The Effects of Information and Network on Non-Point Source Pollution: A Laboratory Experiment

by

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ABSTRACT

The Effects of Information and Network on Non-Point Source Pollution: A Laboratory Experiment

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This research employs a laboratory experiment to analyze the impact of information networks, an emissions-reduction technology subsidy, and a pro-abatement nudge on non-point source (NPS) pollution levels. Participants made input and technology decisions which generated pollutants under an ambient tax. Three information treatments are evaluated in a 3x2 design, orthogonal to a nudge. When combined with the nudge, the ambient mechanism induces socially optimal emissions levels when no information on others' technology adoption and/or subsidy provision is known. Under certain conditions, observing another's technology adoption is found to increase an individual's own likelihood of adoption. Subsidies are found to lower pollutants and increase adoption regardless of the level of information flows in a network. The findings suggest that subsidies and nudges may be effective in reducing NPS levels, but that care must be taken when incentivizing producers in scenarios with high information flows regarding others' technology adoption.

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Chapter 1 Introduction

Non-point source (NPS) water pollution is characterized by the diffuse nature of emissions in which individual sources are not easily observable and therefore regulation of this form of environmental damage can be challenging (Wu, Palm-Forster & Messer, 2021; Suter et al., 2008). Runoff and nutrient deposition are two common NPS emissions sources which can, if left unabated, lead to a variety of environmental problems including water quality degradation as well as issues of algal blooms, hypoxia, and negative impacts to aquatic ecosystems (Moxey 2012; Xepapadeas, 2011; Suter at al., 2008). According to the U.S. Environmental Protection Agency (EPA), NPS pollution is a leading cause of water quality issues in many areas (EPA, 2021). The OECD reports that within Canada reducing water pollution can yield tangible economic benefits stemming from local water quality improvements, reductions in impacts to recreational fishing, and through lessening the burden on water treatment requirements (Moxey, 2012).

Monitoring of NPS pollution is often prohibited by issues of multiple emitters as well as pollutant accumulation which can occur far from the initial source. In addition, as emission levels at a given source are often not observable, this can lend to issues of free-riding and incentive problems at the individual-level with regards to policy regulation of NPS pollution. Contemporary economics literature has analyzed the potential mechanisms which can motivate reduction of NPS pollution levels (Wu, Palm-Forster & Messer, 2021; Griesinger 2017).

Agriculture is a leading global cause of water pollution (Wu, Palm-Forster & Messer, 2021; Food and Agriculture Organization of the United Nations, 2017). Agricultural activities can deposit excess nutrients into surrounding environments through the runoff of sediment, fertilizers, and manure (Palm-Forster, Suter, & Messer, 2018; Xepapadeas, 2011). The environmental impacts of runoff may occur far from the source of the agricultural activity and individual sources are not always observable. Agricultural pollution is therefore a form of non-point source (NPS) pollution characterized by multiple and diffuse emission sources. Due to these characteristics, regulation of agricultural runoff to reduce the environmental externalities associated with production presents a challenge for policy regulation (Moxey, 2012; Weersink et al. 1998). According to the Government of Canada (2016), NPS pollution from agricultural runoff is expected to increase in future years due to higher demand for food and fibre which necessitates higher densities of livestock kept on farms and the intensification of cropping. Additionally, increased temperature and snowmelt associated with climate change is expected to amplify the negative impacts of agricultural runoff (Jain & Singh, 2019; Xepapadeas, 2011).

Motivating farmers to adopt Best Management Practices (BMPs) and technologies which can manage runoff from their production is therefore necessary to help mitigate the current and future negative environmental impacts of agricultural activities (Government of Canada, 2016). However, widespread adoption of many BMPs which can improve environmental outcomes has not generally occurred (Palm-Forster, Swinton, & Shupp, 2017). Policy which promotes adoption of such abatement practices can be informed through research which seeks to understand the behavioural factors which may affect farmer decision-making in the adoption process (Streletskaya, et al., 2020; Weersink & Fulton, 2020).

Economic experiments are a powerful tool that can be utilized to understand the factors which influence agricultural technology adoption (Maertens & Barrett, 2012). According to Cochard, Wilinger, & Xepapadeas (2005), economic experiments can be effective when studying the efficacy of mechanisms which can manage NPS pollution. Experiments can be employed to measure direct variables of interest which are not easily observed in the real world (Al-Ubaydli et al., 2019; Palm-Forster et al., 2019). Insight from experiments can therefore be used to develop evidence-based policy, identifying the behavioural factors which may influence adoption of abatement practices. Informing effective policy through these insights can improve welfare through preservation of water quality and reduction of the environmental externalities associated with agricultural practices (Czap et al., 2019; Lourenço et al., 2016; Moxey, 2012). However, to date there has been limited research within the field of behavioural economics which focuses specifically on agri-environmental issues (Palm-Forster et al., 2019).

The research presented in this thesis employs a laboratory experiment to understand how information and policy instruments can influence producers' decisions to adopt emissions-reductions practices. In the experiment participants made decisions regarding whether to adopt an emissions-reduction technology analogous to a BMP in the real world which has the potential to reduce a farmer's agricultural runoff. In the experiment participants also made individual production input decisions. Together, these decisions generated pollutants in a context-free experiment environment. The experiment utilized a social network design whereby the effect of information amongst participants on other's adoption decisions could be analyzed. In addition to information networks, subsidies for the emissions-reduction technology were also included as a component of the experiment. Therefore, this experimental design allowed for a direct analysis of the impact of information networks as well as subsidies on abatement decisions in the context of a NPS pollution problem. A nudge encouraging individual-level abatement decisions was also evaluated and the effectiveness of pro-abatement messaging within networks with varying levels of information between producers was analyzed.

This research acts as a proof-of-concept study and the hypotheses examined in this experiment relate to the impact of several policy and behavioural factors on NPS pollution levels under conditions of an ambient tax. Specifically, the effect of a pro-abatement nudge, a subsidy for an emissions-reduction technology, and varying levels of information flows within a producer's network are examined. The following research questions are then explored: First, whether a pro-abatement nudge can induce lower NPS pollution levels and increase technology adoption. Second, if subsidization of an emissions-reduction technology will lead to lower NPS pollution levels and higher adoption rates. Third, if information regarding other producers' technology adoption in the network influences an individual's own adoption behaviour. Fourth, if information on whether a direct neighbour has received a subsidy affects an individual's adoption decisions. Finally, if the level of information flows within a network between producers affects the aggregate pollution level. Of note, the interaction effects between the information level in a network, other producers' behaviour and the pro-abatement nudge are analyzed in this research.

The experiment was conducted with 228 participants in groups of six who made both input and technology decisions over 20 rounds of decision-making. The experiment was administered in a context-free environment and participant's decisions in the game impacted their final payoff. A 3x2 treatment design was employed with between-group information treatments orthogonal to a pro-abatement nudge shown to approximately half the groups. Data was analyzed at both the aggregate and individual-level with respect to the pollutants generated in the experiment through the input and technology decisions made by participants. A random-effects Generalized Least-Squares (GLS) regression analysis was conducted at the group-level to determine the effect of the nudge and the amount of information provided in the network on the aggregate level of pollutants. This regression analysis was also conducted at the individual-participant level to determine the impact of information, the pro-abatement nudge, as well as subsidy provision and neighbour's adoption behaviour on the level of pollutants generated by each individual. Finally, a random-effects logit regression was employed to assess the aforementioned factors on individual decisions to adopt the emissions-reduction technology.

The results indicate that in the low information scenario, where participants have no knowledge of other's technology adoption decisions, that the pro-abatement nudge was able to effectively reduce NPS pollution levels. Furthermore, the evidence suggests that pro-abatement messaging can be effective under conditions of low information between producers in inducing a socially optimal emissions level where neighbour's adoption decisions are not known. However, the results indicate that pro-abatement messaging may prove ineffective in scenarios where producers have high levels of information regarding each other's adoption behaviour and whether other producers have received a subsidy. These finding signals that care must be taken in the implementation of pro-abatement messaging in networks with high levels of information flows between producers. The experiment yields evidence that, in certain situations when a producer has knowledge of another's adoption behaviour, that they will be more likely to adopt the technology themselves if they view another producer doing so, and vice versa. This suggests evidence of peer-influence amongst producers with regards to their adoption of emissions-reductions practices. Finally, the results indicate a positive impact of technology subsidy provision on lowering NPS pollution levels and increasing technology adoption. Within the experiment, receipt of a subsidy was found to increase the likelihood of technology adoption by 22-35%. Of note, the results indicate that subsidy provision can be effective regardless of the level of information flows in a producer's network and both with and without the use of a pro-abatement nudge.

This research contributes to the literature on information networks and BMP adoption and addresses the need for more robust experimental designs in the context of agri-environmental NPS pollution issues (Omotilewa, Ricker-Gilbert, & Ainembabazi, 2020; Wu, Palm-Forster, & Messer, 2021). There is evidence that information networks can influence farmers' decisions to adopt new practices or technologies (Omotilewa, Ricker-Gilbert, & Ainembabazi, 2020; Weersink & Fulton, 2020; Foster & Rosenzweig, 2010). According to Maertens & Barrett (2012), research regarding new technology adoption is enhanced by considering the role of social networks which may influence the decision-making of a potential adopter and can therefore help inform effective policy. Note that a farmer's own information network can comprise people who are socially close, the greater farming community, and can also include formal outreach from government institutions (Weersink & Fulton, 2020; Krishnan & Patnam, 2013). Therefore, by understanding the influence of social networks on farmer behaviour policy can potentially utilize these networks to design outreach avenues which motivate adoption of emissions-reduction practices. The behavioural insights gathered from this experiment can therefore inform policy which seeks to mitigate the negative impacts of agricultural runoff. In addition, this research furthers the understanding of individual behaviour under a profit-maximization framework in the context of a NPS problem and, specifically, allows for an analysis of how decision-making agents may respond under an ambient policy. To this end, this research utilizes a Nash Equilibrium framework to develop the economic theory as it relates to agent's decisions under varying policy treatments (i.e. subsidy and no subsidy provision) and the corresponding outcomes with respect both producer payoffs and pollution generation.

The layout of the remainder of this paper is as follows: Section 2 examines the literature on non-point source pollution and policy instruments as well as agricultural BMP adoption.

Related economic experiments which address these topics are also discussed in the context of this research. Section 3 outlines the conceptual framework of the experiment including the social planner's problem with respect to NPS pollution levels and the associated ambient tax mechanism as well as the Nash Equilibrium for participant's decisions made within the experiment. Section 3 details the experimental design including a description of each treatment as well as the testable hypotheses. Section 4 presents the summary statistics and employs random-effects GLS regressions of pollution levels at both the aggregate and individual-level. A random-effects logit regression of individual adoption decisions is also evaluated. Finally, Section 5 discusses the contribution of this research to the literature. The main findings are then summarized and policy implications as well as future research avenues are developed.

Chapter 2 Literature Review

2.1 Non-Point Source Pollution

Non-point source (NPS) pollution can be defined as pollution from diffuse emitters, in which the individual source can not be easily identified (Suter et al., 2008). NPS pollution is particularly challenging from a policy perspective as monitoring and enforcement on an individual-level is often infeasible or too costly (Griesinger et al. 2017; Xepapadeas, 2011; Weersink et al. 1998).

The literature acknowledges the considerable impact agriculture can have on environmental quality and the importance of Best Management Practices (BMPs) in limiting negative externalities from farming (Weersink et al. 1998). Runoff from agriculture contributes to water pollution through sediment, fertilizer, and manure displacement which can introduce additional phosphorus, nitrogen, and pathogens into the environment (Griesinger et al. 2017;

Xepapadeas, 2011). NPS pollution can impact a diverse range of water sources, including groundwater, soil, streams, lakes, coastlines, and watersheds (Pett, 2001). Pollution of water can lend to issues of eutrophication, algal blooms, and hypoxia which may result from excessive nutrient loads and reduced oxygen in aquatic environments (Palm-Forster, Suter, & Messer, 2018; Xepapadeas, 2011). The deleterious impacts of agricultural pollution may occur near the emissions source but in many cases can also have far-reaching effects (Weersink et al. 1998).

In Canada, incidence of agricultural runoff is expected to increase in the absence of abatement practices due to increased densities of livestock and the expansion of cropping to satisfy higher demand for food and fibre (Government of Canada, 2016). Additionally, the environmental consequence of agricultural runoff is estimated to be amplified in future years due to climate change and the associated impacts on temperature, snowmelt, and precipitation (Xepapadeas, 2011).

2.1.1 Policy Instruments for Managing NPS Pollution

NPS pollution control presents a unique challenge from the standpoint of the social planner. This is because contributors to NPS water pollution, be they producers or residents, each act in their own self-interest and individual pollutant levels can seldom be directly observed (Li et al., 2021; Palm-Forster et al. 2019; Palm-Forster, Suter, & Messer, 2018; Xepapadeas, 2011). Rather, ambient pollution levels are often the only indicator of environmental damages from NPS pollution.

Unlike point-pollution which is traceable to individual sources, NPS pollutants can not be monitored effectively outside of individual receptor points. Enforcement then presents a potentially costly challenge for policy remedies as no precise control methods are available

(Xepapadeas, 2011). In recent decades policy has turned to regulatory control instruments to lessen NPS emissions into shared water bodies. Technology subsidies and ambient control schemes are instruments which can be potentially employed to induce efficient levels of NPS pollution (Lopez et al. 2010). These two mechanisms are discussed further in the subsequent sections and are evaluated as instruments to manage agricultural runoff in this research.

2.1.2 Technology Subsidies

Subsidies for BMPs and new technologies are a mechanism which can encourage adoption. One way subsidies can be allocated is homogeneously in which all eligible farmers have the opportunity to receive a payment towards initial adoption. Alternatively, subsides can be allocated to specific producers such as individuals likely to be early adopters. Discussions of subsidies in the environmental conservation literature support the efforts to increase BMP adoption and environmental stewardship at the farmer level can be aided by BMP subsidies and that this approach can increase social welfare (Duflo, Kremer, & Robinson, 2011; Chouinard et al. 2008).

Field and laboratory experiments have been conducted to estimate the effect of provision of a one-time technology or input subsidy on subsequent and persistent adoption behaviour (Omotilewa, Ricker-Gilbert, & Ainembabazi, 2020; Channa et al. 2019; de Janvry et al. 2016). A field experiment by Carter, Laajaj, & Yang (2014) found that when farmers in Mozambique were given a one-time subsidy for fertilizer and improved seeds that this led to long-term substantial increases in adoption. Notably the subsidy was determined to encourage learning-by-doing among the farmers which motivated adoption in future seasons. A study by Duflo, Kremer, & Robinson (2011) found that a 50% subsidy paid to farmers for inputs led to an increase in fertilizer use by 13-14%. Similarly, a field study by Omotilewa, Ricker-Gilbert, & Ainembabazi (2020) demonstrated that farmers in Uganda subsidized to buy a new agricultural technology were more likely to purchase the technology at full price at a later time, compared to farmers who were aware of the technology but did not receive a prior subsidy.

These results support that the provision of subsidies to encourage farmers to adopt new technologies can also generate long-term demand. Experimental evidence regarding the effect of a direct subsidy for technologies which can reduce environmental externalities associated with production, particularly where a voluntary adoption decision for the subsidized technology is presented, is limited (Palm-Forster, Suter & Messer, 2018). Additionally, further research is needed to account for heterogeneity in available subsidies to producers (Palm-Forster, Suter & Messer, 2018).

Jaffe, Newell, & Stavins (2005) assert that, generally, most countries see support in the subsidization of new technology and practices. However, the characteristics of the subsidy provided and the length of time in which the subsidy is available to potential adopters is critical in the design of effective policy. There is evidence that large subsidies that cover in excess of half a technology or BMP's cost may be less efficient from a welfare perspective than more conservative subsidies (Duflo, Kremer, & Robinson, 2011). Additionally, it is potentially disadvantageous to instill "permanent" ongoing subsidies which may have negative impacts in long-run social efficiency (Omotilewa, Ricker-Gilbert, & Ainembabazi, 2020). The number of subsides provided may also prove to be an important consideration in influencing adoption. For instance, the field experiment by Carter, Laajaj, & Yang (2014) found that there was a significant effect of having up to 2 subsidy recipients in a social circle of potential adopters but there was no influence of further subsidy provision in increasing overall adoption. Notably, the effect of subsidy provision on adoption of emissions-reductions practices within a network, as well as the impact of subsidy provision amongst both recipients and non-recipients, is of interest to this research.

2.1.3 Ambient Control Instruments

The diffuse nature of agricultural runoff and issues of information asymmetry due to the NPS pollutant aspect of this problem preclude the effective use of conventional control instruments such as a Pigouvian tax to internalize the environmental externalities of production (Xepapadeas, 2011; Pigou, 1921). Rather, a common approach for inducing NPS pollution levels to a desired outcome studied in the NPS pollution literature is the use of an ambient tax or ambient subsidy method as proposed by Segerson in 1988. Segerson's framework on potential policy approaches which can reduce producers' emissions demonstrates the potential effectiveness of ambient control schemes in inducing an optimal total emissions level (Wu, Palm-Forster, & Messer, 2021). Under an ambient control method all emitters incur the same penalty for the total level of pollution, also known as the *aggregate level* of pollution, and hold equal liability as a group (Griesinger et al. 2017; Segerson, 1988).

