weather variability, presence of a subsidy, and the interactions of *subsidy* with standard and high or very high weather variability—affect the log of the amount of measured downstream damage. We find that the presence of a subsidy policy significantly reduces downstream damage (approximately 63%). Also, in response to the interaction of a subsidy with high or very high weather variability, the amount of downstream damage (a function of production) decreases significantly.

Dependent Variable	**Model A_1** Log(Damage)	**Model B_1** Log(Total Production)	**Model C_1** Log(Welfare)
Standard Weather Variation	–0.139 (0.088)	–0.084* (0.050)	0.152 (0.081)
Higher Weather Variation	–0.106 (0.072)	–0.062 (0.041)	0.141 (0.100)
Subsidy	–1.00*** (0.070)	–0.728*** (0.048)	0.561*** (0.081)
Subsidy X Standard Weather Variation	–1.64 (0.134)	0.081 (0.068)	–0.129 (0.117)
Subsidy X Higher Weather Variation	–0.699*** (0.128)	0.011 (0.003)	–0.047 (0.094)
Treatment Round	0.006 (4.87)	0.011*** (0.003)	–0.013*** (0.004)

Constant	4.87*** (0.083)	5.55*** (0.040)	4.26*** (0.082)
Number of Observations	794	794	794
R^2	0.3331	0.6441	0.5923

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

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

Table 8 presents the results of three additional random-effects models that address the two types of subsidies separately. These models treat the targeted and ambient-based subsidies and their interactions with weather variability as independent variables. Once again, the baseline is no subsidy and no weather variability. In model A_2, the dependent variable is log(*damage*), and it explains how the independent variables affect the log of the amount of measured downstream damage. We find that both subsidy mechanisms significantly reduce damage compared to the baseline. Model A_2 also shows that, in the presence of a subsidy, downstream damage decreases as the likelihood of extreme events increases (higher and very high weather variability). In addition, we find that the interaction of the targeted subsidy and high or very high weather variability decreases the amount of downstream damage.

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

	Model A_2	**Model B_2**	**Model C_2**
Dependent Variable	Log(Damage)	Log(Total Production)	Log(Welfare)
Standard Weather Variation	–0.140 (0.088)	–0.085 (0.050)	0.152 (0.115)
High Weather Variation	–0.154** (0.077)	–0.082 (0.043)	0.197** (0.100)
Very High Weather Variation	–0.060 (0.077)	–0.043 (0.043)	0.087 (0.103)

Ambient Subsidy	–0.905*** (0.078)	–0.627*** (0.054)	0.546*** (0.082)
Targeted Subsidy	–1.11*** (0.067)	–0.828*** (0.048)	0.577*** (0.082)
Ambient Subsidy X Standard Weather Variation	–0.052 (0.151)	0.083 (0.085)	–0.162 (0.122)
Ambient Subsidy X High Weather Variation	–0.228 (0.159)	0.040 (0.085)	–0.139 (0.105)
Ambient Subsidy X Very High Weather Variation	–0.830*** (0.251)	0.001 (0.077)	0.023 (0.112)
Targeted Subsidy X Standard Weather Variation	–0.273 (0.164)	0.080 (0.060)	–0.096 (0.116)
Targeted Subsidy X High Weather Variation	–0.329** (0.144)	0.054 (0.058)	–0.124 (0.101)
Targeted Subsidy X Very High Weather Variation	–1.40*** (0.167)	–0.048 (0.072)	0.049 (0.105)
Treatment Round	0.006 (4.87)	0.012 (0.003)	–0.013** (0.004)
Constant	4.87*** (0.083)	5.55*** (0.040)	4.26*** (0.082)
Number of Observations	794	794	794
R^2	0.4181	0.7201	0.6122

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

Our second hypothesis is that changes in risk due to an increase in extreme weather do not affect downstream damage under the targeted subsidy because the utility bears the risk of such weather events when the subsidy is based on the individual firm's production rather than on the collective amount of pollution downstream. We expected to find that only interactions of weather with the ambient-based subsidy would have a significant effect on damage. Instead, the null hypothesis is rejected, and we see that the interactions with weather result in significant additional damage (relative to the baseline of no weather variability) under both types of subsidies (See model A_2 in Table 8).

