Title
Essays in Environmental Economics

Author
Bao, Ken

Publication Date
2023

University of California
Santa Barbara

Essays in Environmental Economics

A dissertation submitted in partial satisfaction
of the requirements for the degree

Doctor of Philosophy
in
Economics

by

Ken Bao

Committee in charge:

Professor Chris Costello, Chair
Professor Olivier Deschenes
Professor Antony Millner

June 2023

The Dissertation of Ken Bao is approved.

Professor Olivier Deschenes

Professor Antony Millner

Professor Chris Costello, Committee Chair

May 2023

Essays in Environmental Economics

I dedicate my disseration to my parents and siblings who have supported me throughout these many years.

Acknowledgements

I would like to acknowledge the incredible support and advice from my advisor Chris and committee members Olivier and Antony. I could not have done this without the support from my friends and peers especially my office mates, cohort mates, 290 group and lab mates.

Curriculum Vitæ

Ken Bao

Education

2023	Ph.D. in Economics (Expected), University of California, Santa Barbara.
2017	M.A. in Economics, University of Missouri, Saint Louis.
2014	B.A. in Business Administration - Finance, University of Missouri, Saint Louis

Publications

Jill M. Bernard Bracy, Ken Q. Bao, and Ray A. Mundy. "Highway infrastructure and safety implications of AV technology in the motor carrier industry". In: Research in Transportation Economics 77 (2019), p. 100758

Abstract

Essays in Environmental Economics

by

Ken Bao

This dissertation consists of three essays. The first aims to compare the cost-effectiveness between command-control and market instruments in addressing non-point source pollution. By definition, non-point source pollution (NPSP) is extremely difficult to observe individual level discharge and thus, very hard to implement market incentive policies. I exploit a policy setting where agricultural runoff is in fact, a point source pollution but is regulated as if it were NPSP which allows the study of abatement behavior in what is typically a NPSP setting. I study a program called the Florida Everglades Forever Act intended to reduce phosphorus runoffs from entering the sensitive Everglades ecosystem. The program consists of both a command-control component as well as a market incentive component which I am able to disentangle using a new dataset I developed on annual farm level discharge and subsidies for pollution reduction. I use the two-step Arellano-Bond estimator to estimate a marginal abatement cost (MAC) curve for the average farm. With the estimated MAC curve, I simulate the costs under the market mechanism and compare that with both data-estimated and engineer-estimated costs under command-control. I find that to achieve the same benchmark pollution outcome, the market mechanism would reduce compliance cost by 20%.

The second chapter examines the theoretical efficacy of an ambient mechanism in ameliorating the NPSP problem. Specifically I examine theoretically how an ambient mechanism to ameliorate the NPSP problem can produce free-riding incentives. Specifi-

cally, I show the conditions in which uncertainty about firm types may lead to incorrectly setting the uniform ambient tax rate which then creates the potential for free-riding. I also compare the Nash and Sub-game Perfect Nash equilibria and analyze the potential welfare gains of adding more water quality monitoring points. I find that expanding the network of water monitors in such a setting does not always reduce free riding potential compared to the single-monitor case though it never rises above this level. The reason is that splitting the group by adding more monitors could simply be redistributing the free-riding potential to the multiple groups rather than actually decreasing the free-riding potential of all groups together.

Chapter three is joint work with Chris Costello which discusses the role of indemnity in Payments for Ecosystem Services programs (PES). PES programs are voluntary programs where private or public beneficiaries of ecosystem services (a public good) agree to pay private producers of ecosystem service (ES) inputs. However, when there is private risk to the private provisioning of ES inputs, then there may be gains to offering loss protection (indemnity). This paper characterizes conditions in which it is optimal for a budget constrained regulator to (i) offer indemnity in conjunction with a linear pricing contract and (ii) to pursue the dual objective of poverty alleviation and maximizing social benefits from ES inputs. We find that it is optimal for the regulator to share in the risk of producing ES inputs (or outputs), i.e., offer full indemnity if agents are risk averse. Furthermore, the value from optimally choosing the indemnity, compared to the no-indemnity case, is higher whenever agents are more risk averse and can lead to as much as a 40% increase in ES supply for the same budget. We also provide a guide to practitioners and empirical researchers on how to evaluate the appeal of indemnity in any particular setting for which PES exists and provision of which is risky. Lastly, we identify a estimatable threshold for the business-as-usual ES supply curve slope above which it is optimal to pursue the dual objective.

Contents

Chapter 1

Command-Control Versus Market Incentive Policies for Non-point Source Pollution

1.1 Introduction

Non-point source pollution (NPSP), defined as pollution with transport mechanisms that are too complex and/or sources too diffuse to feasibly monitor individual contributions, poses a unique challenge for regulators and economists. Examples of NPSP include agricultural runoff, litter, car exhaust, etc. The challenge lies in how to best regulate pollution when you cannot observe or measure individual contributions?