To illustrate the ambient control mechanism, consider the case of an ambient tax scheme employed in a water shed bordered by several producers. A maximum allowable amount of total pollution – also known as the *threshold* level – is then determined by the social planner. For each unit of pollution in the shared watershed that exceeds this level every producer along the water body is taxed. The tax is proportional to the level of pollution in excess of the determined threshold and is applied evenly across all producers. In some cases, an ambient subsidy is provided under the same logic in which a payment is allocated to producers proportional to the level of emissions below the threshold. In either case the threshold level of pollution is therefore instrumental in the behaviour of producers as it can impact the aggregate level of pollution (Spraggon, 2013). It is important to note that at no point will information about individual pollutant levels be readily observable to either the producers or the regulator and only the total level of pollution in the water body can be known (Segerson, 1988). Ambient tax methods can offer the benefit of allowing producers more autonomy than command-and-control methods as producers can choose the method by which they achieve pollution abatement while employing their own expertise and primary knowledge of time-and-place (Weersink et al. 1998; Hayek, 1945).

The characteristics of the selected ambient method has been demonstrated to be an important factor in influencing efficient outcomes. For instance, a laboratory experiment by Cochard, Wilinger, & Xepapadeas (2005) found that use of an ambient tax was both effective and reliable in inducing an efficient outcome in the context of a NPS pollution problem. However, this study also found that the combination of an ambient tax and subsidy, in which a tax is applied for each unit exceeding the threshold and conjointly a subsidy is provided for each unit below, decreased social efficiency. Additionally, a laboratory experiment by Palm-Forster, Suter, & Messer (2018) which looked at the impact of ambient policy in reducing pollution via adoption of a "green technology" found that participants were significantly more likely to adopt if they were assured that they would not be liable for excessive group pollution, contingent on their adoption. In the absence of this assurance Palm-Forster, Suter, & Messer (2018) found that participants would instead choose the lowest-cost abatement level in lieu of adopting the green technology. These results then stress not only the policy mechanism in place to induce pollution abatement but also the characteristics of the policy.

As is the nature of methods which rely on group compliance, free-riding is an issue of considerable difficulty under ambient control methods (Wu, Palm-Forster, & Messer, 2021 Griesinger et al. 2017; Segerson, 1988). Notably, where large water bodies with many heterogenous polluters are concerned problems of free-riding may be more prevalent (Weersink et al. 1998). As emphasized by Spraggon (2002), the ambient control scheme can not guarantee emissions compliance at the individual level. Therefore, individual producers may incur a large emissions tax should the aggregate level greatly exceed the set threshold - even if a producer appropriately adopted conservation practices (Spraggon, 2002; Wu, Palm-Forster, & Messer, 2021). Xepapadeas (2011) cautions that unfair taxation of producers who individually exercised "good behaviour" is a potential drawback of ambient tax schemes. This then emphasizes the importance of effective and well-planned policy design which takes into account local conditions where ambient schemes are concerned. Therefore, understanding the factors affecting the behaviour to adopt emissions-reduction technology and practices under ambient control schemes is a necessary element in the formation of effective policy (Baerenklau, 2005).

2.2 Technology Adoption

The level of water pollution generated from a farming operation depends on several factors including the size and other physical characteristics of the farm, location, seasonal conditions, and importantly, the conservation practices and technology employed by the farmer (Wu, Palm-Forster, & Messer, 2021; Weersink et al. 1998). There are available practices and technologies which can help limit agricultural runoff if adopted by farmers. However, adoption rates are generally low (Maertens & Barrett, 2012). It is a goal of the contemporary literature on NPS pollution to identify the factors in addition to policy instruments that can effectively encourage BMP adoption.

The cost of BMPs to reduce agricultural runoff can be a prohibitive factor in dissuading adoption. Should a new practice or technology be too expensive to be profitable adoption is unlikely to occur (Chouinard et al. 2008). However, there is evidence in the literature that there are factors which influence farmer decisions to adopt BMPs that defy the traditional profit-maximization assumption including social goals such as recognition from others and the "warmglow" effect associated with environmentally beneficial actions (Chouinard et al. 2008). The impact of social pressures and information must then be explored further as there is research to suggest the influence of these factors in agricultural technology adoption (Streletskaya, et al., 2020). In particular, and as discussed by Weersink & Fulton (2020), these factors are likely influential at early stages in the adoption process.

2.2.1 Social Factors Affecting Technology Adoption

The individual characteristics of the farmer are a key factor which can motivate BMP adoption (Palm-Forster, Swinton, & Shupp, 2017). There is some evidence to suggest that demographic influences can potentially affect adoption rates. For example, a study of dairy farmer's adoption of BMPs by Rahelizatovo & Gillespie (2004) yielded evidence that older as well as less educated farmers may be less receptive of new technologies. Further, analysis of smallholder farmer adoption of soil management technology in Ghana by Martey & Kuwornu (2021) found that females had lower adoption rates in general – however the authors discuss that discrepancies in capital availability may be a contributing factor.

Risk preferences of farmers have also been identified as a potential factor in whether technology is adopted or not. A study by Baerenklau (2005) asserts that a major variable in impacting adoption of agricultural conservation technologies was risk attitudes. Similarly, a field experiment by Liu (2013) which elicited risk preferences of farmers in China found that risk-averse producers were more likely to be late adopters of new agricultural technology. In contrast, an experiment eliciting farmer's risk preferences combined with a survey on farmer adoption in Peru by Engle-Warnick, Escobal & Laszlo (2006) found that risk was not a predictor of adoption of a new agricultural technology. Similarly, Palm-Forster, Suter, & Messer (2018) found that risk preferences played no significant role in influencing technology adoption in a laboratory setting.

2.2.2 Social Networks

Social networks have the potential to influence farmer behaviour and BMP adoption. The role of the social network in affecting new technology adoption rates amongst farmers is an area of contemporary interest amongst economists (Maertens & Barrett, 2012). In these social networks the practices of farmers within close proximity, both socially and geographically, may influence the behaviour of those around them. This effect can continue from neighbour to neighbour and may therefore have far-reaching effects throughout the social network[1].

The actions of producers within the network can influence the behaviour of others which can even lend to feedback effects and alter economic outcomes in the network (Maertens & Barrett, 2012). Social networks can vary greatly in size and connectedness as well as in their characteristics. A farmer's network can include those who are socially close such as family, the greater community, and even information passed through formal institutions such as government outreach (Weersink & Fulton, 2020). Social networks may contain very similar producers with high levels of information about each other's actions or may be dissimilar with little communication between producers (Spraggon, 2013). Of particular importance to this work is the influence that information passed through a farmer's social network can have on individual decisions to adopt BMPs via a peer-effect. According to Weersink & Fulton (2020), awareness of new practices or technology, a starting point in the adoption process, can be influenced by the social network.

Choi, Gallo, & Kariv (2016) asset that observational learning occurs in a social network when individuals alter their behaviour in response to being informed of another's actions.

[1] Referred to by Baerenklau (2005) as the *'neighbourhood effect'* of social networks (p.3).

Importantly, as discussed by Weersink & Fulton (2020) in a review of the agricultural adoption literature, a farmer's network can feasibly impact BMP adoption behaviour in both directions – it can motivate or dissuade adoption of new practices depending on the behaviour of others in the network. Social networks are therefore a tool that can potentially be used to motivate BMP adoption to reduce agricultural runoff - however care must be exercised in how information on conservation technology is disseminated. The network can also facilitate social pressures, discussed further in the subsequent sections, thereby affecting individual behaviour through the mechanism of group conformity (Weersink & Fulton, 2020).

2.2.3 Effect of Information

Transmission of information amongst farmers on available BMPs is a major driver of adoption. Initial awareness about a new practice can be influenced by the size and the connectedness of a farmer's social network (Weersink & Fulton, 2020). According to Choi, Gallo, & Kariv (2016) social networks can act as a catalyst for information dissemination amongst producers. There is also evidence that technology subsidies can be effective in encouraging adoption along the social network whereby individuals are motivated to adopt a new technology because they view their neighbour, who received a subsidy, doing so. This social learning effect as it pertains to subsidies has been found to have positive impacts on adoption behaviour even amongst individuals who did not receive the subsidy (Omotilewa, Ricker-Gilbert, & Ainembabazi, 2020; Dupas, 2014; Foster & Rosenzweig, 2010).

Baerenklau (2005) asserts that policies to encourage adoption can be reinforced most effectively by increasing the extent in which information can be shared amongst farmers rather than relying on a *laissez-faire* or "band-wagon" approach reliant on early adopters. Additionally, the literature finds that opportunities to learn about available BMPs to manage NPS pollution and the details of implementation can be key motivators of technology adoption (Baerenklau, 2005). Therefore, farmers can potentially have the opportunity to learn from early adopters about new practices which can in turn influence their own adoption behaviour (Weersink & Fulton, 2020).

The level of information flows within a network may also prove to be an important factor in influencing policy effectiveness. A laboratory experiment by Suter et al. (2008) which analyzed the effect of an ambient tax mechanism found that policy was most effective at achieving optimal emissions when producers in the experiment could communicate amongst one another. Similarly, evidence from the literature suggests that the type of information available and its method of dissemination are also key factors in influencing BMP adoption (Griesinger et al. 2017; Wu, Palm-Forster, & Messer, 2021). Of note, Choi, Gallo, & Kariv (2016) assert that assumptions of perfect information about the network structure in both theoretical and experimental research are prevalent – however in reality the actual extent of a social network is not known by an individual. Laboratory experiments are then a useful tool which can be employed to analyze the impact of the social network in influencing individual decision-making. The role of information transmission throughout the network is important in an analysis of social networks as they relate to BMP adoption decisions.

2.3 Experimental Literature

The effectiveness of ambient instruments and information networks in inducing socially optimal behaviour can be analyzed effectively through economic experiments (Wu, Palm-Forster, & Messer, 2021). According to Choi, Gallo, & Kariv (2016), "despite being still relatively small, the experimental literature on communication and information networks has already accumulated insightful evidence on the role of network structure in equilibrium selection and coordination outcomes" (p. 16). Economic experiments can yield insight into human behaviour and preferences which are otherwise not easily observable. In the context of agri-environmental problems, experiments can allow for effective analysis of treatments, including policy interventions and behavioural influences, on achieving efficient outcomes while controlling for exogenous factors (Palm-Forster et al. 2019; Choi, Gallo, & Kariv, 2016).

From this experimental literature interesting results regarding the factors which can affect effectiveness of NPS control policies are evident. Wu, Palm-Forster, & Messer (2021) emphasize that empirical work from experiments has yielded evidence that ambient policy mechanisms and other factors can feasibly reduce pollution to optimal levels. For instance, a laboratory experiment by Wu, Palm-Forster, & Messer (2021) found that, in the absence of pro-conservation nudges, heterogeneity in characteristics amongst producers led to higher than optimal pollution levels under an ambient control scheme. However, under the same conditions of producer heterogeneity, when information regarding past individual and group decisions was available, an ambient policy to manage NPS pollution levels was deemed effective. Experimental results from Banerjee et al. (2014) found that when participants in a circular network received information on other players actions that the coordination amongst the group was more efficient in a laboratory setting. A key finding from this study is then that policy to encourage socially optimal behaviour can benefit from assisting the pathways in which information can be communicated between farmers. In contrast, Spraggon (2013) asserts that there is evidence from the experimental literature that ambient policy instruments are not always able to generate efficient outcomes in controlled laboratory environments.

A key theme then emerges in the adoption literature regarding the role of conformity, whereby farmers may adopt a new technology or practice because another farmer did so (Weersink & Fulton, 2020; Sampson & Perry, 2018, Griesinger, 2017). Motivations to conform to others' behaviour are particularly evident in the experimental literature (Lopez et al. 2010). For example, a laboratory experiment by Griesinger (2017) found that when participants could signal their decision to adopt an emissions-reduction technology to others in a group setting that aggregate pollution in the experiment fell by 4.64% on average. Cason & Gangadharan (2013) also found that introducing an element of punishment amongst peers, which could reduce a participant's payoff, improved the efficiency of the ambient pollution reduction policy in a laboratory experiment. The impact of social pressure on adoption behaviour is therefore a valuable area of future study.

2.4 Contribution to the Literature

The research presented contributes to the growing literature on agricultural BMP adoption to manage NPS pollution with attention paid to the role of technology subsidy provision, the network effect, and pro-abatement messaging. In addition, this study considers how these factors interact in networks which vary in the level of information available about the adoption decisions of other producers. Analyzing the behavioural factors which can influence BMP adoption and reduce pollution levels will build on the prior literature which examines why farmers may be motivated to make decisions to reduce their own pollution levels.

Research regarding behavioural factors which influence NPS pollution abatement actions, including the role of nudges and information networks, has not been widely examined (Streletskaya et al., 2020; Wu, Palm-Forster, & Messer, 2021). Wu, Palm-Forster, & Messer (2021) state that, "it is reasonable to assume that information nudges can be used to improve efforts to abate NPS pollution, but few studies have addressed this question" (p. 3). According to Palm-Forster et al. (2019), as agri-environmental programs which encompass motivating new technology adoption strive to influence long-term producer behaviour nudges may have unique impacts. In particular, Palm-Forster et al. (2019) emphasize the importance of understanding how nudges affect behaviour for agri-environmental issues such as pollution management. Notably, the role of a pro-abatement nudge in influencing producer decisions will be assessed in the research presented in this thesis and how varying levels of information interact with provision of a nudge to influence pollution levels. Additionally, as the experiment conducted was designed to analyze behaviour under an ambient tax, the results of this research can also inform policy which utilizes ambient control mechanisms or other threshold-based targets to manage NPS pollution levels.

The experimental design of this research builds on existing experimental work on technology adoption behaviour. As discussed by Palm-Forster, Suter, & Messer (2018) there is a need for experimental designs which mimic real-world conditions more accurately through offering multiple decision actions (Wu, Palm-Forster, & Messer, 2021). This research then employs an adoption decision in conjunction with an input condition whereby both actions affect participants' individual pollution levels. Furthermore, Omotilewa, Ricker-Gilbert, & Ainembabazi (2020) assert that, "with notable exceptions in Dupas (2014) and Carter et al. (2014) […] indirect information effects of [a] subsidy on neighbors who are non-subsidy recipients are seldom estimated" (p. 755). Of note, this research then builds on the previous literature by estimating both the direct and indirect effect of subsidy provision on abatement behaviour.

Finally, this research expands on the broader network literature through an experimental lens which is asserted as an area of need of future research by Choi, Gallo, & Kariv (2016). According to Maertens & Barrett (2012), while the influence of social networks is considered important by economists in influencing adoption of agricultural technology and pollution abatement, that this "this literature remains distinctly underdeveloped" (p. 358). Specifically, the experiment conducted addresses this gap by employing a circular network structure to facilitate information flows amongst participants which can be analyzed to assess the impact of social networks on abatement decisions under multiple levels of information within the network.

This research utilizes a context-free design to analyze the impact of the network effect, technology subsidies, and a nudge on NPS pollution levels and technology adoption. This design allows for greater control of exogenous factors in order to directly analyze the variables of interest. Additionally, the design of this research allows for an analysis of the economic theory surrounding individual behaviour in a NPS pollution setting under conditions of an ambient tax and can then act as a proof-of-concept study which can later be effectively adapted and employed to analyze producer behaviour.

Chapter 3 Conceptual Framework and Experimental Design

3.1 Information Network

Subjects in six-person groups are assumed to be arranged around a network in the experiment. Figure 1 represents a circular information network and, in the context of NPS pollution, is comparable to producers arranged around a shared water body. The circular network has been explored as a potential mechanism to study participant decision-making to some degree, for example by Banerjee (2017). Within the network described in Figure 1 it is assumed that the marginal damage function and production revenue functions of all producers are homogenous. The network employs a one-way information flow, also known as a uni-directional link, whereby participants have knowledge of only a singular neighbour's actions. The uni-directional network flow is a classic approach in the experimental and theoretical network literature (Choi, Gallo, & Kariv, 2016; Maertens & Barnett, 2012; Acemoglu et al., 2011; Conley & Udry, 2001). The use of a simplified one-way information flow versus a scenario where information is transmitted in multiple directions is appropriate in the context of this experiment as the emissions-levels of other producers are assumed not to directly affect an individual's own production. In addition, there is evidence that a farmer's information network can realistically be characterised by fewer information nodes in which a farmer receives information from only a limited number of persons in the network (Conley & Udry, 2001). Employing a one-way information flow also allows for a more direct analysis of the impact of information networks on individual's abatement decisions.

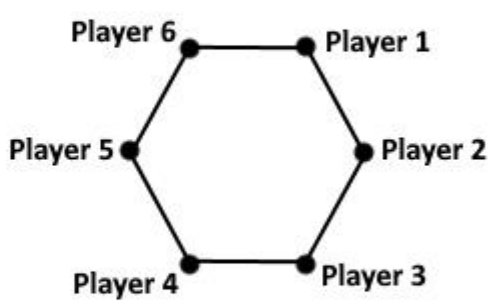

Figure 1 Network of Participants

Participants are assumed to be producers arranged around the circular network shown above for purpose of the experiment. The network employs a clockwise one-way information flow.