Our third hypothesis is that the ambient-based and production-targeted subsidies have an approximately equal ability to reduce downstream damage. To test this, we use equation 17 and focus on the null hypothesis:

$$H_0\colon \partial_4 = \partial_5.$$

We find that the null hypothesis is rejected and that there is a significant difference in the impacts of the subsidies. Average total downstream damage is $35.89 with the targeted subsidy and $49.21 with the ambient-based subsidy.

We performed a two-tailed paired t-test and found significant differences in the mean values for damage under the targeted and ambient-based subsidies ($p = 0.000$). In addition, we performed a chi-squared test and found that the coefficients for the subsidies in model A_2 (shown in Table 8) are significantly different. Both subsidies result in less downstream damage, but the targeted production-based subsidy is more effective than the ambient-based subsidy in decreasing pollution. The targeted subsidy is probably more effective because the firms know how much they are producing and the amount of the subsidy offered to them for that level of production under various weather scenarios. The firms also know that the utility possesses exact information about their production because of the individual sensors and can precisely identify how much pollution each firm contributes. Consequently, the firms choose to reduce their production, resulting in less downstream damage.

Our fourth hypothesis is that a stream group's total production is not influenced by the degree of weather variability. To test this, we estimate

$$Total\ Production = \ c + \partial_0 None + \ \partial_1 Standard + \partial_2 High + \partial_3 Very\ High + \in \tag{18}$$

and test a null hypothesis that

$$H_0\colon \partial_0 = \partial_1 = \partial_2 = \partial_3 = 0.$$

In our analysis of subsidies in general (see Table 7), we find that having a subsidy in place reduces total production by 52% on average relative to the baseline of no subsidy and no weather variation (see model B_1 in which the dependent variable is log(*total_production*)). When we analyze the targeted and ambient-based subsidies separately (model B_2 in Table 8), we see that both of the subsidies significantly reduce total production relative to the baseline of no subsidy and no weather variation. The dependent variable in the model is log(*total production*), which explains how the independent variables affect the log of the amount of total production. The results from model B_2 in Table 8 support our hypothesis; the degree of weather variability does not influence total production. In general, we find that total production decreases slightly as weather variability increases from no variability to standard, high, and higher variability but the change is not significant.

Our results reject our fifth hypothesis that the targeted and ambient-based subsidies would have approximately equal effects on total production. We find that the production-targeted subsidy is more effective than the ambient-based subsidy, resulting in average individual production of 19 units and average total production of 114 units versus 23 and 143.28 units, respectively, with the ambient-based subsidy Recall that the socially optimal level is reached when total production is 144 units. We performed a two-tailed paired t-test, which identified a statistically significant difference in average total production under the two subsidy mechanisms ($p = 0.000$). Because the targeted subsidy involves individual sensors that identify the production/damage contributed by each firm, some of the information asymmetry is removed, so we expect the targeted subsidy to be more effective.

Table 9 reports the results of our analysis of the effects of subsidies on social welfare, which is measured as a stream group's income minus its damage. We find that average social welfare is 38% higher with a subsidy than without. Figure 5 compares social welfare with and without a subsidy in response to changes in weather variability. With a subsidy, the utility comes much closer to achieving the socially optimal level of welfare regardless of the degree of weather variation. A two-tailed paired t-test shows that the differences are statistically significant ($p = 0.000$). In model C_1 (Table 7), the dependent variable is log(*welfare*), which explains how the independent variables affect the log of the amount of total social welfare. The results of that model indicate that both mechanisms significantly increase social welfare relative to the baseline of no subsidy and no weather variation.