There are two main approaches in the realm of mandatory policies used to regulate pollution and those are command-and-control and market-based incentive polices. The goal of this paper is to compare the cost effectiveness of a command-control policy with the effectiveness of a market incentive policy in a NPSP setting. This study is especially important for water pollution in the U.S. where almost $5 trillion dollars (or 0.8% of GDP every year) has been spent since the start of the Environmental Protection Agency to clean up the nation's waters (Keiser and Shapiro, 2019) but there is evidence that the costs may have exceeded the benefits. According to the 2017 National Water Quality Inventory: Report to Congress, roughly half of the nation's waters are still too impaired to support swimming and fishing due to NPSP. Annual economic damages from nutrient runoffs alone amount to roughly $4 billion each year (Chatterjee, 2009) and therefore, there is a pressing need to find cost-effective means in addressing NPSP.

I study a program called the Everglades Forever Act (EFA) passed in Florida in 1994 and was designed to regulate phosphorus runoffs from a specific farming region known as the Everglades Agricultural Area (EAA). This empirical setting is extremely attractive for this exercise because it overcomes the observability problem unique to NPSP. Due to the atypical geographical features of the EAA, the farm runoff problem is truly point-source with individual level discharge monitoring. However, runoff in this region is regulated as if it were NPSP due to a stakeholder process with farmer participation. I find that the market incentive could achieve the same aggregate pollution outcome as the command-control policy with an estimated 20% savings in average compliance cost.

This paper contributes to a larger literature that compares the cost-effectiveness of market incentives with command control. There have been many papers that investigate the relative cost performance of command-control and market-based policies for point-source (Goulder et al., 1999; Newell and Stavins, 2003; Goulder and Parry, 2008) and conservation contexts. However, there has not, to the best of my knowledge, been as much progress in this area for the non-point source pollution because market incentive policies have rarely been implemented in NSPS settings and studies on their cost effectiveness would require observations at the individual level. Rendleman, Reinert and Tobey (1995) is the only paper so far that has tried to do this by using a computable general equilibrium model calibrated to match estimated elasticities of input substitution. They estimate that the cost-effectiveness of input taxes compared to mandated input levels produce only a ten percent cost savings. In contrast, the comparison made in this paper is between command-control and a different market incentive mechanism for NPSP known as the ambient market mechanism.

In the agricultural runoff setting, command-control policies typically come in the form of mandatory best management practices (henceforth BMPs) which are structural (digging a detainment pond) or non-structural changes (stricter fertilizer application) that are designed to be verifiable and to reduce runoff. Though they can offer significant reductions in runoffs, they also produce little flexibility for firms to undergo the least cost abatement actions.

Ambient-based market mechanisms (henceforth AMMs) offers much more flexibility on the other hand. Economists have developed an eloquent theory of ambient based market mechanisms beginning with Segerson (1988)'s seminal paper which followed the works of Holmstrom (1982) and Meran and Schwalbe (1987). AMMs either tax or subsidize (or both) all known polluters based on the entire group's performance (ambient pollution) relative to an ambient standard. The pecuniary reward/punishment is based on the difference between observed ambient pollution and the ambient standard. For situations in which ambient pollution can feasibly be observed, Segerson (1988) showed theoretically how a regulator could impose an individual specific ambient tax/subsidy rate that achieves the first best outcome as a Nash equilibrium. This has led to a large literature focusing on the theoretically optimal design of AMMs under various contexts (Cabe and

Herriges, 1992; Hansen and Romstad, 2007; Herriges, Govindasamy and Shogren, 1994; Horan, Shortle and Abler, 1998; Xepapadeas, 1991, 1992). These theoretical developments produced a large experimental literature testing various ambient mechanisms in a laboratory setting (Camacho and Requate, 2004; Cochard, Willinger and Xepapadeas, 2005; Poe et al., 2004; Spraggon, 2002; Suter, Vossler and Poe, 2009). By and large, these studies suggest that ambient mechanisms can achieve pollution targets at least cost.

The cost advantages from ambient mechanisms compared to command-control is more ambiguous than in other contexts and thus the comparison should be of great interest. On the one hand, AMMs provide the greatest flexibility for firms to abate. On the other hand, AMMs could have too much flexibility that leads to free-riding therefore undercutting potential cost advantages. For instance, there may be some polluters who are polluting more than the cost efficient level while others compensate by polluting less than optimal so that the ambient target is still met (Kotchen and Segerson, 2020).