3.2 Treatments

The conceptual framework utilized to develop the experimental design builds upon the existing NPS pollution experimental literature including contributions by Zia, et al. (2020), Palm-Forster, Suter, & Messer (2018), Banerjee (2017), Wu, Palm-Forster, & Messer (2017), Spraggon (2013), Suter, Vossler, & Poe (2009), Cochard, Wilinger, & Xepapadeas (2005), Poe, Schulze, & Segerson (2004) and Spraggon (2002). In the experiment participants are organized into six-person fixed-groups and engage in 20 rounds of decision-making. In each round one subject in each group is randomly selected to receive a 50% technology subsidy[2]. The subsidy covers 50% of the emissions-reduction technology's cost the recipient subject can choose to adopt or not adopt the technology at the discounted price that round. A participant who receives a subsidy in that round will be notified on the decision page in which they make their input and technology decisions. The amount of the subsidy is fixed between subjects and between rounds.

A 3 x 2 between-group information treatment design is employed. The three information treatments vary in the level of information available on a neighbour's behaviour within the network and relies on the structure of the network in Figure 1. In the Full Information treatment participants know if their direct-clockwise neighbour adopted the technology in previous rounds and whether this neighbour has received a technology subsidy. In the Partial Information treatment only the neighbour's adoption behaviour is known. In the No Information treatment the participant has no knowledge of their neighbour's actions. Descriptions of each treatment are provided below in Table 1 and the breakdown of participants in each treatment is provided in Table 2.

[2] Subsidy-receivers are randomly selected from the group as in Miller and Mobarak (2015)'s experimental design. This subsidy level was selected as it aligns with the level of subsidy (as a percentage of cost) provided by several similar agri-environmental programs offered by the Ontario Ministry of Agriculture, Food and Rural Affairs to agricultural producers (CAP Program Guide, 2021).

	Information on direct-clockwise neighbour adoption?	Information on direct-clockwise neighbour subsidy?	Nudge in rounds **11-20**?
No Information - No Nudge	N	N	N
No Information - Nudge	N	N	**Y**
Partial Information - No Nudge	**Y**	N	N
Partial Information - Nudge	**Y**	N	**Y**
Full Information - No Nudge	**Y**	**Y**	N
Full Information - Nudge	**Y**	**Y**	**Y**

Table 1 3x2 Treatment Descriptions

Outline of the 3x2 between-group treatment design. Note that "Y" denotes that the given treatment employs the information and/or nudge mechanism stated in each column, "N" denotes it does not.

	No-Nudge	Nudge
No Information	36	42
Partial Information	30	42
Full Information	36	42

Table 2 Treatment Breakdown

Number of participants within each information and nudge treatment. Total n=228.

3.2.1 Information Treatment Descriptions

No Information

Under the No Information - No Nudge treatment subjects receive no information regarding other participant's adoption behaviour or whether other participants receive a subsidy.

Partial Information

In the decision stage of the experiment, before input and technology decisions are made, subjects are given information on whether their direct-clockwise neighbour adopted the emissions-reduction technology in the previous rounds. No information on whether other participants will receive a subsidy for the current round or previous rounds is provided.

Full Information

The Full Information treatment builds upon the Partial Information treatment by providing participants information on whether their direct neighbour will receive a subsidy in the current round. Therefore, in each round participants in this treatment will have knowledge of 1) whether their direct clockwise-neighbour adopted the technology in the previous rounds and 2) whether their direct clockwise-neighbour has received a subsidy in the current and previous round.[3]

The three information treatments are designed orthogonal to a pro-abatement nudge presented to half the groups, described below:

Nudge

To test the impact of messaging on input and technology decisions, which in turn affect an individual's own pollution level, participants in nudge treatment groups will receive a pro-abatement message on the decision page of the experiment. This message is provided to all participants in the nudge treatment groups and will be shown in rounds 11-20. The message shown is as follows:

"Decreasing the number of Penalty Points will reduce the penalty. Help everyone in your group by reducing the Penalty Points you contribute."[4]

[3] To control for memory, participants are able to view all past decisions and/or subsidy provision (treatment dependent) of their direct neighbour on the decision page in addition to current round information. The most up-to-date information on the direct neighbour is available to the participant – this therefore includes up to the last round's technology adoption decision and the current round's subsidy provision of their clockwise-neighbour.

[4] Note that "Penalty Points" are synonymous to individual units of pollution contributed and the "penalty" refers to the ambient tax.

Specifically, this nudge is shown as a standalone message after round 10 of decision-making concludes and is re-stated on all subsequent decision pages for the remainder of the experiment. Nudges are employed in the experimental economic literature to assess the impact of messaging on behavioural changes and there is evidence that nudges can improve policy effectiveness (Wu, Palm-Forster, & Messer, 2021; Barron & Nurminen, 2020). Inclusion of a nudge allows for an empirical assessment of the impact of messaging on individual-decision making and how this interacts with the information treatments, with respect to abatement decisions.

3.3 Payoff Calculation

In each round, participants must select an input level and choose to adopt or not adopt an emissions-reduction technology. An individual n's input level, x_n, will affect their production profit in each round.

The basic individual production profit function and parameters are adapted from Spraggon (2002) as follows:

$$\text{Production profit}_n(x_n) = 25 - tech\ cost - 0.002(100 - x_n)^2, \text{ for } n = 1,\ldots,6 \qquad (1)$$

The quadratic form of this production profit function and the associated parameters are commonly employed in the experimental literature on NPS pollutants[5]. Participants are endowed with 100 points each round which they can allocate between input (x_n) and technology adoption. This is a viable approach in the NPS literature and is comparable to a scenario where a farmer

[5] For example, the quadratic form of the production profit function is evidenced by Zia, et al. (2020), Guilfoos et al. (2019), Cason & Gangadharan (2013 & 2014), and Spraggon (2013). The production profit function is presented to participants in general terms, as a formula, and through the example input and technology adoption payoff table shown on each decision page.

must forgo some production capacity to adopt a BMP, such as employing cover cropping (Spraggon, 2002). Participants act in the role of producers within the context of the experiment. The input decisions made by participants are designed to represent the production decisions made by real-world firms. Additionally, for each unit of input supplied by participants pollutants are contributed to a shared pool. These pollutants are described to participants as "Penalty Points" contributed to a shared "Penalty Pool"[6]. Pollutants are added to the shared pool in each round according to the following equation:

Pollutants Contributed by Participant n, $P(x_n) = x_n$, for $n = 1,\ldots,6$ (2)

The linear form of this pollution function is adapted from NPS pollution experimental literature (Suter, Vossler, & Poe, 2009; Poe, Schulze, & Segerson, 2004; Spraggon, 2002). The total level of pollutants contributed in each round by all participants is then:

Total Pollutants $P(X) = \sum_{n=1}^{6} P(x_n)$ (3)

Note that the level of pollutants is assumed to not directly impact producer's production profit functions and only impacts the ambient tax which the participant may pay at the end of each round. The implementation of the ambient tax mechanism is explained further in a subsequent section.

3.3.1 Technology Decision

In addition to an input choice, participants must also choose to adopt or not adopt an emissions-reduction technology in each round. The technology costs the participant 12 points that round should they choose to adopt it. If adopted, the technology will decrease the number of pollutants a

[6] For the purpose of this section discussion of pollution levels is analogous to "Penalty Points" as viewed by participants.

participant contributes to the shared pool per-unit of input for that round according to the following equation:

$$P(x_n) = \begin{cases} x_n \; if \; Technology = Not \; Adopted \\ 0.25 \times x_n \; if \; Technology = Adopted \end{cases} \qquad \text{for } n = 1,\ldots,6 \qquad (4)$$

Note that the pollution produced is reduced by 75% when participants employ the technology. The cost of the technology and its emissions-reduction potential are analogous to any "high-cost high-reward" practice, or likely a combination of practices, to reduce runoff[7]. The inclusion of both an input choice and a binary technology adoption decision has been explored to some degree in the experimental economics literature by Wu, Palm-Forster, & Messer (2021) and Palm-Forster, Suter, & Messer (2018).

3.3.2 Social Planner's Problem

From Equation 3 it can then be seen that the total unabated level of inputs, in the scenario that each of the six participants in the group select a maximum input level of 100 points, is 600 units. This corresponds to a scenario where no technology adoption occurs and yields a maximum emissions level of 600 units.

The *social planner's problem*, adapted from Spraggon (2002, p. 430) which yields the optimal input level, is presented below for the extreme case where no technology adoption takes place:

Social Planner's Problem

[7] For example a technology such as conservation buffers which have the potential to decrease nutrient runoff by 50% (Wu, Palm-Forster, & Messer, 2021).

$$= max\{\sum_{n=1}^{6}[25 - 0.002(100 - x_n)^2] - 0.3 \times \sum_{n=1}^{6} x_n\} \quad (5)$$

The scalar multiplier (0.3) of the aggregate pollutant level relates the input level to the social cost of a participant's input decision, via the environmental damages generated from production, and is adapted from Spraggon (2002). The first-order derivation of Equation 5 yields an optimal input level of 25 units per participant in the scenario that technology is not adopted. Therefore, with no emissions-technology the optimal aggregate input level is then 150 units.[8] To maintain consistency with the previous non-point source literature and parameters, an aggregate level of 150 input units, which is derived from the social planner's problem in Equation 5, will be considered the optimal aggregate pollutant level for the purpose of this experiment. The optimal input level corresponds to the threshold pollutant level for the ambient tax mechanism discussed further in the following section. From the perspective of the social planner the socially optimal input level which corresponds to the optimal emissions level is calculated under the no-technology scenario presented in Equation 5. This will be referred to as the *status quo threshold* for the remainder of this paper.

The optimal aggregate pollutant level is calculated in the absence of emissions-reduction technology as this *status quo threshold* level would be feasibly observable to the social planner. Technology choice and additional variables such as subsidy provision are therefore fixed as exogenous factors. Additionally, if emissions-reduction technology were to be employed this would increase the optimal input level as determined by the social planner's problem as each unit of input now generates less emissions. Therefore, selection of the lower of the two potential optimal level via opting for the no-technology scenario to inform the *status quo threshold* value

[8] $\sum_{n=6}^{1} x_n = 150$ where $x_n = 25$.

also helps ensure that participants are faced with a tangible impact on their final payoffs with respect to their decisions. Additionally, this approach allows for a greater focus of this analysis on technology decisions by participants - a key variable of interest.

3.3.3 Ambient Emissions Tax

At the end of the round, after all decisions have been made by participants, a tax may be deducted from each participant which depends on the total number of pollutants. This tax is the same for each participant and is given by Equation 6 below:

$$T = \text{Tax}[P(X)] = \begin{cases} 0 & if\ P(x) \leq 150 \\ 0.3 \times [P(X) - 150] & if\ P(X) > 150 \end{cases} \qquad (6)$$

The use of a per-unit emissions tax as an instrument to induce lower pollution levels is presented in Segerson (1988) and Segerson & Wu (2006) and the parameters used in Equation 6 are adapted from Spraggon (2002). Following a standard approach in the non-point source pollutant literature participants are taxed if the aggregate level of emissions exceeds the optimal level which was determined in the previous section by the social planner's problem to be 150 units of emissions. The cost of the tax scales proportionally with each additional unit of input. Equation 6 is comparable to a scenario in which firms are taxed uniformly for the level of pollutants which could occur, for example, in a shared water body. Combining the tax given in Equation 6 and the production profit function in Equation 1 gives us the final payoff for an individual participant at the end of a round:

$$\text{Payoff}_n(x_{n,}) = 25 - 0.002(100 - x_n)^2 - \textit{tech cost} - T[P(X)], \quad \text{for } n = 1,\ldots,6 \qquad (7)$$

Where the Tax, T[P(X)], is a function of the participant's input (x_n) and technology decision ($tech_n$) as well as all other group member's participant's input (x_{n-1}) and technology decisions

($tech_{n-1}$) (Equation 6). Recall that the technology costs 12 points if adopted in the absence of a subsidy. Note that if participants receive a subsidy for the technology adoption will cost 6 points. One subsidy will be provided randomly to each participant per round. This final payoff for each round is then shown to the participant in points and contributes to the participant's final earnings.

3.4 Nash Equilibrium

The following section analyzes the theoretical Nash Equilibrium (NE) for the laboratory experiment. To inform the experimental design and to select appropriate parameters employed in the equations described in the previous section it is beneficial to develop the NE of participants decision-making under the feasible scenarios. Therefore, the best response actions with regards to both a participant's input and technology choice are discussed in this section. The NE is first assessed under the absence of any subsidy provision in Table 3. Table 4 then develops this framework to account for the subsidy. The following analysis references the socially optimal input choices under both assumptions of no-technology and full-technology adoption, described in Appendix C.1 Social Optimal Input Levels.

Strategic Game: No Subsidy Provision

The best response actions for *Player 1* and *Player 2* are given below for each scenario (bolded in in the left value in each set for *Player 1* and the right value for *Player 2*):

Player 2

			No Technology		Technology	
			$x_n{}^*{}_{no\ tech}$	$x_n{}^{max}{}_{no\ tech}$	$x_n{}^*{}_{tech}$	$x_n{}^{max}{}_{tech}$
Player 1	No Technology	$x_n{}^*{}_{no\ tech}$	A (**13.75**,**13.75**)	B (**-98.75**,-87.5)	C (**13.75**,12.30)	D (**13.75**,12.71)
		$x_n{}^{max}{}_{no\ tech}$	E (2.5,-8.75)	F (-110.0,-110.0)	G (9.53,**-3.17**)	H (7.0,-5.29)
	Technology	$x_n{}^*{}_{tech}$	I (12.30,**13.75**)	J (-98.80,-86.09)	K (12.30,12.30)	L (12.30,12.71)
		$x_n{}^{max}{}_{tech}$	M (12.71,**13.75**)	N (-98.89,-86.6)	O (12.71,12.30)	P (12.71,12.71)

Table 3 NE: No Subsidy

Note:

Payoffs reported as (*Player 1*, *Player 2*) where *Player 1 = Player n* and *Player 2 = Player* $n^{-1}{}_a$. *Player n* represents a singular participant in the game. *Players* n^{-1} are all other players. Therefore, *Player* $n^{-1}{}_a$ (where a=1,…,5) represents the actions of another individual player and assumes *Players* n^{-1} act symmetrically.

Input levels are fixed to the optimal (*) and maximum (max) possible input decisions under no technology adoption (*status quo*) and complete technology adoption scenarios for each participant, *n*, where no technology: x_n*=25, x_n^{max}=100; with technology: x_n*=81.25, x_n^{max}=88. (See Appendix C Nash Equilibrium Supplemental Information for a detailed calculation of these values)

From analysis of Table 3 a unique Nash Equilibrium (NE) exists, denoted as scenario *A*. Scenario *A* occurs when all participants act symmetrically and do not adopt the technology and all participants choose the optimal input decision, x_n* = 25. Participants have no incentive to switch their input or technology decision in Scenario *A* given that no other player deviates from the NE.

Under the NE the total group payoff is the highest and the aggregate pollution is at the threshold level (See Appendix C.2: Strategic Game (No Subsidies)).

Strategic Game: Subsidy Provision

Player 2 *(No Subsidy)*

			No Technology		Technology	
			$x_n*_{no\ tech}$	$x_n^{max}{}_{no\ tech}$	x_n*_{tech}	$x_n^{max}{}_{tech}$
Player 1 *(Subsidized)*	No Technology	$x_n*_{no\ tech}$	A (13.75,**13.75**)	B (-98.75,-87.5)	C (13.75,12.30)	D (13.75,12.71)
		$x_n^{max}{}_{no\ tech}$	E (2.5,-8.75)	F (-110.0,-110.0)	G (9.53,**-3.17**)	H (7.0,-5.29)
	Technology	x_n*_{tech}	I (18.30,**13.75**)	J (**-92.80**,-86.09)	K (18.30,12.30)	L (18.30,12.71)
		$x_n^{max}{}_{tech}$	M (**18.93**,**13.75**)	N (-93.12,-87.05)	O (**18.93**,12.30)	P (**18.93**,12.71)

Table 4 NE: Subsidy

Note:

Payoffs reported as (*Player 1, Player 2*) where *Player 1 = Player n* and *Player 2 = Player* $n^{-1}{}_a$. *Player n* represents a singular participant in the group who receives a subsidy in a given round. *Players* n^{-1} are all other players who do not receive the subsidy. Therefore, *Player* $n^{-1}{}_a$ (where a=1,…,5) represents the actions of another individual player and assumes *Players* n^{-1} act symmetrically.

Input levels are fixed to the optimal (*) and maximum (max) possible input decisions under no technology adoption (*status quo*) and complete technology adoption scenarios for each participant, *n*, where no technology: x_n*=25, x_n^{max}=100; with technology: x_n*=81.25, x_n^{max}=94 for Player 1 (due to the subsidized technology cost) and x_n^{max}=88 for Player 2. (See Appendix C Nash Equilibrium Supplemental Information for a detailed calculation of these values)

From Table 4 a new NE is found, in Scenario *M*. When Player 1 is provided a 50% subsidy to cover the cost of the emissions-reduction technology the best response when the other participants all select the full input level (x_n^{max}=100) and no technology adoption is for Player 1 to adopt the technology. Therefore, with subsidy provision to one producer the NE moves from

Scenario A to M. When a subsidy is provided the pollutant level under the NE (Scenario M in Appendix Table 4) is lower than the NE in the absence of a subsidy for Player 1 (Scenario A Appendix Table 2). Note that the aggregate group payoff was 82.50 under the no-subsidy NE and is 87.68 in the new NE where Player 1 is subsidized. Therefore, the overall group total at NE is also higher in when a subsidy is allocated.