Figure 5: Average Social Welfare under different Weather Variations

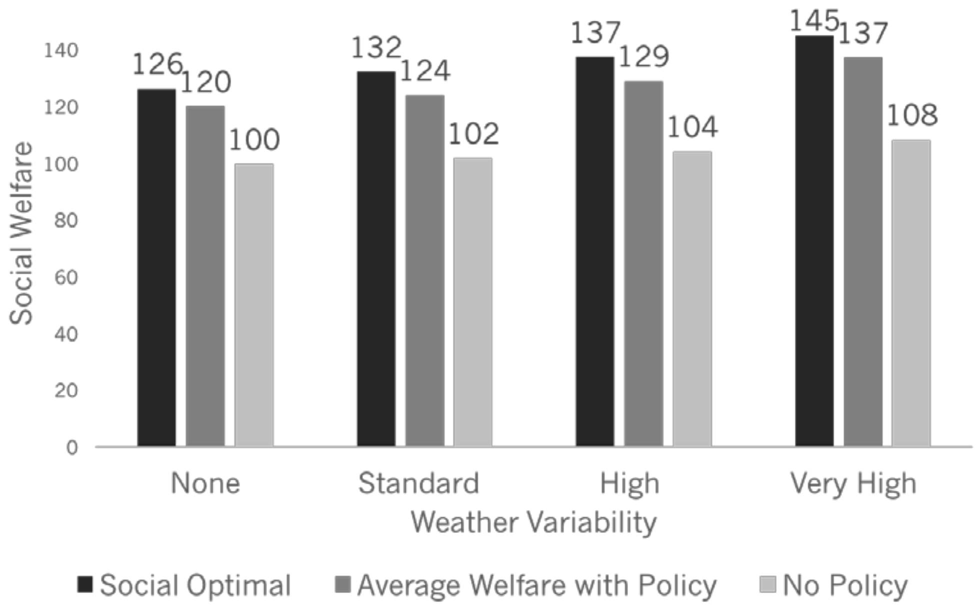


Table 9. Average Social Welfare

	Average Social Welfare		
	Social Optimal	**With Subsidy**	**Without Subsidy**
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

Our results reject the sixth hypothesis that ambient and targeted subsidies have the same impact on social welfare and find, instead, that the targeted subsidy is more effective than the ambient-based subsidy in increasing social welfare. We conducted a chi-squared test comparing the coefficients for the ambient (0.546) and targeted (0.577) subsidies and found a significant difference between the two ($p = 0.05$). This result is similar to the results for the targeted and ambient-based subsidies in response to high and very high weather variability.

4. Conclusions

We use an economic experiment to test participants' behavioral responses to two incentives to reduce their NPS pollution of a waterway that could be measured by a sensor. One subsidy is based on the ambient level of pollution in downstream and the other is based on firms' production. We further extend our analysis by comparing the ability of the subsidy mechanisms to reduce damage from pollution in the face of greater variability in weather associated with climate change. The results from our experiment show that both the ambient-based and the production-targeted subsidies work to reduce pollution and improve social welfare. We also find that the targeted subsidy becomes more effective in reducing pollution as the likelihood of extreme weather events increases. This occurs because, under the ambient-based policy, the individual producers risk losing some or all of their subsidies because of weather-related pollution; the targeted subsidy severs the connection between weather-related pollution and the amount of subsidy they receive. Thus, we find that the participants are risk-averse under conditions of high weather variability and react to the additional risk associated with more severe weather by reducing production to increase the amount of subsidy granted.

Utilities that provide drinking water can subsidize upstream users to improve the quality of the water on which they rely. The results of our experiment suggest that DWUs might prefer to implement targeted (production-based) subsidies to reduce pollution despite the additional cost relative to subsidies based solely on the downstream ambient pollution level. We find that targeted subsidies are more effective than ambient-based subsidies at reducing production and pollution and increasing social welfare. Under ambient-based subsidies, the individual contributors to the pollution downstream bear equal risk of losing their subsidies if some contributors exceed the target and/or severe weather increases the amount of pollution in the stream. Under the targeted subsidy, the individual contributors are not affected by other contributors or by more-frequent severe weather events. In effect, the targeted subsidy allows regulators to manage NPS pollution much like they manage source-point pollution.

Currently, targeted subsidies are difficult and/or expensive to implement. Advanced sensors are needed to measure individual contributions of pollution. Our research shows that NP pollution targets will be easier to reach once advanced sensors that can predict or measure individual activity at a micro level are readily available. There is a political need for further research and development to advance such technologies.