Despite the apparent advances in the development of AMMs, they have rarely been implemented in practice. There are a few notable examples of pseudo AMMs used in practice (Wong et al., 2019; Reichhuber, Camacho and Requate, 2009), however it is hard to argue that those studies are applicable to the agricultural runoff context. The policies under those studies were implemented in common pool resource settings and did not always target the extractors themselves. Consequently, these studies cannot disentangle the total effect between abatement by peer enforcement or abatement by pecuniary incentives. Furthermore, in these settings, an extractor would have to go to the extraction site without being caught by a voluntary enforcer which strengthens the enforcement mechanism. In contrast, there is much less of a role for the enforcement mechanism to play in settings like agricultural runoffs or ground water extraction.

To do the cost comparison set out in this paper, I proceed as follows. First, I study the EFA which had both a command-control and a market incentive component. Using a two-step Arellano-Bond estimator, I estimate how farms' discharge responded to an effective abatement subsidy by using fixed effects to control of the impacts coming from the command-control component. This exercise allows me to recover the marginal abatement cost curve which can then be used to estimate the efficient ambient tax and compliance costs for various pollution targets. The same empirical exercise also allows me to estimate the ambient pollution outcomes under the command-control component only which I then use as my benchmark polluion target. Compliance costs under the command-control are taken from engineer estimates and validated using USDA state level annual agricultural expenditure data. I find that the market incentive component of the EFA did cause meaningful reductions in discharge and that it could have achieved the same ambient pollution outcome as the command-control policy but with a 20% cost savings.[1].

Evolution of NPSP Policies in Practice

U.S., Europe and various other OECD countries have historically relied heavily on voluntary financial incentive tools, i.e., pay-the-polluter principle, to address agricultural runoff (Drevno, 2016; Shortle and Horan, 2013; Shortle et al., 2012) which have had a limited effect on water quality. These policies typically involve payments to farmers in exchange for implementing best management practices (BMPs) that target pollution reduction and such agreements are made voluntarily. However, in the U.S., the majority of voluntary programs only treat NPSP as a secondary goal.

[1]This result relies on assumptions made under standard AMM theory which are: (1) no cooperation and (2) farms understand how their decisions affect ambient pollution.

Relatively recently, water quality trading mechanisms were suggested and implemented in an effort to implement a more focused voluntary program that targets runoffs directly (Dowd, Press and Los Huertos, 2008; Shortle and Horan, 2001). These trading systems work by allowing point source polluters to purchase additional pollution permits from a non-point source polluter. In return, the non-point polluter must either change their use/management of polluting inputs (e.g., install a vegetation buffer strip) or achieve some level of abatement (which is estimated using models). Stephenson and Shabman (2017) have argued that such mechanisms have largely failed at addressing non-point source pollution because the law does not absolve the point source polluter from responsibility if the non-point source person does not hold up their end of the bargain. This has led to virtually no trades happening between point-source and non-point source polluters.

Likely as a response to the failings of the previous approaches, states have begun to shift towards applying the polluter-pays principle in addressing agricultural runoff. In recent decades, this has typically come in the form of mandatory BMPs (Shortle et al., 2012). However, without a proper study on the cost effectiveness of BMPs, this new policy direction may be misguided. Thus, the reason for comparing the mandatory BMPs with AMM is because AMMs have the potential to achieve pollution reductions at least cost (Suter et al., 2008; Hansen and Romstad, 2007; Hansen, 1998) though it is far from guaranteed. The extent to which a uniform ambient tax/subsidy can lead to least cost abatement depends in large part the degree of free-riding and collusion. Despite some of its potential drawbacks, ambient mechanisms have a number of appealing aspects. First, it can be designed to be consistent with either the polluter-pays principle or pay-the-polluter principle giving policy makers flexibility to choose the more politically appetizing design. Second, it circumvents the need to observe or estimate contributions individually. Lastly, it is based on actual performance which maintains flexibility for firms to choose their most desired methods of abatement.

1.2 Everglades Forever Act (EFA)

The Everglades Forever Act was signed into law by the Florida Legislature in 1994 to address the issue of nutrient loading into the Everglades, specifically phosphorus loadings from farms within the Everglades Agricultural Area (EAA).[2] The policy has two major components relevant to this study and the regulatory agency in charge of enforcement and oversight is called the South Florida Water Managment District (SFWMD).

Command-Control Component of the EFA

The first component was a mandate that required all owners of commercial agricultural parcels within the EAA to obtain a permit in order to continue commercial farming operations.[3] To obtain a permit, parcel owners needed to develop a best management practice (BMP) plan and a water quality/quantity monitoring plan. The water monitoring plan requires a qualified third party to collect and analyze the farm-specific runoff samples. Although this data is not directly used by the regulatory agency to determine regulatory compliance, it is still gathered so that the SFWMD regulator has it in the case of non-compliance[4]. Once approved by the SFWMD, applicants must achieve full implementation of both plans by the start of the 1996 water-year to remain in compliance.[5] The BMPs that are implemented in the EAA must be set in accordance with the goal of reducing total phosphorus (TP) loads attributable to the EAA by 25% of historical TP loads. The regulator presented a menu of BMP options for permit applicants to choose

[2]For a full overview of the policy context, see Milon (2018).