3.5 Experimental Design

This laboratory experiment is incentive-compatible whereby unboundedly rational participants act to maximize their own profit which corresponds to a real-world payoff as described above in Equation 7. The experiment takes place in a context-free environment. Therefore, information regarding the environmental nature of the problem is not disseminated to participants. All wording presented to participants employs neutral language – for example no mention of "pollution" is viewed by participants. The nature of the participant's role is discussed only as a general "producer". This design allows for direct and measurable analysis of technology adoption behaviour which aligns with the profit-maximation assumption of producers in absence of confounding factors such as environmental values and is standard in the literature on NPS experiments (Cochard, Wilinger, & Xepapadeas, 2005). The experiment was administered online using Python o-Tree (Chen, Schonger, & Wickens, 2016).

3.5.1 Organization of Rounds and Treatment Provision

The experiment took place over 20 rounds. During the experiment the 50% technology subsidy was provided to one participant each round. Subsidy provision was implemented with replacement in which one participant would randomly receive the subsidy in each round. The information treatments were administered between groups. The nudge treatment was also provided between groups whereby approximately half the groups in each information treatment receive a pro-abatement message for rounds 11-20 of the experiment and was designed orthogonal to the information treatments

3.5.2 Post-experiment Questionnaire

Standard demographic information was collected from participants through participation in a post-experiment questionnaire (see Appendix B Questionnaire). The questionnaire elicited information including participant's age, gender, household income and education. The survey also elicited participant's risk preferences through the following question adapted from (Dohmen et al., 2011):

"How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please tick a box on the scale, where the value 0 means: 'not at all willing to take risks' and the value 10 means: 'very willing to take risks'."

Participants could then select an option corresponding to this scale from 0 to 10. Dohmen et al. (2011) support the behavioural validity of this measure in the context of incentive-compatible experiments. The questionnaire was administered online via Python O-Tree directly following a participant's completion of the experiment (Chen, Schonger, & Wickens, 2016).

3.6 Testable Hypotheses

A table summarizing the testable hypotheses of this research and main conclusions is presented below. The testable hypotheses are discussed in further detail in the subsequent section.

Null Hypotheses	**Sub – Hypotheses**	**Test Statistics**	**Conclusion**
$H_0$1: The pro-abatement nudge has no effect on participant behaviour.	The nudge has no effect on the aggregate pollutant level within Nudge Treatments (Rounds 11-20): **$H_0$1a**: NInfo#nudge round = NInfo#no nudge **$H_0$1b**: PInfo#nudge round = PInfo#no nudge **$H_0$1c**: FInfo#nudge round = FInfo#no nudge The nudge will have no effect on technology adoption within Nudge Treatments (Rounds 1-20): **H_0 1d**: NInfo#nudge round = NInfo#no nudge **H_0 1e**: PInfo#nudge round = PInfo#no nudge **H_0 1f**: FInfo#nudge round = FInfo#no nudge	**Table 9** NInfo: $\chi^2(1) = 6.69$ PInfo: $\chi^2(1) = 3.72$ FInfo: $\chi^2(1) = 0.09$ **Table 11** NInfo: $\chi^2(1) = 0.00$ PInfo: $\chi^2(1) = 14.66$ FInfo: $\chi^2(1) = 2.27$	Reject at 1% Reject at 10% Fail to Reject at 10% Fail to Reject at 10% Reject at 1% Fail to Reject at 10%
$H_0$2: The emissions-reduction technology subsidy has no effect on participant behaviour.	The subsidy has no effect on individual pollutants (Rounds 1-20): **$H_0$2a**: NInfo No N#subsidy = NInfo No N#no subsidy **$H_0$2b**: PInfo No N#subsidy = PInfo No N#no subsidy **$H_0$2c**: FInfo No N#subsidy = FInfo No N#no subsidy **$H_0$2d**: NInfo N#subsidy= NInfo N#no subsidy **$H_0$2e**: PInfo N#subsidy = PInfo N#no subsidy **$H_0$2f**: FInfo N#subsidy = FInfo N#no subsidy The subsidy has no effect on technology adoption (Rounds 1-20): **$H_0$2g**: NInfo No N#subsidy = NInfo No N#no subsidy **$H_0$2h**: PInfo No N#subsidy = PInfo No N#no subsidy **$H_0$2i**: FInfo No N#subsidy = FInfo No N#no subsidy **$H_0$2j**: NInfo N#subsidy= NInfo N#no subsidy **$H_0$2k**: PInfo N#subsidy = PInfo N#no subsidy **$H_0$2l**: FInfo N#subsidy = FInfo N#no subsidy	**Table 10** NInfo (No N): $\chi^2(1) = 5.96$ PInfo (No N): $\chi^2(1) = 5.53$ FInfo (No N): $\chi^2(1) = 24.27$ NInfo (N): $\chi^2(1) = 1.99$ PInfo (N): $\chi^2(1) = 15.47$ FInfo (N): $\chi^2(1) = 19.41$ **Table 11** NInfo (No N): $\chi^2(1) = 38.88$ PInfo (No N): $\chi^2(1) = 38.87$ FInfo (No N): $\chi^2(1) = 49.06$ NInfo (N): $\chi^2(1) = 29.96$ PInfo (N): $\chi^2(1) = 58.98$ FInfo (N): $\chi^2(1) = 43.38$	Reject at 5% Reject at 5% Reject at 1% Fail to Reject at 10% Reject at 1% Reject at 1% Reject at 1% Reject at 1% Reject at 1% Reject at 1% Reject at 1% Reject at 1%
$H_0$3: A direct neighbour's adoption behaviour has no effect on participant behaviour. (*Note: "neigh tech" indicates a neighbour adopted the technology in the previous round*)	A direct neighbour's adoption behaviour has no effect on an individual's pollutant level (Rounds 1-20): **$H_0$3a**: NInfo No N#neigh tech= NInfo No N#no neigh tech **$H_0$3b**: PInfo No N#neigh tech = PInfo No N#no neigh tech **$H_0$3c**: FInfo No N#neigh tech = FInfo No N#no neigh tech **$H_0$3d**: NInfo N#neigh tech= NInfo N#no neigh tech **$H_0$3e**: PInfo N#neigh tech = PInfo N#no neigh tech **$H_0$3f**: FInfo N#neigh tech = FInfo N#no neigh tech A direct neighbour's adoption behaviour has no effect on technology adoption (Rounds 1-20): **$H_0$3g**: NInfo No N#neigh tech= NInfo No N#no neigh tech **$H_0$3h**: PInfo No N#neigh tech = PInfo No N#no neigh tech **$H_0$3i**: FInfo No N#neigh tech = FInfo No N#no neigh tech **$H_0$3j**: NInfo N#neigh tech= NInfo N#no neigh tech **$H_0$3k**: PInfo N#neigh tech = PInfo N#no neigh tech **$H_0$3l**: FInfo N#neigh tech = FInfo N#no neigh tech	**Table 10** NInfo (No N): $\chi^2(1) = 0.22$ PInfo (No N): $\chi^2(1) = 0.13$ FInfo (No N): $\chi^2(1) = 1.77$ NInfo (N): $\chi^2(1) = 2.07$ PInfo (N): $\chi^2(1) = 1.87$ FInfo (N): $\chi^2(1) = 0.97$ **Table 11** NInfo (No N): $\chi^2(1) = 0.04$ PInfo (No N): $\chi^2(1) = 4.17$ FInfo (No N): $\chi^2(1) = 0.29$ NInfo (N): $\chi^2(1) = 0.75$ PInfo (N): $\chi^2(1) = 1.82$ FInfo (N): $\chi^2(1) = 0.01$	Fail to Reject at 10% Fail to Reject at 10% Fail to Reject at 10% Fail to Reject at 10% Fail to Reject at 10% Fail to Reject at 10% Fail to Reject at 10% Reject at 5% Fail to Reject at 10% Fail to Reject at 10% Fail to Reject at 10% Fail to Reject at 10%
H_0 4: A direct neighbour's subsidy receipt has no effect on participant behaviour. (*Note: "neigh sub" indicates a neighbour received the*	A direct subsidy receipt has no effect on an individual's pollutant level (Rounds 1-20): **$H_0$4a**: NInfo No N#neigh sub= NInfo No N#no neigh sub **$H_0$4b**: PInfo No N#neigh sub = PInfo No N#no neigh sub **$H_0$4c**: FInfo No N#neigh sub = FInfo No N#no neigh sub **$H_0$4d**: NInfo N#neigh sub= NInfo N#no neigh sub **$H_0$4e**: PInfo N#neigh sub = PInfo N#no neigh sub **$H_0$4f**: FInfo N#neigh sub = FInfo N#no neigh sub A direct neighbour's subsidy receipt has no effect on technology adoption (Rounds 1-20): **$H_0$4g**: NInfo No N#neigh sub= NInfo No N#no neigh sub **$H_0$4h**: PInfo No N#neigh sub = PInfo No N#no neigh sub	**Table 10** NInfo (No N): $\chi^2(1) = 0.25$ PInfo (No N): $\chi^2(1) = 0.00$ FInfo (No N): $\chi^2(1) = 0.27$ NInfo (N): $\chi^2(1) = 0.14$ PInfo (N): $\chi^2(1) = 0.86$ FInfo (N): $\chi^2(1) = 0.00$ **Table 11** NInfo (No N): $\chi^2(1) = 0.15$ PInfo (No N): $\chi^2(1) = 0.21$	Fail to Reject at 10% Fail to Reject at 10% Fail to Reject at 10% Fail to Reject at 10% Fail to Reject at 10% Fail to Reject at 10% Fail to Reject at 10% Fail to Reject at 10%

subsidy in the current round)	**$H_0$4i**: FInfo No N#neigh sub = FInfo No N#no neigh sub **$H_0$4j**: NInfo N#neigh sub= NInfo N#no neigh sub **$H_0$4k**: PInfo N#neigh sub = PInfo N#no neigh sub **$H_0$4l**: FInfo N#neigh sub = FInfo N#no neigh sub	FInfo (No N): $\chi^2(1) = 0.15$ NInfo (N): $\chi^2(1) = 0.703$ PInfo (N): $\chi^2(1) = 0.97$ FInfo (N): $\chi^2(1) = 0.01$	Fail to Reject at 10% Fail to Reject at 10% Fail to Reject at 10% Fail to Reject at 10%
H_0 5: The level of information in a network on other producer's behaviour does not affect the aggregate pollutant level.	The level of information does not affect the aggregate pollutant level, before the nudge (Rounds 1-10): **$H_0$5a**: FInfo = PInfo **$H_0$5b**: FInfo = NInfo **$H_0$5c**: NInfo = PInfo The level of information does not affect the aggregate pollutant level, before the nudge (nudge-only treatments) (Rounds 1-10): **$H_0$5d:** FInfo N = PInfo N or NInfo N **$H_0$5e:** PInfo N = FInfo N or NInfo N **$H_0$5f:** NInfo N = FInfo N or PInfo N	**Table 9** FInfo Vs PInfo: $\chi^2(1) = 0.44$ FInfo Vs NInfo: $\chi^2(1) = 0.60$ NInfo Vs PInfo: $\chi^2(1) =1.60$ **Table 7** FInfo N Vs Non-FInfo N: Pr(|T| > |t|) = 0.7981 PInfo N Vs Non-PInfo N: Pr(|T| > |t|) = 0.6148 NInfo N Vs Non-NInfo N: Pr(|T| > |t|) = 0.4476	Fail to Reject at 10% Fail to Reject at 10% Fail to Reject at 10% Fail to Reject at 10% Fail to Reject at 10% Fail to Reject at 10%

Table 5 Testable Hypotheses

Note: "NInfo", "PInfo", and "FInfo" in the above table indicate one of the three information treatments, i.e. "No Information", "Partial Information" and "Full Information", respectively. "N" represents a nudge treatment and "No N" represents a non-nudge treatment.

With the common null hypothesis that the tested variables do not affect participants' behaviour, alternative hypotheses are discussed below:

H1: Viewing a pro-abatement nudge will affect participant behaviour.

Participants who view the nudge which encourages pollution abatement are hypothesized to be more likely to adopt the emissions-reduction technology. The aggregate pollutant level in nudge rounds is also expected to be lower. There is evidence of a positive impact of pro-social messaging on reducing pollution levels in the experimental literature (Wu, Palm-Forster, & Messer, 2017). The effectiveness of the nudge within each information treatment is of interest.

H2: Receipt of a technology subsidy in a round will reduce individual pollutant levels and increase technology adoption.

H2 signifies that receipt of a subsidy is hypothesized to yield lower pollutant levels in the round where the subsidy is received. Participants who receive a subsidy in a round are expected to be more likely to adopt the technology themselves that round. Field experiments by Omotilewa, Ricker-Gilbert, & Ainembabazi (2020) and Duflo, Kremer, & Robinson (2011) have found positive relationships between subsidy provision and agricultural-technology adoption.

H3: Adoption of the technology in the previous round by a participant's (clockwise) neighbour will affect the participant's own technology adoption.

It is hypothesized that the likelihood that a participant will adopt the emissions-reduction technology will be impacted by whether their direct-clockwise neighbour adopts the technology. In the Partial and Full Information treatments it is expected that participants who view their neighbour's technology adoption choice will alter their own adoption behaviour, either by increasing or decreasing adoption. There is potential for participants to be more likely to adopt the emissions-reduction technology after being informed that their neighbour adopted in the previous round. Likewise, there is potential that participants who view that their neighbour has not adopted may be less inclined to adopt themselves. Oppositely, due to motivations of free-riding participants may be less likely to adopt if they see their neighbour has adopted the emissions-reduction technology.

The role of social pressure and a perceived obligation to conform, especially when decisions affect other group members as they do in the case of this experiment, has been identified in the BMP adoption and NPS pollution literature (Weersink & Fulton, 2020; Wu, Palm-Forster, & Messer, 2021; Griesinger et al., 2017). Additionally, the potential for free-riding behaviour when participants have knowledge of other's adoption of the group is also of interest as there is demonstrated evidence in the literature of this behaviour under ambient control methods (Wu, Palm-Forster & Messer, 2021; Segerson 1988). In the absence of information on neighbour's adoption, there is the potential that a neighbour's adoption may affect a participant's own adoption indirectly through a spill-over effect, in either direction. Therefore, the effect of neighbour's adoption between the information treatments is valuable to analyze.

H4: Subsidy provision to a participant's (clockwise) neighbour will affect the participant's own technology adoption.

H4 hypothesizes that providing information on whether a neighbour receives a subsidy in a round may positively or negatively influence a participant's own likelihood of adoption. If **H3** yields evidence of a positive effect of neighbour's adoption behaviour on a participant's own adoption, potentially through the channel of social pressure, then viewing that a neighbour has received the subsidy may signal to the participant that their neighbour is more likely to adopt that round and therefore increase their own likelihood of adoption. Oppositely, participants who view their neighbour received the subsidy may decrease the likelihood a participant adopts in a given round. This may occur if participants feel that, when faced with knowledge that their neighbour has received the subsidy, they are less likely to adopt the technology themselves at full price. The effect of neighbour's subsidy receipt within the treatments where this information is not revealed, and in the Full Information treatment where this information is known, is of interest.

H5: The aggregate pollutant level will be different depending on the level of information available in the network.

It is expected that participants who view their neighbour's technology adoption choice and/or subsidy receipt will alter their own abatement behaviour, either by increasing their pollutant levels or decreasing them. Provision of neighbour's adoption behaviour can feasibly impact aggregate pollution levels in either direction. As described in **H3**, it is possible that provision of adoption information can positively impact adoption, through the channel of social pressure. It is also possible that information about a neighbour's adoption behaviour can negatively impact a participant's adoption if they view their neighbour is not adopting, or potentially due to free-riding. In the Full Information treatment where neighbour's subsidy provision is known there is the potential that learning a neighbour received the subsidy can increase adoption behaviour through social pressure, or decrease it through free-riding. This analysis will therefore investigate how the level of information flows within a network influences the aggregate pollution level.

3.7 Experiment Administration, Payment and Timeline

Data collection took place from June to July 2021. The experiment was administered online and hosted by the University of Guelph FARE Laboratory for Experimental and Applied Economics (Guelph, ON, Canada) (REB#20-11-003). 228 people participated in the experiment in 24 sessions with one of the treatments described in Table 1 randomly allocated to all groups in particular session. Participants were compensated a base amount of $20 CAD to limit the possibility of a negative payoff and points were earned during the experiment dependent on participant's decisions which affected the final payoff. Within the experiment 50 points equated 1 CAD and points were accrued at the end of every round. The minimum and maximum payoffs were $15.38 and $27.82, respectively. At the end of the experiment a participant's point total and base amount were summed by the computer and participants were paid electronically dependent on these earnings. An experiment session took approximately 1-1.5 hours to complete.