In addition, the results of this study show that both types of subsidies work to reduce pollution and production and increase social welfare, particularly under extreme weather conditions. To draw more general conclusions regarding the relationship between the type of subsidy offered and improvements in water quality, several of our assumptions could be modified in future studies. For instance, spatial dimensions could be incorporated to further characterize the relationship between production and ambient damage. Conducting the experiment with farmers could determine whether their experience with production decisions and subsidies would affect their decisions. This study could also be extended to analyze an entire watershed by increasing the number of firms and amount of land. We assumed that the firms were homogeneous; future studies could relax that assumption and study heterogeneous agents by differentiating the size and capacity of the firms. Finally, it could be interesting to allow communication between the participants in the experiment.

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Appendix A – Experiment 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.

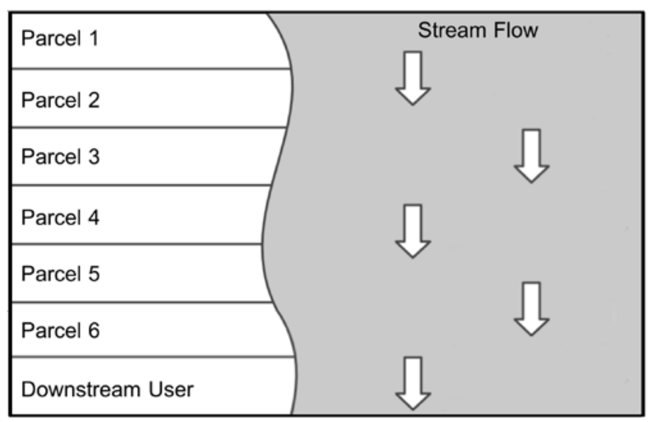
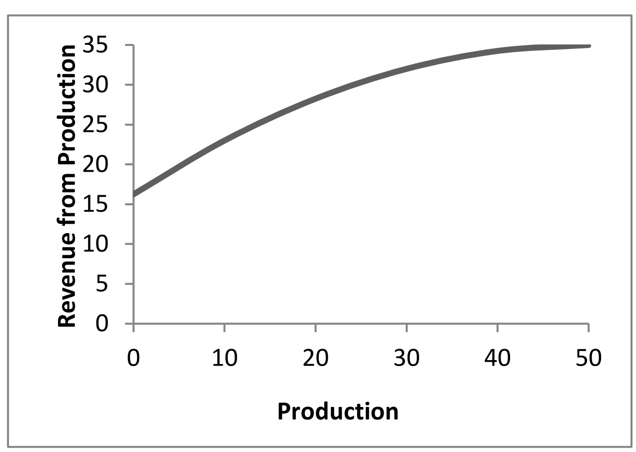


Figure 1. Stream Flow

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

Figure 2. Production and Revenue

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.