Prior to the start of the experiment the instructions were presented to participants within the online decision-making game screen and were also read aloud via a virtual meeting where participants could privately interact with the researchers and ask questions if needed. Following the instruction pages a quiz to ensure understanding was provided to the participants (Appendix A Experiment Instructions). The quiz was provided in multiple-choice format and the correct answers were revealed to participants after completion of the quiz. The instruction pages were also available at the bottom of participant's decision-making screens throughout all 20 rounds (See Appendix A Experiment Instructions for the instructions viewed by participants). On each decision-making screen participants were able to view a payoff table with example input and technology decisions under subsidy and no-subsidy scenarios and the corresponding production profit values.

Chapter 4 Data and Analysis

4.1 Summary Statistics

Table 6 presents the demographic breakdown of the 228 participants. Table 6 demonstrates that the majority of the participants were students and the majority identified themselves as women.

Variable	*Category*	*Value/Percentage*
Age	Mean	26
	Min	18
	Max	73
Gender	Woman	58.8%
	Man	38.6%
	Choose not to respond or identity not listed	2.6%
Ethnicity	Prefer not to respond	2.2%
	Black/African/Caribbean	11.8%
	Indigenous	1.3%
	Latin American	0.88%
	Other	21.93%
	South Asian	13.2%
	West Asian	1.3%
	White	47.4%
Education Level	Prefer not to respond	1.3%
	Professional degree(s)	4.4%
	Completed graduate education	13.2%
	Some graduate education	7.5%
	Completed college/university	31.6%
	Some college/university	38.2%
	Completed high school	3.1%
	Apprenticeship training/trades	0.44%
	Some high school	0.44%
Student	Yes	61.4%
	No	38.6%
Income (CAD 2020$)	Choose not to respond	18.9%
	<20,000	13.6%
	20-39,999	13.2%
	40-59,999	14.5%
	60-79,999	12.7%
	80-99,999	11.8%
	100-149,999	7.9%
	>150,000	7.5%

Table 6 Demographic Summary Statistics

Summary statistics and demographic profile of participants (n=228).

4.2 Analysis of Aggregate Pollution Level

The aggregate pollutant level generated by a group through individual's input and technology decisions can be analyzed across treatments and across rounds. Of interest to this research is the aggregate pollutant level in each information treatment. In addition, the total group pollutants when the pro-abatement nudge is shown is analyzed in the subsequent sections.

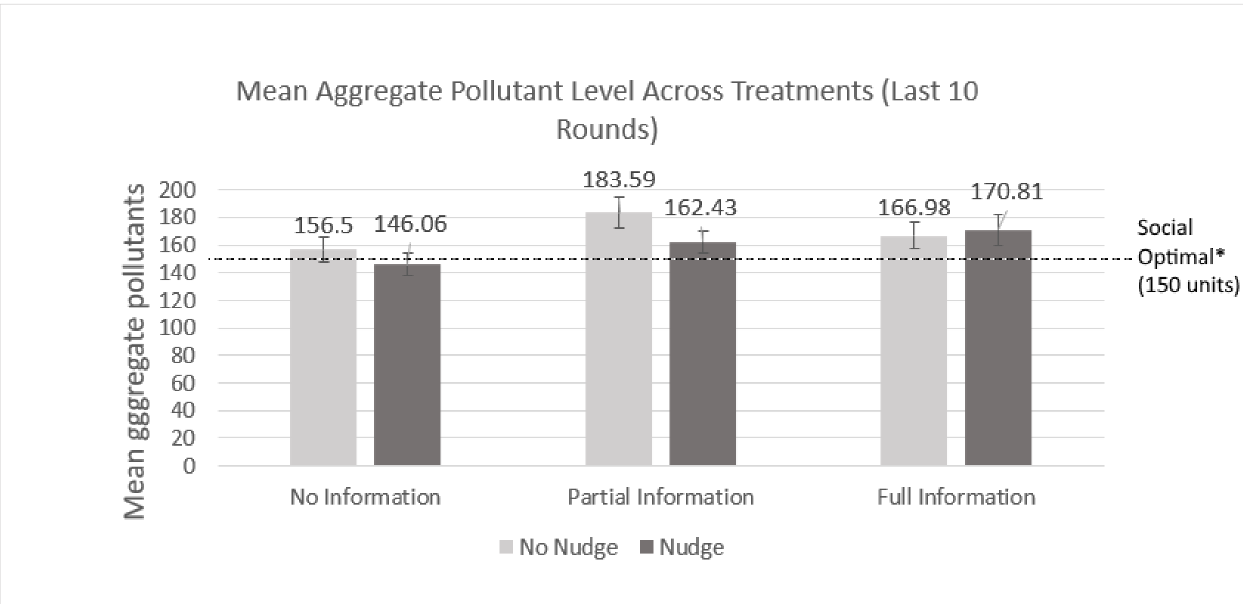

Figure 2 Mean Pollutants by Treatment

Mean aggregate pollutant level in the last 10 rounds (after nudge), by information and nudge treatment. 95 % CI intervals presented for each treatment. N=380.

Figure 2 displays the mean aggregate pollutant level of the 38 groups for each of the treatments. The aggregate pollutant levels for the last 10 rounds of decision-making are shown to effectively demonstrate any potential impact of differing levels of information about others in the network, as well as the nudge shown only in the last 10 rounds, on pollution levels. Overall, the mean pollutant level across all treatments and rounds was 161 [95% C.I.157.7-164.6] units. Note that this aggregate level is 11 units higher than the socially optimal level as determined by the social planner's problem in Section 3.3.2, found to be 150 units.

For the last 10 rounds of decision-making after the nudge is in place, the highest pollutant level is observed in the Partial Information - No Nudge treatment with a mean of 184 units [95% C.I. 172.6-194.6]. During the same rounds, the lowest aggregate pollutant levels are observed in the No Information treatments, with the minimum level of 146 units in the No Information - Nudge treatment [95% C.I.137.5-154.4]. Of note, this is the only treatment which yields an average aggregate pollutant level below the *status quo threshold* value of 150 units. This provides some evidence that the ambient tax mechanism may be able to induce optimal pollutant levels in low information scenarios when pro-abatement messaging is in place.

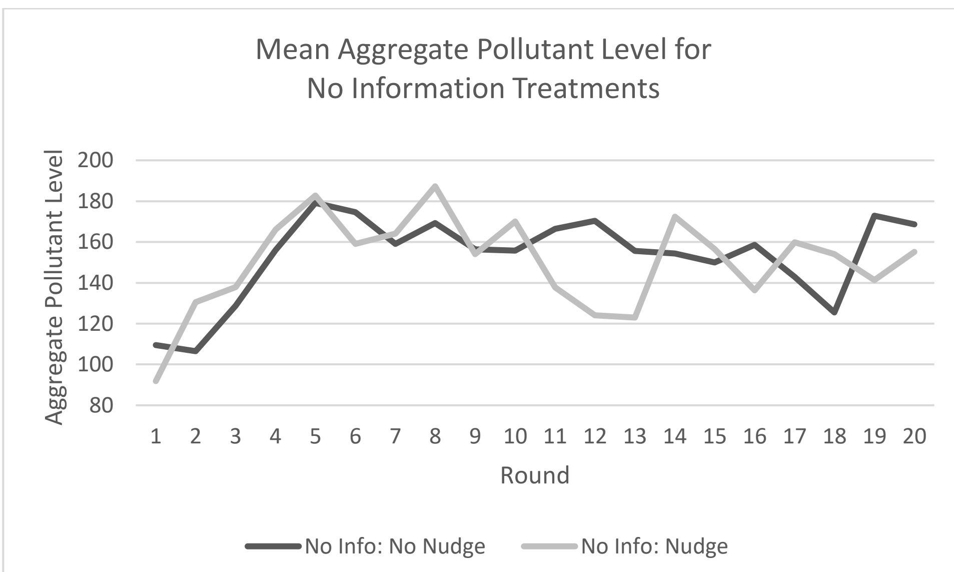

Figure 3 Mean Pollutants: No Information

Average aggregate pollutant levels per round for the No Information treatments. N=13 groups.

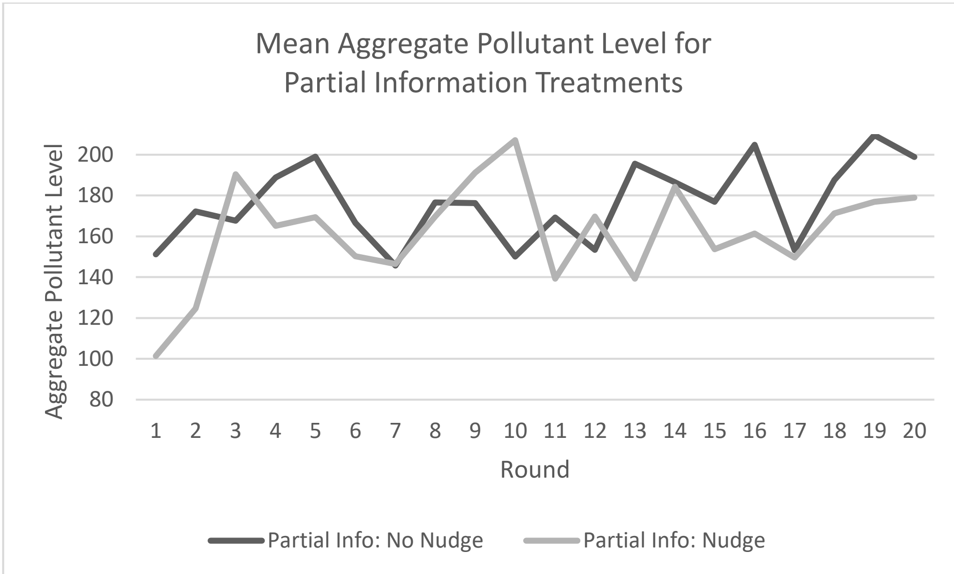

Figure 4 Mean Pollutants: Partial Information

Average aggregate pollutant levels per round for the Partial Information treatments. N=13 groups.

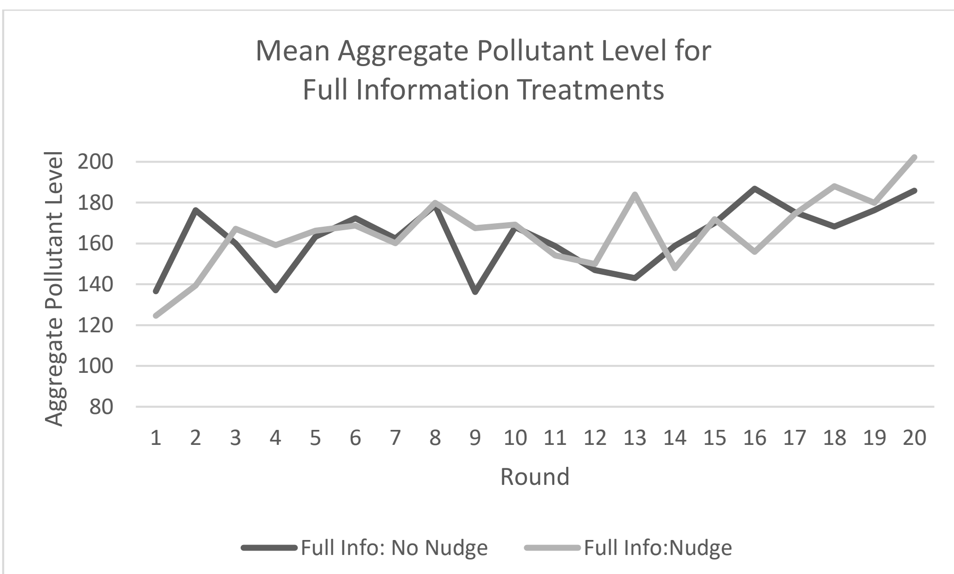

Figure 5 Mean Pollutants: Full Information

Average aggregate pollutant levels per round for the Full Information treatments. N=12 groups.

Figure 3, Figure 4 and Figure 5 demonstrate the aggregate pollutant level across rounds for both the nudge and non-nudge groups for the No Information, Partial Information, and Full Information treatments, respectively. For the No Information - Nudge treatment in Figure 3 a decrease in the aggregate pollutant level in rounds 11-13 is observed. Note that this decrease follows immediately after the introduction of the nudge in round 11. Little difference in aggregate pollutant levels in the Full Information treatment between the nudge and non-nudge treatments are evident in Figure 5.

	Mean	Std. Err.	[95% C.I.]	
No Info - Nudge	154.37	7.65	139.29	169.46
Partial Info – Nudge	161.59	6.56	148.66	174.52
Full Info - Nudge	160.18	6.75	146.87	173.49

Table 7 Aggregate Pollutants by Nudge Treatment (Rounds 1-10)

Aggregate Pollutant Level by Treatment: Nudge only treatments, first 10 rounds before nudge. N = 210

	Mean	Std. Err.	[95% C.I.]	
No Info - Nudge	146.06	4.23	137.73	154.39
Partial Info – Nudge	162.43	4.05	154.44	170.42
Full Info - Nudge	170.81	5.71	159.55	182.07

Table 8 Aggregate Pollutants by Nudge Treatment (Rounds 11-20)

Aggregate Pollutant Level by Treatment: Nudge only treatments, last 10 rounds after nudge. N = 210

The aggregate pollutant levels between only the nudge treatments can be compared within the three information scenarios to analyze the effect of pro-abatement messaging. Table 7 demonstrates the aggregate pollutant level in the nudge treatments for the first 10 rounds of decision making before any nudge is seen by participants. T-test analysis yields no evidence of no significant difference in aggregate pollution level between the three information types. Table 8 displays the same comparison between the nudge treatments but for the last 10 rounds of decision-making after the pro-abatement messaging is displayed. After the nudge is employed it is found that groups in the No Information - Nudge treatment have significantly lower pollutants when compared to the groups in the other information treatments [Pr(T > t) <0.000]. The Full Information - Nudge groups are found to have significantly higher pollutants in rounds 11-20 compared to groups in the other information treatments where the nudge is employed [Pr (T < t) = 0.003].

Therefore, from the analysis presented in this section evidence is not found to suggest that aggregate NPS pollution levels differ significantly between the three information scenarios in absence of a nudge. The results do suggest, however, that after the introduction of the pro-abatement nudge that groups in the No Information treatment have lower pollution levels compared to the groups in the Partial and Full Information treatments when participants have knowledge of their neighbour's adoption behaviour and/or whether the neighbour received a subsidy. These results suggest that use of a pro-abatement nudge may be more effective in the No Information scenario. This and other explanatory variable of interest will be explored further via regression analyses in the following section.

4.2.1 Aggregate Pollution (Group-Level) GLS

A random-effects GLS regression analysis was conducted to determine the factors which may affect the aggregate pollutant level. A random-effects specification is a common approach to analyze panel data collected from laboratory experiments (Palm-Forster, Suter, & Messer, 2018; Banerjee, 2017; Griesinger, 2017). For panel data generated from laboratory experiments the random-effects estimator provides consistent and efficient co-efficient estimates which assumes no correlation between unobserved heterogeneity in individual or group-level observations and the explanatory variables (Palm-Forster, Suter, & Messer, 2018).[9] Additionally, a GLS specification allows for the model to relax the OLS assumption of non-correlation between residuals which is necessary given the nature of laboratory experiment datasets containing multiple observations per individual (Fox & Sanford, 2019). The dependent variable for this analysis is a group's aggregate pollutant level in a round and is given by the following equation:

$$\begin{aligned}\textit{Aggregate Pollutants}_{gr} = {} & \beta_{01} + \beta_1 \textit{No Info}_{gr} + \beta_2 \textit{Full Info}_{gr} + \beta_3 \textit{Full Info} \times \textit{Nudge}_{gr} \\ & + \beta_4 \textit{Partial Info} \times \textit{Nudge}_{gr} + \beta_5 \textit{No Info} \times \textit{Nudge}_{gr} + \mu_g + \varepsilon_{gr}\end{aligned} \tag{8}$$

The independent variable of interest to this model is the effect of each between-group information treatment on the aggregate-pollutant level. The subscripts *g* and *r* are indicators for the group and round number, respectively. β_1 and β_2 are β estimates which correspond to the effect of a group being in a No Information or Full Information treatment, respectively, on the aggregate pollutant level compared to the Partial Information treatment. The Partial Information treatment is selected as the baseline for Equation 8 as this treatment offers the median amount of information to participants, allowing only the neighbour's adoption to be viewed. β_3, β_4 and β_5 estimate the interaction effect of a group, *g*, seeing a nudge in round *r* in the Full Information, Partial Information, or No Information treatment, respectively, compared to a group being in the same type of information treatment but not viewing a nudge in round *r*. Equation 8 is a random-effects

[9] A Hausman test was also conducted to determine if a random-effects versus a fixed-effects model was appropriate (Hausman test Prob> χ^2 = 0.7072) (Hausman, 1978).

regression model which can account for the unobserved individual, or in this case group-level, differences in the model (Greene, 2002). Therefore, the error term consists of two dimensions, μ_g and ε_{gr}, which represent the within-entity (μ_g) and between-entity (ε_{gr}) errors, respectively (Griesinger 2017; McManus, 2015; Greene, 2002). Standard errors are clustered at the session level. Clustered standard errors can account for bias in the standard errors which may be underestimated if observations are not clustered at the higher session level (Chandar et al., 2019).

Aggregate Pollutants

Variables	(1) *(Rounds 1-20)*	(2) *(Rounds 1-10)*	(3) *(Rounds 11-20)*
	Coef. Est	Coef. Est	Coef. Est
No Info	-14.9	-12.73	-27.09**
	(9.85)	(10.07)	(10.61)
Full Info	-6.92	-5.18	-16.61
	(8.66)	(7.81)	(12.98)
Full Info x Nudge	10.08**	NA	3.82
	(4.84)		(12.72)
Partial Info x Nudge	-1.79	NA	-21.16*
	(7.13)		(10.97)
No Info x Nudge	-8.05	NA	-10.43***
	(10.89)		(4.03)
Constant	168.57***	164.86***	183.59***
	(7.02)	(5.79)	(10.50)
Prob > χ^2	0.0058	0.4457	0.0006
N	760	380	380

Table 9 Random-Effects Regression Results: Aggregate-Level

Random-effects GLS regression examining how information available in the network and the pro-abatement nudge affect aggregate pollution levels. Standard errors clustered at session-level (reported in brackets). *,**,*** represent significance of P>|z| at the 10%,5% and 1% significance level, respectively. Baseline comparison for *No Info* and *Full Info* indicator variables is being in a Partial Information treatment group.

From Table 9 the effect of each information treatment on the aggregate pollutant level can be analyzed. Column 1 of Table 9 displays the coefficient estimates of Equation 8 with observations from all 20 rounds of data. It is found that neither the No Information or the Full Information treatments differed significantly in aggregate pollutant level, compared to the Partial Information treatment. Note that the Full Information treatment and No Information treatments were also not significantly different from each other in aggregate pollutant levels across all 20 rounds [$\chi^2(1) = 0.86$, Prob > $\chi^2 = 0.35$]. When analyzing all rounds of decision-making no significant interaction effect is found between being in a nudge round versus not in a nudge round for either the Partial Information or No Information treatments. However, groups in the Full Information treatment and in a nudge round are observed to have an aggregate pollutant level 10.08 units higher compared to groups in a Full Information treatment, in a non-nudge round [$\chi^2(1) = 4.34$, Prob > $\chi^2 = 0.037$). This demonstrates that the nudge may actually lend to an increase in the aggregate pollution level within the Full Information treatment.

By stratifying Equation 8 to the first 10 and last 10 rounds, before and after a nudge is implemented in any treatment, further analysis of the impact of information treatments and the pro-abatement nudge on aggregate pollutant levels can be conducted. Column 2 of Table 9 demonstrates the same equation as Equation 8 and analyzes the first 10 rounds of aggregate pollutants in the groups. As in Column 1, no significant difference in aggregate pollutant levels between the No Information and Full Information treatments are observed.

Column 3 of Table 9 outlines the analysis of Equation 8 stratified to the last 10 rounds of decision-making, after a nudge is implemented. Of note, there is evidence that the pro-abatement nudge is effective in the latter rounds of decision making within the Partial Information and No Information treatments. The results indicate that the No Information groups have an aggregate pollutant level 27.09 units lower, on average, compared to the Partial Information groups [$\chi^2(1) = 6.52$, Prob > $\chi^2 = 0.0107$]. Evidence is found that the interaction effect between being in the Full Information treatment, in a nudge round versus a non-nudge round, is not significant when stratifying the data to only the latter 10 rounds of decision-making. Finally, the results indicate that, compared to groups shown Partial Information with no nudge, the Partial Information groups who view a nudge in a round generate 21.16 units of pollutants less, on average [$\chi^2(1) = 3.72$, Prob > $\chi^2 = 0.054$]. Similarly, within the No Information treatment groups who view a nudge have an aggregate pollution level 10.43 units lower, on average, compared to groups who do not view a nudge in a given round [$\chi^2(1) = 6.69$, Prob > $\chi^2 = 0.0097$]. Therefore, comparison of the interaction between the information treatment and whether a nudge was shown provides evidence to suggest a positive impact of the nudge in the No Information and Partial Information scenarios on aggregate, where information on a neighbour's technology subsidy receipt is not known.

Therefore, the results suggest that of the three information scenarios the No Information treatments have lower pollutant-levels on average after the nudge is employed. It is observed that being in the No Information treatment and viewing the nudge has a positive effect on reducing pollutants on aggregate. Note that in the last 10 rounds the No Information - Nudge treatment is the only treatment with a mean aggregate pollutant level below the target *status quo threshold* as determined by the Social Planner's Problem (seen in Figure 2). This is important to highlight as the mean average pollutant level across all treatments exceeded the threshold level. Therefore, the results indicate that the pro-abatement nudge may be effective at reducing pollutant to efficient levels below the threshold in the scenario where no information on neighbours' decision-making is available.

Similarly, evidence was found to support that the nudge is effective at reducing pollutants when used in combination with the Partial Information treatment. Note that in both the No Information and Partial Information treatments information on whether their neighbour received the technology subsidy is not disclosed. In addition, when analyzing all 20 rounds of decision making, the results suggest that the interaction between being in the Full Information treatment and viewing a nudge yielded higher pollution levels on aggregate. These findings then demonstrate that a pro-abatement nudge under an ambient tax mechanism may be more effective in reducing pollution levels in scenarios where information about neighbours is not fully available. The subsequent section will develop the behavioural intuition of the factors which affect NPS pollution levels, including the effect of information and nudges, by analyzing individual's decision-making.

4.3 Analysis of Individual Pollution Level

4.3.1 Individual-Level GLS

Employing a random-effects GLS regression at the individual-participant level allows for further analysis into how subsidy provision, information, neighbour's actions, and the use of a pro-abatement nudge may impact individual abatement decisions. The GLS equation to analyze the impact of the independent variables on a participant's own pollution level in a round is as follows:

$$\begin{aligned} \textit{Individual Pollutants}_{\mathrm{ir}} = \beta_{02} + \beta_{6}\textit{Subsidy}_{\mathrm{ir}} + \beta_{7}\textit{Neighbour Tech}_{\mathrm{i(r-1)}} \\ + \beta_{8}\textit{Neighbour Subsidy}_{\mathrm{ir}} + \beta_{9}\textit{Nudge Round}_{\mathrm{ir}} + \mu_{i} + \varepsilon_{\mathrm{ir}} \end{aligned} \tag{9}$$

The data is truncated to each of the six treatment types described in Table 1 and Equation 9 is then estimated for each treatment. The dependent variable of interest is the individual pollution-level generated in each round. The subscripts *i* and *r* are indicators for the participant and round number, respectively. For the independent variables, *Subsidy* is an indicator representing if participant *i* was offered a subsidy in a given round, *r*. *Neighbour Tech* and *Neighbour Subsidy* are binary indictor variables for whether participant *i*'s direct neighbour adopted the technology in the previous round (*r*-1), or received a subsidy in the current round (*r*), respectively. *Nudge Round* indicates whether the current round, *r*, displays the nudge. Note that this indicator will be equal to 1 for the latter 10 rounds in the nudge treatments and this variable is be omitted for the non-nudge treatments. As in Equation 8, Equation 9 is a random-effects regression model and therefore the error term consists of two dimensions, μ_i and ε_{ir}, which represent the within-entity (μ_i) and between-entity (ε_{ir}) errors, respectively. The model assumes that the individual-specific heterogeneity (μ_i) and the observations for each independent variable at the individual- and round-level are unrelated and do not bias the β estimates (McManus, 2015; Greene, 2002).

	No Info No Nudge	Partial Info No Nudge	Full Info No Nudge	No Info Nudge	Partial Info Nudge	Full Info Nudge
	Coef. Est	Coef. Est	Coef. Est	Coef. Est	Coef. Est	Coef. Est
Nudge Round	NA	NA	NA	-2.57** (1.23)	-1.26 (1.24)	1.05 (1.35)
Subsidy	-4.09** (1.67)	-4.60** (1.96)	-8.12*** (1.65)	-2.43 (1.72)	-6.86*** (1.74)	-8.28*** (1.88)
Neighbour Tech	0.70 (1.49)	-0.62 (1.75)	-2.10 (1.58)	-2.28 (1.58)	-1.93 (1.41)	-1.50 (1.53)
Neighbour Subsidy	0.84 (1.67)	-0.14 (1.96)	-0.86 (1.65)	0.64 (1.72)	-1.62 (1.74)	-0.03 (1.88)
Cons	26.05*** (2.16)	30.78*** (3.26)	29.90*** (3.83)	28.59*** (2.86)	30.54*** (2.57)	29.50*** (2.87)
Prob > χ^2	0.062	0.1224	0.0000	0.0676	0.0010	0.0002
N	684	570	684	798	798	798

Table 10 Random-Effects GLS Regression Results: Individual-Level

Random-effects GLS regression examining how information available in the network and the pro-abatement nudge affect individual pollution levels. SE in brackets. *,**,*** represent significance of P>|z| at the 10%,5% and 1% significance level, respectively

Note: 19 observations per participant are presented as the *Neighbour Tech* variable is lagged 1 round, therefore no observations are included for round 1.

Table 10 displays the results of Equation 9 for the information and nudge treatments. A positive and significant effect of subsidy provision to a participant in a round on inducing a lower pollutant level is found across all treatments, with the exception of the No Information - Nudge treatment. The results did not find evidence of significant impact of a direct neighbour's last-round technology decision on individual pollutant levels. Similarly, there is no significant impact of whether a direct neighbour receives a technology subsidy in the current round on a participant's own level of pollutants. With regards to the nudge treatments in the three information scenarios a significant effect of a nudge in lowering one's own pollutant level is found only in the No Information - Nudge treatment [$\chi^2(1) = 4.41$, Prob > $\chi^2 = 0.036$]. This supports the earlier findings at the aggregate-level analysis which yielded evidence that a nudge may be effective in No Information scenarios at reducing NPS pollution levels. In contrast, when analyzing the effectiveness of the nudge within the Partial Information - Nudge treatment no significant effect of being in a nudge round is found on individual pollution levels when controlling for subsidy receipt and neighbour's actions.

Appendix Table 6 demonstrates the results of Equation 9 with controls for demographic variables (See Appendix D Supplementary Regression Tables). The co-efficient estimates with respect to the direction of effect and significance are consistent with the estimates for the independent variables of interest, when compared to Table 10. Additionally, Equation 9 was conducted again for each treatment with a different variable capturing the effect of a participant's direct neighbour's adoption decision. For this specification an indicator for the neighbour's adoption-decision is included and is equal to 1 if the neighbour had *ever* adopted the technology in *any* round prior to the current round, *r*. These results can be viewed in Appendix Table 7. The results are consistent with Table 10 and no major deviations are observed for the co-efficient estimates for the independent variables of interest on individual pollutant levels.

Therefore, from the results presented in Table 10, evidence is found to support that a pro-abatement nudge may be effective in reducing individual pollution levels in the No Information scenario when no information regarding a neighbour's actions is provided. No evidence is found to suggest a significant impact of a neighbour's technology adoption decision or a neighbour's subsidy receipt in a round on a participant's own pollution level - even within the Partial and Full Information treatments where this knowledge is accessible. The effect of subsidies, neighbour decisions, and the pro-abatement nudge will be explored further in the subsequent section and how these factors may specifically impact technology adoption decisions.

4.3.2 Analysis of Technology Adoption

Figure 6 demonstrates the level of technology adoption across the information and nudge treatments. Overall, technology adoption is observed to be higher in the No Information treatments and lowest in the Full Information treatment when participants have knowledge of their neighbour's technology decisions and whether the neighbour received a subsidy. Notably, it is seen that the nudge has appears to have a negative impact on technology adoption in the Partial Information scenario.

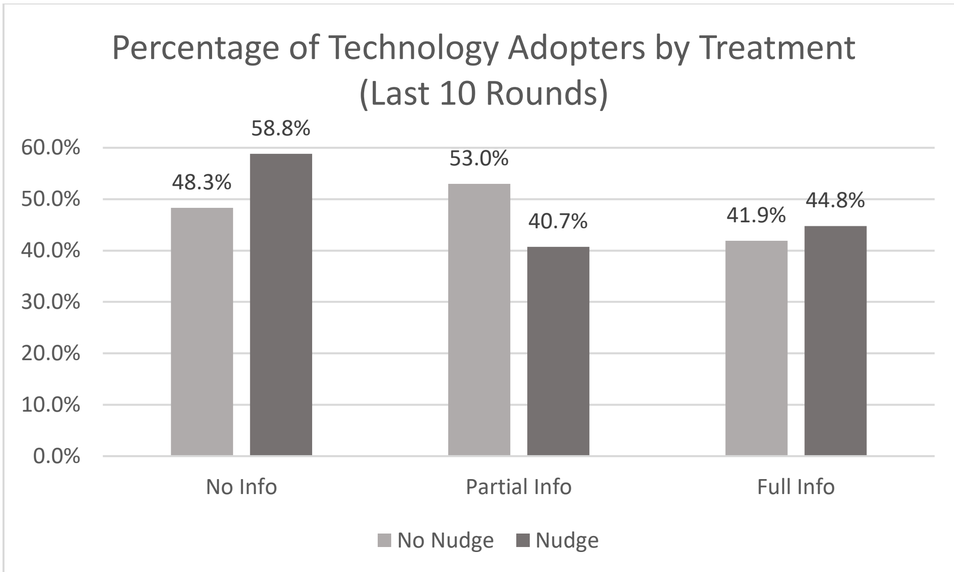

Figure 6 Technology Adoption by Treatment

Technology adoption by treatment for the last 10 rounds of decision-making (n=228).

A random-effects logit regression is employed to analyze the impact of the explanatory variables of interest on decisions to adopt or not adopt the technology by participants - a binary response. Logit regression analysis is a common approach used to analyze discrete technology choices in the agri- and environmental adoption literature (Miller & Mobarak, 2015; Daberkow & McBride, 2003). The effect of subsidy provision, neighbour's adoption and subsidy provision, and the pro-abatement nudge are analyzed with respect to their impact on the dependent variable of technology adoption for each between-group treatment. The logit regression equation is therefore:

$$\begin{aligned} \textit{Tech Choice}_{ir} = \beta_{03} + \beta_{10}\textit{Subsidyi}_{\mathrm{ir}} + \beta_{11}\textit{Neighbour Tech}_{\mathrm{i(r-1)}} \\ + \beta_{12}\textit{Neighbour Subsidy}_{\mathrm{ir}} + \beta_{13}\textit{Nudge Round}_{\mathrm{ir}} + \mu_i + \varepsilon_{\mathrm{ir}} \end{aligned} \tag{10}$$

Equation 10 presents the equation for the random-effects logit model. This model is repeated for each of the information and nudge treatments given in Table 1. Note that the β values demonstrate the effect of the stated independent variable on the likelihood of increasing a participant's own technology adoption. A positive β co-efficient demonstrates an increase in the likelihood of technology adoption. The subscripts *i* and *r* are indicators for the participant and round number, respectively. As in Equation 8 and 9, *Subsidy* is an indicator for whether a participant received the technology in the current round, *r*. *Neighbour Tech* and *Neighbour Subsidy* are indictor variables for whether participant *i*'s direct neighbour adopted the technology in the previous round (*r*-1), or received a subsidy in the current round (*r)*, respectively. *Nudge Round* indicates whether the current round *r* displays the nudge. Equation 10 is characterised as a partial-equilibrium model approach as it accounts for a participant's technology decision (the dependent variable) but not the input decision. Therefore, this analysis isolates for the impact on adoption decision. The error term consists of two dimensions, μ_i and $\varepsilon_{\mathrm{ir}}$, which represent the within-entity and between-entity errors, respectively.

Marginal Effect Estimate (*dy/dx*)	No Info No Nudge	Partial Info No Nudge	Full Info No Nudge	No Info Nudge	Partial Info Nudge	Full Info Nudge
Nudge Round	NA	NA	NA	-0.002 (0.03)	-0.11*** (0.03)	-0.04 (0.03)
Subsidy	0.26*** (0.04)	0.31*** (0.05)	0.30*** (0.04)	0.22*** (0.04)	0.35*** (0.04)	0.30*** (0.04)
Neighbour Technology	0.007 (0.03)	0.08** (0.04)	0.02 (0.04)	0.03 (0.03)	0.04 (0.03)	0.004 (0.03)
Neighbour Subsidy	-0.01 (0.04)	-0.02 (0.04)	0.01 (0.04)	0.01 (0.04)	0.04 (0.04)	-0.003 (0.04)
Prob > chi2	<0.0000	<0.0000	<0.0000	<0.0000	<0.0000	<0.0000
Log likelihood	-341.98	-280.34	-316.99	-394.03	-444.27	-471.88
N	684	570	684	798	798	798

Table 11 Random-Effects Logit Regression Results on Technology Adoption

Random-effects logit regression for each treatment presented as average marginal effects (calculated via the delta method) where the dependent variable is technology adoption. SE in brackets. *,**,*** represent significance of P>|z| at the 10%, 5% and 1% significance level, respectively.

Note: 19 observations per participant are presented as the *Neighbour Tech* variable is lagged 1 round, therefore no observations are included for round 1.