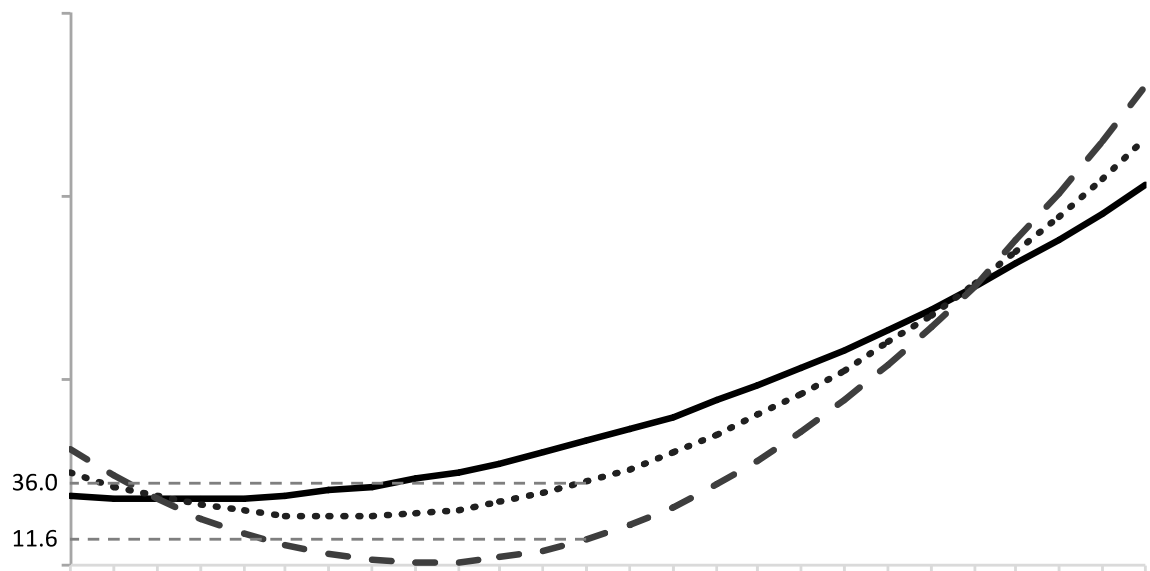


Figure 3. Production and Downstream Damage

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.

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

<u>Example 2</u>: 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.

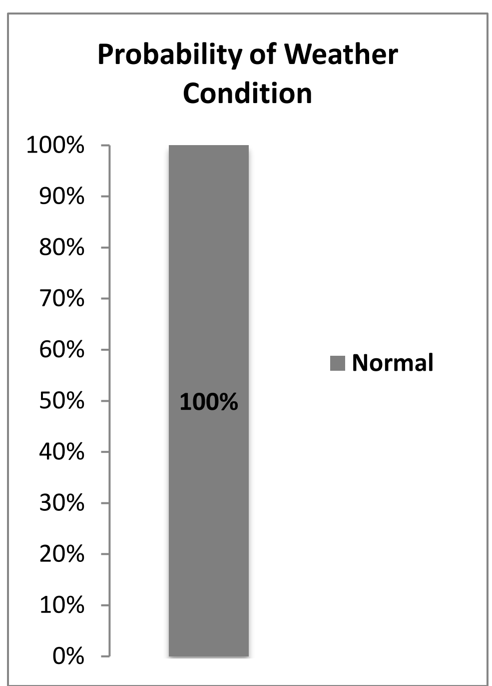
The calculator will be available to you throughout the experiment and will update throughout the parts so that you can try out different strategies. You can enter production decisions for each parcel by typing it directly into the column labeled "Production", you can also change production by using the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

No Weather Variation

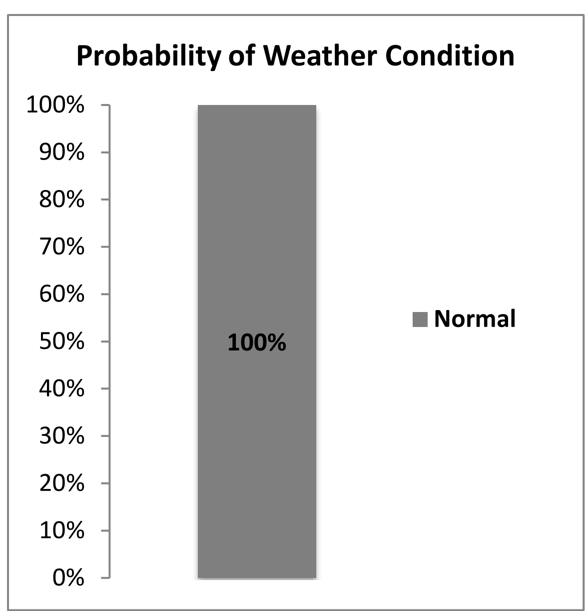
Note how, in this part, your production decision will influence the profits of everyone in your group and the production decisions of others affect your profit.

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.

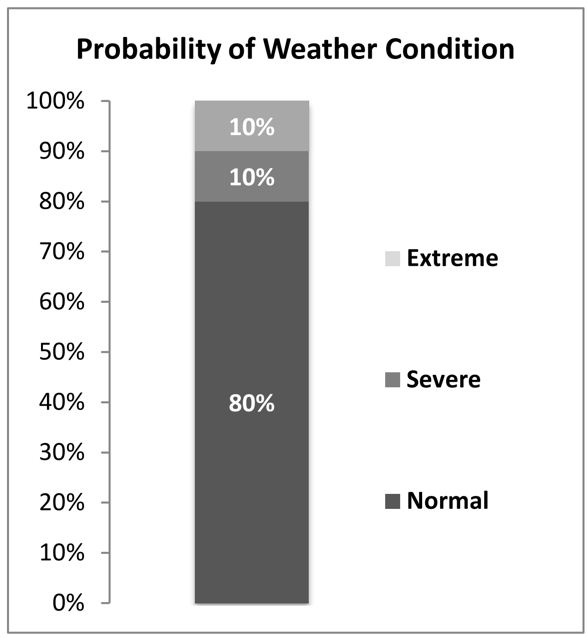
Example 2: If everyone else produces 20, but you produce 35 then your normal weather subsidy will be $0. Everyone else will have a normal weather subsidy of $20.28. Your subsidy is less than everyone else because you produced more.