From the results in Table 11 subsidy provision is found to increase the likelihood a participant will adopt the technology in a round across treatments. For example, the results indicate that, on average, technology adoption increases by 26% when a participant receives a subsidy in a round in the No Information - No Nudge treatment compared to non-subsidy recipients [$\chi^2(1)$ = 38.88, Prob > χ^2 = <0.000]. The nudge is not observed to be a significant influence in increasing the marginal effect of technology adoption in the No Information - Nudge treatment. This finding may indicate that lower pollutant levels achieved in the nudge rounds within this treatment, as observed in Table 10, are more greatly affected by participant's input decisions rather than their technology decisions. This result is reasonably associated with the general wording of the nudge itself which promotes pollution reduction but not specifically technology adoption. Furthermore, when comparing the effect of the nudge within the Partial Information - Nudge treatment the results indicate that participants were less likely to adopt the technology. In nudge rounds, the likelihood of adoption in the Partial Information - Nudge treatment decreases by 11% [$\chi^2(1) = 14.66$, Prob > $\chi^2 = 0.0001$].

As in Table 10, generally a direct-neighbour's technology decisions or a neighbour's subsidy provision is not observed to influence a participant's own adoption behaviour. However, the exception of is this is found for the Partial Information - No Nudge treatment where a neighbour adopting a technology in the previous round significantly increased the likelihood of a participant's own adoption, on average, by 8% [$\chi^2(1) = 4.17$, Prob > $\chi^2 = 0.041$]. This finding could potentially align with the fact that in this treatment only a neighbour's technology decisions are visible while the neighbour's subsidy provision is not known and provides some evidence of a peer-effect of adoption behaviour.

Therefore, further evidence is found that receipt of a subsidy increases pollution reduction behaviours of the recipient, via increasing the likelihood of adopting the emissions-reduction technology, and that this effect is significant across all treatments. The results indicate that, while there is evidence that a pro-abatement nudge can decrease both aggregate and individual-level pollutants (Table 9, Table 10), that a nudge which encourages generally worded emissions-reduction message does not necessarily translate to significantly different technology adoption behaviour.

Finally, evidence of a negative effect of the nudge on adoption rates was found within the Partial Information - Nudge treatment. Technology adoption within this treatment was lowest when the nudge was is presented. Therefore, participants may be less inclined to adopt the technology when pro-social messaging is presented and this is more salient, and significant, in the treatment where participants have access to information on solely their neighbour's adoption decision. In addition, the results indicate that when participants in the Partial Information – No Nudge treatment viewed that a direct neighbour adopted the technology in the previous round that this increases the likelihood that the participants will adopt the technology themselves in the current round. As this treatment allows participants to view only their neighbours' adoption behaviour this then presents some evidence of a peer-effect within the network - whereby when participants view that their neighbour is not adopting the technology that they themselves are less likely to adopt.

Chapter 5 Discussion and Conclusion

5.1 Importance and Contribution

NPS pollution is a challenging environmental issue to manage due to its diffuse nature. According to the OECD, reduction of runoff is critical as this form of pollution can lead to water quality degradation which can lend to a variety of issues including negative impacts to aquatic species and ecosystem health, fishing, and recreation (Moxey, 2012). Within agriculture, motivating adoption of BMPs which can help reduce runoff from farming is necessary to lessen NPS water pollution and the environmental externalities of production. The need to manage NPS pollution from agriculture will be critical as runoff is expected to increase in upcoming years due to increased snowmelt attributed to climate change as well as higher densities of livestock and intensified cropping operations to meet demand (Government of Canada, 2016; Jain & Singh, 2019).

Policy motivating adoption of BMPs to manage agricultural pollution can be effectively informed through analyzing the behavioural factors which affect farmer's adoption decisions. As discussed by Weersink & Fulton (2020), the BMP adoption process is rooted in behavioural change which necessitates an understanding of the motivators of farmer decision-making. Understanding these behavioural mechanisms can also lend insight into where improvements in existing policy frameworks can be made (Streletskaya et al, 2020). Additionally, analyzing the role of information and messaging and how these factors may facilitate the adoption process is meaningful for NPS pollution policy development. Well-designed and holistic policy which intends to utilize BMP adoption to manage water pollution therefore requires not only recognition of the economic factors which influence abatement actions but also the behavioural factors which affect farmer's decisions.

Within the topic of NPS pollution abatement the factors of subsidy provision, information networks, and the role of nudges are key areas of research which require further development. Pro-abatement messaging is one such behavioural mechanism which requires further study with regards to its effectiveness in inducing lower NPS pollution levels (Wu, Palm-Forster, & Messer, 2021). In the context of agricultural runoff, nudges and their role in influencing NPS pollution abatement are a necessary element in developing realistic and effective policy. Similarly, research regarding how the level of information in a producer's network can affect abatement behaviour is also valuable - but little research into how networks affect BMP adoption and abatement decisions is available (Wu, Palm-Forster, & Messer, 2017; Maertens & Barnett, 2012). Additionally, limited literature exists with regards to the effect of information between subsidy and non-subsidy recipients on an individual's own abatement behaviour (Omotilewa, Ricker-Gilbert, &

Ainembabazi, 2020). Understanding how nudges, subsidy provision, and the level of information flows within a network impact NPS pollution is therefore a valuable contribution to the literature. In addition, research into how these factors interact with one another can enhance the experimental literature on NPS pollution abatement and help inform comprehensive policy.

5.2 Summary of Findings

This research employed a laboratory experiment with 228 participants to analyze the impact of information within a network, subsidy provision, and a pro-abatement nudge on aggregate NPS pollution levels under conditions of an ambient tax. In groups of six, participants engaged in 20 rounds of decision-making with two management decisions: an input level and a binary adoption choice of an emissions-reduction technology. Both decisions affected individual pollution contributions to the group. A subsidy for technology adoption was randomly allocated to one participant per group in each round. This experiment utilized a 3x2 treatment design which incorporated three information scenarios. The information treatments varied in the level of information the participants in a group could view regarding their direct neighbour's adoption decision and whether the neighbour received the technology subsidy. In the "No Information" treatment participants had no knowledge of their neighbour's actions, in the "Partial Information" treatment participants were informed of their direct neighbour's technology adoption decisions in previous rounds, and in the "Full Information" treatment participants were informed of both their direct neighbour's technology adoption decision as well as if their neighbour received a technology subsidy. Finally, orthogonal to the information treatments, a nudge encouraging pollution abatement behaviour was randomized and shown to approximately half the groups in each information treatment.

The results indicate that subsidy provision for an emissions-reduction technology can reduce NPS pollution levels. Participants who received a subsidy in a round generated lower individual pollution levels on average in that round. Additionally, the results of this experiment indicate that subsidy provision increased the likelihood a participant will adopt the emissions-reduction technology across all information scenarios. It was found that, on average, participants who receive a subsidy in a round are more likely to adopt the technology by 22-35% that round. The finding that BMP subsidies can effectively increase adoption rates has been evidenced in the related agri-environmental literature (Duflo, Kremer, & Robinson, 2011; Chouinard et al. 2008). Furthermore, the field experimental literature has yielded similar results when analyzing the impact of a 50% subsidy as employed in this research – such as the experiment by Duflo, Kremer, & Robinson (2011) which found that a 50% subsidy paid to farmers for inputs led to an increase in fertilizer use by 13-14%.

Overall, the average aggregate pollutant level was found to be above the threshold value as determined optimal by the social planner's problem. This finding aligns with Spraggon (2013) which determined that ambient policy instruments, as employed in this research through an ambient tax, are not always able to induce efficient outcomes in laboratory settings. The exception however was the No Information - Nudge treatment for which the aggregate pollution level was below the optimal level in the last 10 rounds of decision-making after the nudge was shown. The results indicate that the Partial Information and Full Information treatments, where information on neighbour's actions is available, do not produce more efficient pollution levels compared to the No Information scenario. This result contradicts findings by Banerjee et al. (2014) who utilized a laboratory experiment to analyze coordination of land-use which affected generation of ecosystem services and found that allowing information between neighbours on others' actions increased policy effectiveness. This result aligns with the laboratory experiment by Spraggon (2013) who found the reducing the amount of information available about other producers in the network did not decrease the effectiveness of an ambient policy mechanism.

A pro-abatement nudge was found effective at lowering pollution levels within the No Information treatment in which participants did not have any information about their neighbour's actions. As noted, the No Information - Nudge treatment was the only between-group treatment which, on average, did not exceed the threshold pollutant level during the nudge rounds of decision-making. This finding signals that nudges encouraging pollution reduction may prove effective in generating efficient pollution levels in scenarios with limited communication amongst producers. However, evidence was found to suggest that when nudges are worded to encourage general abatement that lower pollution levels can be achieved through producers' input decisions - but that this wording does not necessitate increases in adoption of emissions-reduction technology.

Additionally, it is observed that the nudge had a negative impact on technology adoption within the Partial Information - Nudge treatment. Participants who received information about their neighbour's adoption were 11% less likely to adopt the technology when the nudge was shown. Therefore, the results indicate a heterogenous impact of a pro-abatement nudge on technology adoption depending on the level of information in a network. Additionally, the results of the experiment indicate that the nudge was ineffective at reducing pollution levels on aggregate when information on neighbour's adoption and neighbour's subsidy receipt was available in the Full Information treatment. These findings then necessitate that care must be taken in the wording and targeting of such nudges which attempt to reduce NPS pollution and encourage BMP adoption - particularly amongst networks with greater information flows between producers.

In general, no evidence is found to suggest that a neighbour's subsidy receipt impacts an individual's own adoption behaviour. Evidence was found to suggest that a neighbour's technology adoption behaviour may affect an individual's own likelihood to adopt under certain conditions. Notably, within the Partial Information - No Nudge treatment the results indicate that participants who viewed their neighbour adopted the technology were more likely adopt the technology themselves, and vice versa. These results yield interesting insight into the potential effect of peer-influence and information on adoption behaviour when a producer can know only their neighbour's adoption behaviour. This form of altering one's behaviour in response to another's actions is observed in the network and broader agricultural adoption literature (Choi, Gallo, & Kariv, 2016; Baerenklau, 2005). This finding may arise from several behavioural channels including intentions of free-riding – a common occurrence under ambient control methods seeking to manage pollution (Wu, Palm-Forster, & Messer, 2021; Griesinger et al. 2017; Segerson, 1988). Further research into whether this finding may stem from motivations of free-riding, or potentially a "spite effect" - characterized in public goods problems as stemming from non-optimal decision making in response to an individual's desire to outperform the others in a group - would prove constructive (Brunton, Hasan & Mestelman, 2001).

5.3 Policy Implications

The results of this research can motivate comprehensive policy formation with the goal of reducing NPS pollution. The findings indicate that messaging encouraging pollution reduction are more effective in situations where there is little communication amongst farmers and where the BMP adoption of others is not easily observed – such as in dispersed communities or where limited interaction amongst producers can feasibly occur. The results provide evidence that in these networks with limited information flows that pro-abatement nudges, such as messaging facilitated through government outreach, may be able to induce efficient NPS emissions levels under an ambient tax mechanism. However, this research indicates that careful consideration of the effect of peer-influence and free-riding between producers must be taken in social networks with higher levels of information about others' BMP adoption. In these more connected social networks characterized by greater information flows general messaging to encouraging emissions reduction may prove ineffective in inducing lower NPS pollution levels and encouraging BMP adoption.

Additionally, this research indicates that provision of subsidies for BMPs can be effective in lowering NPS pollution levels as well as in motivating adoption. The findings of this research signal that subsidy provision has the potential to induce lower pollution levels and encourage adoption regardless of the level of information flows between producers in a network and both with and without the use of pro-abatement messaging.

As discussed by Segerson (1988), results from NPS water pollution experiments can also be applied to other forms of diffuse emissions problems such as groundwater pollution. To date however there has been little research within the field of behavioural economics specifically on issues which link agriculture and the environment (Palm-Forster et al., 2019). Furthermore, other environmental and resource issues characterized by limited information available to a regulator can benefit from research related to NPS pollution management (Cochard, Wilinger, & Xepapadeas, 2005). The research presented in this thesis can therefore not only assist in the development of policy which seeks to manage NPS pollution from agriculture, but also can be applied to policy which tackles broader agri- environmental issues.

5.4 Limitations and Future Research

Several areas of potential future research emerge from this work. This experiment analyzed multiple behavioural and policy variables and their effect on inducing lower levels of NPS pollutants. The main factors analyzed included the role of information networks, subsidies, and pro-abatement messaging via a nudge. This experiment was limited in its approach in evaluating the effect of subsidy provision on BMP adoption and associated pollution levels since only a fixed subsidy percentage allocated to one participant at a time was employed. This design was selected to simplify the parameters associated with the social planner's problem and Nash Equilibrium calculations and to offer a more straightforward analysis of the interaction effects between subsidy provision and information available in a network. Future studies can develop the experimental design presented here by employing treatments with both heterogenous and homogenous subsidy provision amongst the network, as well as applying an additional within-subject treatments which vary the subsidy amount between rounds.

This laboratory experiment utilized an ambient-based policy approach via an ambient emissions tax dependent on a threshold NPS pollutant level. While ambient policy instruments are often discussed as a potential mechanism to encourage abatement actions in the experimental and theoretical NPS pollution literature the real-world application of ambient-based approaches is currently limited. Notably, the design of this experiment can yield further insight into regulations which rely on threshold-based mechanisms which may be implemented to meet explicit environmental quality objectives. In addition, future research can modify the design of this experiment to analyze the conventional policy approaches presented in this research, namely BMP subsidy provision and pro-abatement messaging from government agencies, and their impact on inducing lower NPS pollution levels and encouraging BMP adoption in the absence of an ambient policy mechanism.

Additionally, laboratory experiments can develop this design through analysis of larger and more complex network structures. For example, linear networks of producers are a potential structure which could more accurately mimic real-world scenarios categorized by heterogenous impacts of pollution amongst producers. Furthermore, analyzing the effect of diverse nudges in the context of this experiment would also prove effective as this research only considered the impact of a singular, generically worded pro-abatement nudge. The impact of messaging which targets decisions concerning quasi-public goods, as evidenced in this research, versus messaging designed to affect behaviour in a pure-public goods context will be a helpful extension of the literature regarding the behavioural impacts of nudges. In addition, future experiments can incorporate messaging which specifically motivates the adoption of BMPs in production decisions and can therefore compare the effect of more general versus targeted wording on influencing abatement decisions.

Laboratory experiments can effectively measure direct variables of interest and are a valuable approach to analysing more complex economic theory as presented in this research. Notably, this work acts as a proof-of-concept study which can inform the design of future experiments at larger scales. Behavioural research in the context of NPS pollution can therefore benefit from adapting the research presented in this thesis into randomized controlled trials (RCTs) which consider real-world factors. Novel experimental design can potentially allow for longer decision-making time horizons as this can more accurately capture farmers' motivations to adopt available practices to manage agricultural runoff. In addition, experiments which account for heterogenous incentives and payoffs amongst decision-makers can assist in the development of comprehensive policy. Future research can build on this work to analyze the effectiveness of not only different subsidy mechanisms, but also the welfare effect generated by BMP subsidies.

Finally, field experiments can adapt the design presented here to further investigate the behavioural factors which may link individual emissions and BMP adoption of producers. In particular, research which analyzes how these outcomes may relate to one another and be influenced through various behavioural mechanisms, such as peer-influence, moral-licensing and free-riding motivations, will be a valuable contribution to the literature.

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Appendix A Experiment Instructions

Introduction

Thank you for participating in today's experiment.

This study session will last approximately 60-90 minutes.

You will be paid $20 CAD compensation for completing the entire experiment and a questionnaire at the end. Your final earnings will depend on your decisions and the decisions of the other participants. During the experiment, your earnings will be shown in points. Points will be converted to CAD at the end of the session and paid to you electronically in cash. *Note that 50 points equal $1 CAD.*

Your Role: You are a producer. In each round participants will individually choose:
1) An input level (0-100)
2) To adopt or not adopt a production technology

The PENALTY Pool: For each unit of input, you will add one Penalty Point to a PENALTY POOL. The PENALTY POOL is shared by all participants. Adopting the production technology will cost you points but will reduce the number of Penalty Points you contribute to the shared PENALTY POOL. If you ADOPT the technology you will contribute 75% less Penalty Points that round. Note that the number of Penalty Points in the PENALTY POOL does not carry between rounds.

PENALTY: In each round, if the total number of Penalty Points contributed by all participants in the group exceeds 150 a PENALTY will be incurred. The penalty will be the same for all participants. The PENALTY is calculated at the end of the round once all participants have chosen their input level and technology decision. The total number of Penalty Points in the PENALTY POOL will not be known to you before input and technology decisions have been made by all participants.

Subsidy: In each round you may receive a subsidy to adopt the technology. You will be notified if you receive a subsidy in a round. If you receive a subsidy you will know how much of the technology cost will be covered by the subsidy.

Information on Your Neighbour: There are 6 players in the group including you. **[Full Information:** One other player will be your neighbour in the game. The screen where you make your decisions will display information about your neighbour's decisions and whether they received a subsidy. Specifically, you will know whether your neighbour chose to adopt the technology in the previous rounds. You will also know if your neighbour received a technology subsidy in the current as well as the previous rounds. You will have the same neighbour for all 20 rounds. Every player will have a different neighbour. You will never know the identity of your neighbour and no other player will know your identity.**] [Partial Information:** One other player will be your neighbour in the game. The screen where you make your decisions will display information about your neighbour's decisions. Specifically, you will know whether your neighbour chose to adopt the technology in the previous rounds. You will have the same neighbour for all 20 rounds. Every player will have a different neighbour. You will never know the identity of your neighbour and no other player will know your identity.]