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.



Standard Weather Variation

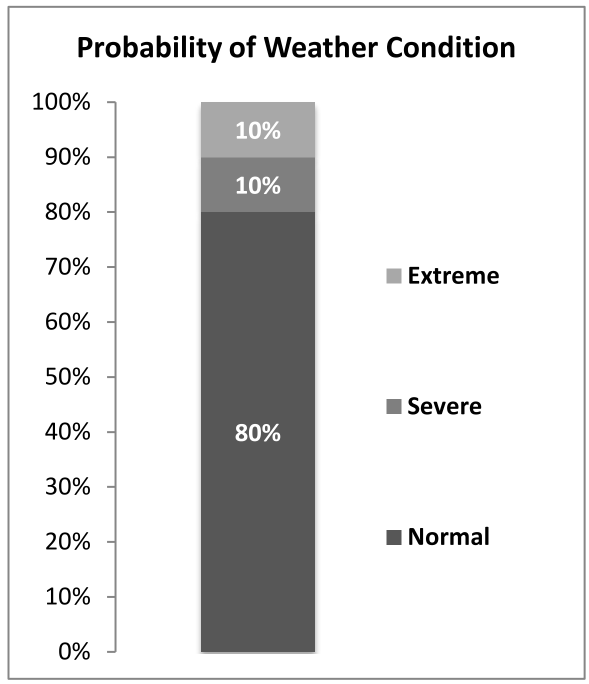
<u>Example 1</u>: If everyone produces 20 then your normal weather subsidy will be $22.55.

<u>Example 2</u>: 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 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.



Standard Weather Variation

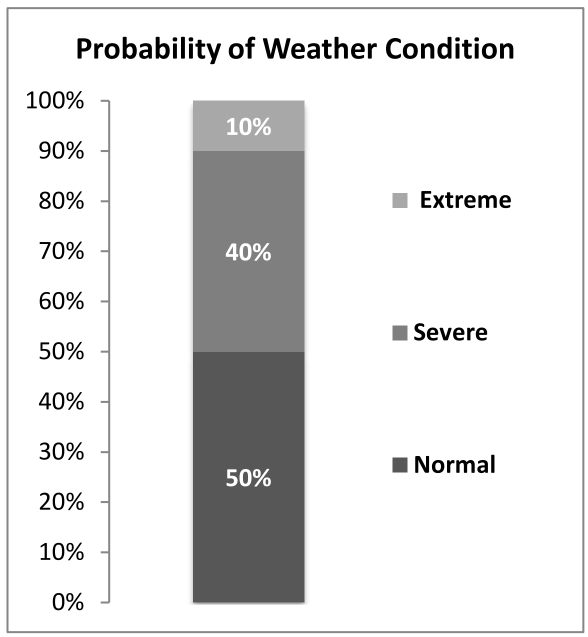
Example 1: If everyone else produces 35, but you produce 15 then your normal weather subsidy will be $22.47. Everyone else will have a normal weather subsidy of $0. Your subsidy is more than everyone else because you produced less.

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.

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.



High Weather Variation

<u>Example 1</u>: If everyone produces 20 then your severe weather subsidy will be $28.70.

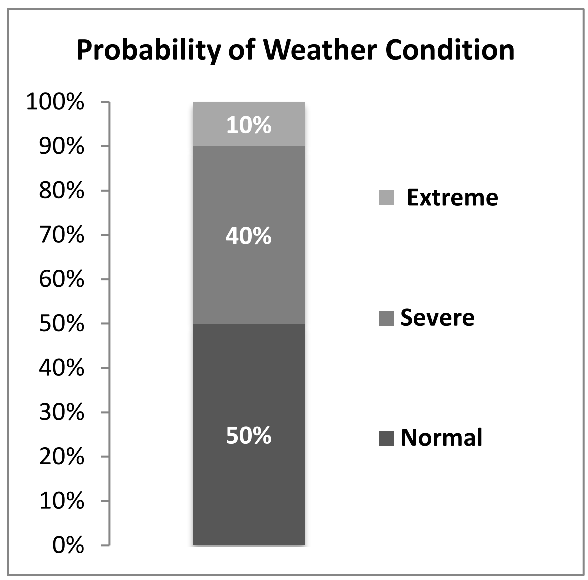
<u>Example 2</u>: If five parcels produce 20 and one parcel produces 50, your severe weather subsidy is $0.

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 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.



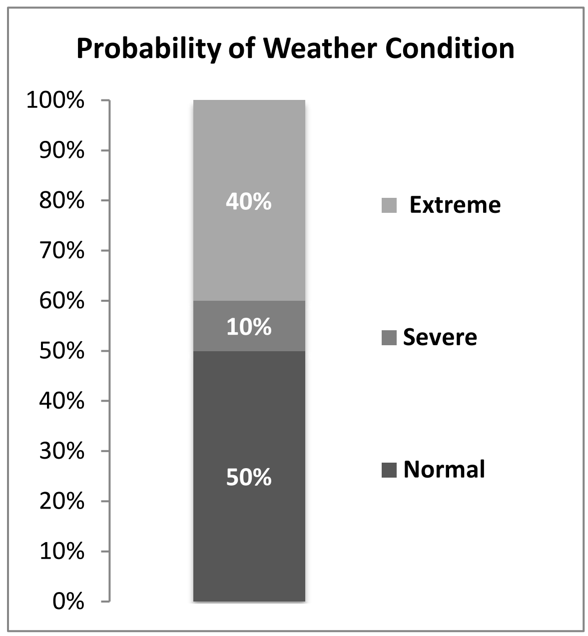
High Weather Variation

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.

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% change of experiencing extreme weather, a 10% chance of experiencing severe weather, and a 50% chance of experiencing normal weather.



Very High Weather Variation

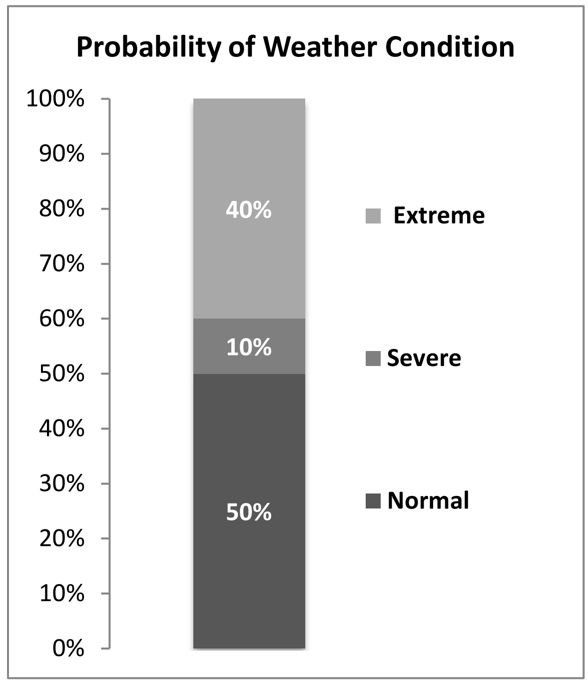
Example 1: If everyone produces 20 then your extreme weather subsidy will be $36.38.

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

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% change of experiencing extreme weather, a 10% chance of experiencing severe weather, and a 50% chance of experiencing normal weather.



Very High Weather Variation

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.

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.