Total Round earnings: This is the amount of points you earn in each round. Your earnings will depend on your production revenue and the total Penalty Points shared by your entire group. Your round earnings will be cumulative and will determine your final payoff in the experiment.

Payoffs

Your total earnings for each round and the penalty are calculated as follows:

Total round earnings in points:
Your Total Round Earnings = Revenue – Penalty

Full equation for your total round earnings:
Your Total Round Earnings = 25 - 0.002(100 - input level)^2 – (technology cost if technology is adopted) - (PENALTY)

The PENALTY will be calculated as follows:
If Total Penalty Points ≤ 150 | Penalty = 0
If Total Penalty Points > 150 | Penalty = 0.3(Total Penalty Points - 150)

You will be able to view this equation on your decision screen. You will be able to view a Payoff Table each round which displays the corresponding revenue and Penalty Points you will contribute for multiple example input decisions.

PENALTY: Recall that the PENALTY will be incurred if the total number of Penalty Points in the PENALTY POOL contributed by all group members exceeds 150.

Result: At the end of each round, you will be notified about the outcome, and you will find out how many points you earned in that round. Your round earnings will affect your final payoff in the experiment.

Example

Sandra is a participant in this this experiment. In each round, she must decide whether or not she wants to adopt a technology which costs 12 points and will reduce the available input level from 100 to 88. This technology will reduce her Penalty Points added to the PENALTY POOL. She will also choose her input level.

Sandra's total round earnings are then calculated as follows:

Sandra's Total Earnings = 25 - 0.002(100 - input level)^2 – (technology cost if technology is adopted) - (PENALTY)

Sandra decides to select an **input level of 45**

If Sandra **does not adopt the technology**:

Total Earnings = 25 – 0.002(100 - input)^2 – (technology cost) – PENALTY
= 25 – 0.002(100 - 45)^2 – (0) – PENALTY
= 25 – 0.002(3025) – 0 - PENALTY
= 25 – 6.05 – 0 - PENALTY
= 18.95 - PENALTY

If Sandra **adopts the technology**:

Total Earnings = 25 – 0.002(100 - input)^2 – (technology cost) – PENALTY
= 25 – 0.002(100 - 45)^2 – (12) – PENALTY
= 25 – 6.05 – 12 - PENALTY
= 6.95 - PENALTY

<u>How many Penalty Points will she add to the PENALTY POOL?</u>

If Sandra **does not adopt the technology** :

Penalty Points added to PENALTY POOL = input
= 45

If Sandra **adopts the technology** her Penalty Points added to the PENALTY POOL will be:

Penalty Points added to PENALTY POOL = 0.25*input
= 0.25*(45)
= 11.25

At the end of the round if the total number of Penalty Points contributed by her and the other five group members exceeds 150 the PENALTY will be incurred and will depend on the total number of Penalty Points in the PENALTY POOL.

The PENALTY will be calculated as follows:

If Total Penalty Points ≤ 150 | Penalty = 0
If Total Penalty Points > 150 | Penalty = 0.3(Total Penalty Points - 150)

Sandra will then be shown her total earnings for the round in points.

General Experiment Guidelines

All decisions will be made online via your personal device (e.g. computer). You will participate in 20 rounds of decision-making. After the 20 rounds are over, you will be asked to complete a questionnaire. Once all activities are over, the computer will sum your earnings from all activities, and you will be paid based on these earnings. Please remember that your decisions in the game will influence your final payoff.

Please Remember

- Make your decision promptly to help the study move forward in a timely manner.
- DO NOT communicate with other participants.
- YOU CANNOT GO BACK to a previous screen. Once you finish a round, you cannot change your decision in that round.

We are now ready to begin the experiment.
On the next screen you will participate in a quiz to gauge your understanding of the experiment's instructions. Please note that your answers in this quiz will not influence your payoffs at the end of the experiment.

Quiz Questions

True or False: You will know if you receive the technology subsidy?

True/False

How many rounds of decision making will there be?

5/10/15/20

How many players are there in this group?

2/6/12

You will incur a point penalty only if the number of Penalty Points in the PENALTY POOL exceeds 150?

True/False

True or False: You will know if your neighbour adopted the technology in the previous rounds?

True/False

Appendix B Questionnaire

1. What is your current municipality (city/town) of residence?
2. How old are you?
3. What is your gender?
    - o Woman
    - o Man
    - o My gender identity is not listed above
    - o Choose not to respond
4. If your gender identity is not listed above please specify (optional):
5. What of the following BEST describes your ethnic background?
    - o Indigenous (Inuit/First Nations/Métis)
    - o White/European
    - o Black/African/Caribbean
    - o Arab (Saudi Arabian, Palestinian, Iraqi, etc)
    - o South Asian (East Indian, Sri Lankan, etc)
    - o Latin American (Costa Rican, Guatemalan, Brazilian, Colombian, etc)
    - o West Asian (Iranian, Afghani, etc)
    - o Other (please specify)
    - o Prefer not to respond
6. If your ethnic background is not listed above please specify
7. Which of the following best describes your HIGHEST level of education?
    - o Some high school
    - o Completed high school
    - o Some college/university
    - o Apprenticeship training and trades
    - o Completed college/university
    - o Some graduate education
    - o Completed graduate education
    - o Professional degree
    - o Prefer not to respond
8. Are you currently a student?
    - o Yes
    - o No
9. What is your profession? (if not applicable leave blank)
10. How many hours do you work each week? (if not applicable leave blank)
    - o Part-time, less than 40 hours per week
    - o Full-time, approximately 40 hours per week
    - o Full-time, more than 50 hours per week
    - o Choose not to respond
11. What was your annual household income in 2020?
    - o Below 20,000 CAD
    - o 20,000 CAD – 39,999 CAD

- 40,000 CAD – 59,999 CAD
- 60,000 CAD – 79,999 CAD
- 80,000 CAD – 99,999 CAD
- 100,000 CAD – 149,999 CAD
- Above 150,000 CAD
- Choose not to respond

12. Including yourself, how many people live in your household?
    - I live alone
    - 2
    - 3
    - 4
    - 5 or more
    - Prefer not to respond
13. How do you see yourself: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please select an option on the scale, where the value 0 means: 'not at all willing to take risks' and the value 10 means: 'very willing to take risks'

Appendix C Nash Equilibrium Supplemental Information

Appendix C.1 Social Optimal Input Levels

Case A: No Technology

The Social Planner's problem derived is as follows:

$$SP_{\text{no tech}} = max_{x1\ldots x6}\left(\sum_{n=1}^{6}[25 - 0.002(100 - x_n)^2] - 0.3 \times \sum_{n=1}^{6} x_n \right)$$

$$0 = 0.004(100 - x_n) - 0.3$$

$$0.1 = 0.004x_n$$

$$x_n{*}_{\text{no tech}} = 25$$

[10]Therefore, with no technology the social optimum level of group input is:

$$\sum_{n=6}^{1} x_{n\ \text{no tech}} * = X * = 150.$$

Case B: With Technology

The Social Planner's problem derived is as follows:

$$SP_{\text{tech}} = max_{x1\ldots x6}\left(\sum_{n=1}^{6}[25 - tech\ cost - 0.002(100 - x_n)^2] - 0.3 \times \sum_{n=1}^{6} 0.25x_n \right)$$

$$0 = 0.004(100 - x_n) - 0.075$$

$$0.325 = 0.004x_n$$

[10] Note that the tax, i.e. the final term $0.3 \times \sum_{n=1}^{6} x_n$, is only incurred if the total pollution exceeds the threshold value.

$x_n*_{tech} = 81.25$

Optimal and Maximum input choices, fixed for no technology (Case A) and with technology adoption (Case B) are therefore:

	Case A: **No Technology**	Case B: **With Technology**	
		No Subsidy	**Subsidy Provision**
Optimal input, x_n^*	25	81.25	81.25
Maximum input, x_n^{max}	100	88	94

Appendix Table 1 : Optimal and Maximum Input Choices

Optimal and maximum input choices available to participants with and without technology adoption and with and without subsidy provision.

Appendix C.2: Strategic Game (No Subsidies)

Player 2

			No Technology		Technology	
			$x_n*_{no\ tech}$	$x_n^{max}{}_{no\ tech}$	x_n*_{tech}	$x_n^{max}{}_{tech}$
Player 1	No Technology	$x_n*_{no\ tech}$	A 150.00	B 525.00	C 126.56	D 135.00
		$x_n^{max}{}_{no\ tech}$	E 225.00	F 600.00	G 201.56	H 210.00
	Technology	x_n*_{tech}	I 145.31	J 520.31	K 121.88	L 130.31
		$x_n^{max}{}_{tech}$	M 147.00	N 522.00	O 123.56	P 132.00

Appendix Table 2 NE Group Pollutant Levels (No Subsidies)

Group Pollutant Level, X, by scenario; no subsidies.

Player 2

Player 1			No Technology		Technology	
			$x_n{}^*{}_{no\ tech}$	$x_n{}^{max}{}_{no\ tech}$	$x_n{}^*{}_{tech}$	$x_n{}^{max}{}_{tech}$
	No Technology	$x_n{}^*{}_{no\ tech}$	A 82.50	B -536.25	C 75.23	D 77.31
		$x_n{}^{max}{}_{no\ tech}$	E -41.25	F -660.00	G -6.33	H -19.44
	Technology	$x_n{}^*{}_{tech}$	I 81.05	J -529.27	K 73.78	L 75.86
		$x_n{}^{max}{}_{tech}$	M 81.46	N -531.89	O 74.20	P 76.27

Appendix Table 3 NE Group Payoffs (No Subsidies)

Total group payoff, $\sum_{n=1}^{6} payoff_n$; no subsidies.

Appendix C.3: Strategic Game with Subsidy Provision

Player 2 (No Subsidy)

Player 1 (Subsidized)			No Technology		Technology	
			$x_n{}^*{}_{no\ tech}$	$x_n{}^{max}{}_{no\ tech}$	$x_n{}^*{}_{tech}$	$x_n{}^{max}{}_{tech}$
	No Technology	$x_n{}^*{}_{no\ tech}$	A 150.00	B 525.00	C 126.56	D 135.00
		$x_n{}^{max}{}_{no\ tech}$	E 225.00	F 600.00	G 201.56	H 210.00
	Technology	$x_n{}^*{}_{tech}$	I 145.31	J 520.31	K 121.88	L 130.31
		$x_n{}^{max}{}_{tech}$	M 148.50	N 523.50	O 125.06	P 133.50

Appendix Table 4 NE Group Pollutant Levels (w/ Subsidies)

Group Pollutant Level, X, by scenario; with subsidy allocated to Player 1.

Player 2 (No Subsidy)

Player 1 (Subsidized)			No Technology		Technology	
			$x_n{*}_{no\ tech}$	$x_n^{max}{}_{no\ tech}$	$x_n{*}_{tech}$	$x_n^{max}{}_{tech}$
	No Technology	$x_n{*}_{no\ tech}$	A 82.50	B -536.25	C 75.23	D 77.31
		$x_n^{max}{}_{no\ tech}$	E -41.25	F -660.00	G -6.33	H -19.44
	Technology	$x_n{*}_{tech}$	I 87.05	J -523.27	K 79.78	L 81.86
		$x_n^{max}{}_{tech}$	M 87.68	N -528.37	O 80.41	P 82.49

Appendix Table 5 NE Group Payoffs (w/ Subsidies)

Total group payoff, $\sum_{n=1}^{6} payoff_n$; with subsidy allocated to Player 1.

Appendix D Supplementary Regression Tables

	No Info No Nudge	Partial Info No Nudge	Full Info No Nudge	No Info Nudge	Partial Info Nudge	Full Info Nudge
	Coef. Est	Coef. Est	Coef. Est	Coef. Est	Coef. Est	Coef. Est
Nudge Round	NA	NA	NA	-2.57** (1.23)	-1.25 (1.24)	1.17 (1.37)
Subsidy	-4.39*** (1.71)	-4.52** (1.95)	-8.36*** (1.70)	-2.44 (1.72)	-6.86*** (1.74)	-8.62*** (1.92)
Neighbour Tech	0.45 (1.53)	-0.44 (1.74)	-2.50 (1.62)	-2.44 (1.58)	-1.90 (1.41)	-1.46 (1.56)
Neighbour Subsidy	0.87 (1.71)	-0.06 (1.95)	-0.85 (1.70)	0.65 (1.72)	-1.48 (1.74)	-0.10 (1.90)
Risk Preference	0.90 (0.78)	4.46*** (1.72)	1.95 (1.40)	2.16* (1.16)	3.41*** (1.14)	0.59 (1.13)
Education	0.04 (1.30)	0.11 (2.63)	-1.69 (1.97)	-1.73 (1.90)	-1.64 (2.26)	-1.19 (2.34)
Female	12.90*** (3.83)	-1.49 (7.04)	-4.30 (6.84)	-0.51 (5.54)	-13.33*** (4.99)	-11.55 (5.56)
Cons	14.58* (7.92)	7.21 (17.40)	27.75** (13.87)	24.73* (13.23)	26.52* (15.98)	38.44*** (13.75)
Prob > χ^2	0.0028	0.0225	0.0000	0.0751	0.0000	0.0002
N	665	570	665	798	798	779

Appendix Table 6 Random-Effects GLS Regression Results: Demographic Controls

Individual-level random-effects GLS with demographic controls where dependent variable is individual pollution level in a round; Education: representing a participant's stated highest level of education (ordered, categorical); Female = 1 if participant selected "Woman" as gender identity; Risk preference selected from 1-10 (discrete integer).

	No Info No Nudge	Partial Info No Nudge	Full Info No Nudge	No Info Nudge	Partial Info Nudge	Full Info Nudge
	Coef. Est	Coef. Est	Coef. Est	Coef. Est	Coef. Est	Coef. Est
Nudge	NA	NA	NA	-2.63** (1.24)	-0.67 (1.25)	1.23 (1.37)
Round						
Subsidy	-4.13** (1.66)	-4.58** (1.96)	-8.11*** (1.65)	-2.41 (1.73)	-6.83*** (1.74)	-8.31*** (1.87)
Neighbour ever adopted	3.78 (3.07)	-1.86 (3.81)	-2.50 (3.62)	2.00 (5.19)	-3.39 (3.24)	-2.03 (4.18)
Neighbour Subsidy	0.84 (1.66)	-0.14 (1.96)	-0.84 (1.65)	0.66 (1.73)	-1.61 (1.74)	0.06 (1.88)
Cons	22.94*** (3.57)	32.20*** (4.67)	30.98*** (4.80)	25.31*** (5.56)	32.43*** (3.78)	30.51*** (4.63)
Prob > χ^2	0.0330	0.1149	0.0000	0.1463	0.0015	0.0003
N	684	570	684	798	798	798

Appendix Table 7 Random-Effects GLS Regression Results: Alternate Specification

Equation 9 with indicator for whether a participant's neighbour adopted the technology in any round prior to the current round. Dependent variable is individual pollution level. SE in brackets. (*,**,***) represent significance of P>|z| at the 10%,5% and 1% significance level, respectively.

Marginal Effect Estimate (*dy/dx*)	No Info No Nudge	Partial Info No Nudge	Full Info No Nudge	No Info Nudge	Partial Info Nudge	Full Info Nudge
Nudge Round	NA	NA	NA	-0.002 (0.03)	-0.12*** (0.03)	-0.05 (0.03)
Subsidy	0.27*** (0.04)	0.31*** (0.04)	0.31*** (0.04)	0.23*** (0.04)	0.38*** (0.04)	0.31*** (0.04)
Neighbour Technology	0.01 (0.03)	0.08** (0.04)	0.01 (0.04)	0.03 (0.03)	0.04 (0.03)	0.001 (0.03)
Neighbour Subsidy	-0.02 (0.04)	-0.02 (0.04)	0.02 (0.04)	0.01 (0.04)	0.04 (0.04)	-0.001 (0.04)
Risk	-0.03* (0.02)	-0.05* (0.03)	-0.04* (0.02)	-0.02 (0.02)	-0.02 (0.02)	-0.02* (0.01)
Education	0.04 (0.03)	0.07 (0.04)	-0.02 (0.03)	0.07** (0.03)	-0.04 (0.04)	-0.01 (0.03)
Female	-0.37*** (0.08)	0.11 (0.11)	-0.05 (0.12)	-0.10 (0.09)	-0.001 (0.10)	0.08 (0.08)
Prob > χ^2	<0.0000	<0.0000	<0.0000	<0.0000	<0.0000	<0.0000
Log-likelihood	-319.85	-272.75	-303.42	-381.85	-429.29	-459.93
N	665	570	665	798	798	779

Appendix Table 8 Random-Effects Logit Regression Results: Demographic Controls

Random-effects logit with demographic controls reported as average marginal effects (delta method); Education: representing a participant's stated highest level of education (ordered, categorical); Female = 1 if participant selected "Woman" as gender identity; Risk preference selected from 1-10 (discrete integer). (*,**,***) represent significance of P>|z| at the 10%,5% and 1% significance level, respectively.