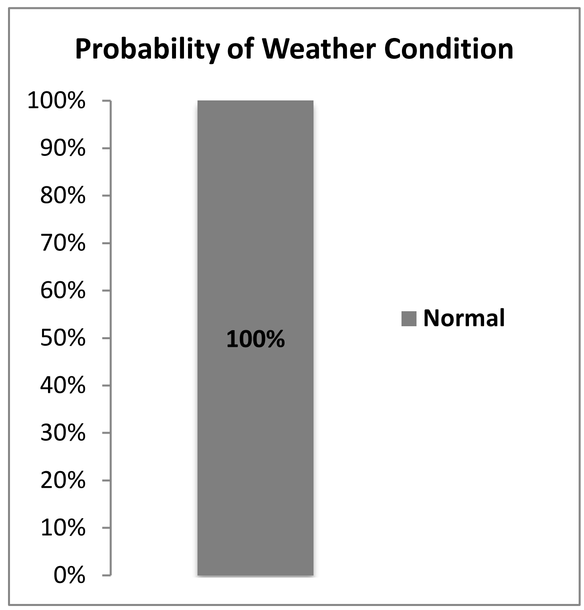
In this part, there is a subsidy that will be offered based on the **average amount of damage** that reaches the downstream user from all six parcels. Everyone in your group will receive the **same** subsidy. There will be a large subsidy for minimal damage, but the subsidy gets smaller as average group 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.



No Weather Variation

G

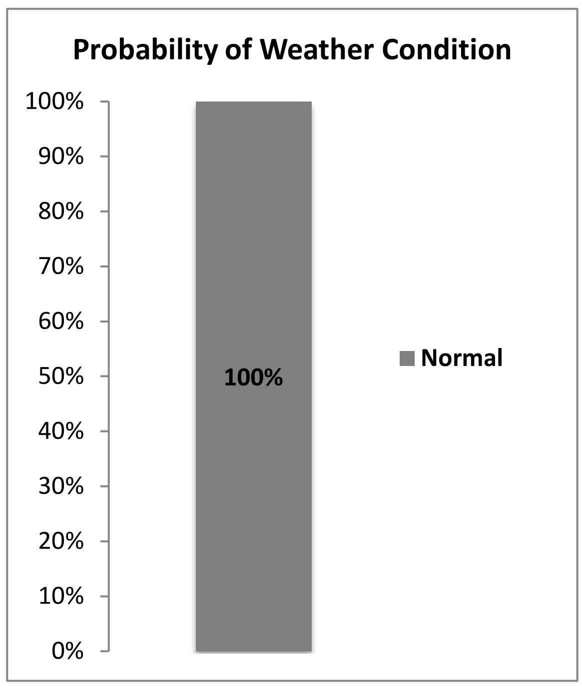
In this part, the subsidy will be based on **individual production**. The subsidy may be **different** for different members of your group. If your production is greater than the target production for individuals, there will be no subsidy. The target for individual production is 24.

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

<u>Example 1</u>: 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.

<u>Example 2</u>: 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.

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.



No Weather Variation

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

The Department of Applied Economics and Statistics carries on an extensive and coordinated program of teaching, organized research, and public service in a wide variety of the following professional subject matter areas:

Subject Matter Areas

- Agricultural Policy
- Food and Agribusiness Management and Marketing
- Natural Resource Management
- Rural and Community Development
- Environmental and Resource Economics
- International Agricultural Trade
- Price and Demand Analysis
- Statistical Analysis and Research Methods

The department's research in these areas is part of the organized research program of the Delaware Agricultural Experiment Station, College of Agriculture and Natural Resources. Much of the research is in cooperation with industry partners, the USDA, and other State and Federal agencies. The combination of teaching, research, and service provides an efficient, effective, and productive use of resources invested in higher education and service to the public. Emphasis in research is on solving practical problems important to various segments of the economy.

The mission and goals of our department are to provide quality education to undergraduate and graduate students, foster free exchange of ideas, and engage in scholarly and outreach activities that generate new knowledge capital that could help inform policy and business decisions in the public and private sectors of the society. APEC has a strong record and tradition of productive programs and personnel who are engaged in innovative teaching, cutting-edge social science research, and public service in a wide variety of professional areas. The areas of expertise include: agricultural policy; environmental and resource economics; food and agribusiness marketing and management; international agricultural trade; natural resource management; operations research and decision analysis; rural and community development; and statistical analysis and research methods.

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