[3]Map of the EAA and its sub-basins are shown in Figure 1.

[4]Non-compliance occurs whenever the entire EAA basin fails to reach an estimated 25% phosphorus reduction for three consecutive water years (Appendix A3 of Florida Statute Chapter 40E-63).

[5]A water-year starts on May 1st and ends on the following April 30th. For example, water year 1994 spans from May 1st, 1993 to April 30th, 1994.

from. Each BMP option is assigned a point value that signals its expected effectiveness in reducing runoff. Applicants are required to choose a combination of BMPs such that the sum of the points from their chosen set is at least 25.[6]

Group Incentive Credit Program

The second component of the EFA policy charges an Agricultural Privilege Tax on parcel owners in the EAA that undergo commercial agricultural operations. This was meant to be both a funding source for cleanup projects as well as providing further incentive to induce TP load reductions beyond the 25% reduction target. The privilege tax started off at $24.89 per acre and weakly increases over time till 2013 according to a set schedule. Details about the exact evolution of this tax scheme is presented in column 2 of Table A.1.

To remain in compliance and avoid excess regulatory burden, the entire EAA basin must achieve a percent TP load reduction of 25% relative to a baseline historic TP level.[7] Water quality monitoring stations are placed downstream of the main canals running through the EAA and are used to measure ambient quality attributed to EAA farmers. If the *entire* EAA basin achieves a TP load reduction by more than the 25% target for reduction, then everyone is awarded one tax credit per acre for each percentage point above 25%. Earned credits can go towards reducing future privilege tax obligations two water years from which it was earned. The rate at which a credit can reduce the tax is the same for all parcels. However, at a minimum, the tax per acre must not fall below $24.89 which implies that for each year, there is a maximum number of exercisable

[6]TP load is a measure of how much phosphorus passes a particular point (typically a point on a moving body of water) over a given time.

[7]Baseline TP values are acquired through a prediction model that incorporates paramter values from the 1980-1988 and meterological conditions of the current year.

credits (shown in column 5 of Table A.1) that prevents one from reducing their per acre tax below the minimum of \$24.89. Between 1994 and 1997, farmers could not exercise any earned credits since the tax is already at the minimum. Between 1998 and 2001, farmers could exercise one unit of earned credit per acre to reduce their tax per acre by \$0.54. However, since the tax cannot be below \$24.89, farmers can only exercise a maximum of 3.91 credits per acre. If farmers have more credits than they need in any given period, then the credits can be carried forward for future use but the value of a single credit changes over time and is shown in the third column of Table A.1.

Individual Incentive Program

Additionally, farms can earn credits based on individual performance as well as through group performance (EAA wide credits)[8]. Farms can submit applications to further earn credits through their individual performance by proving that their TP load reductions exceeded the target given by column 4 of Table 1.[9] In this way, polluters can "double dip", so to speak, on the same level of abatement effort. All credits, whether earned through the ambient quality performance or individual performance, are used in *almost* the same way and the accounting system for both are the same which makes it difficult to isolate and measure the effect of the ambient subsidy.[10] By 2013, the ambient and individual incentive credit program will end so that all leftover credits will expire and no more credits can be earned or used to reduce the Agricultural Privilege Tax. This terminal date for the tax credit program was written into law back in 1994 and so knowledge of this terminal date was public information.

[8]The language in this paper will treat each observed unit *as if* they are individual farms. However, the regulatory unit is at a sub-sub basin level so that each "unit" in the data can actually be composed of multiple farms.

[9]It should be noted that all farms are required to disclose their individual loadings. It is then unclear what is additionally being reported by the application for individual credits.

[10]Individual credits can also be earned if farms show that their TP loads were below 5 ppb. However, credits earned in this manner cannot be rolled over for future use.

If the EAA basin is determined to be out of compliance for at least three consecutive years, then enforcement action will be taken. The SFWMD will then use the reported TP loads from each farm to target those who are not reducing their TP loads enough. If there is further non-compliance by said farms, punitive measures such as fines or arrests are possible though such measures were never required. Between 1994 and 2013, the aggregate abatement target had been exceeded except for one year (Milon, 2018). Throughout the empirical analysis, there is no need to distinguish how credits are earned because once a credit is earned, they are used in virtually the same way. I do this for simplicity and because it is rather innocuous because I discuss later that other aspects of the EFA policy dissolves the strategic interactions among farms anyway.

Why the Everglades?

An empirical investigation of any policy that addresses NPS pollution problems would ideally have data at the individual polluter level so that polluting behavior can be analyzed. However, the very nature of NPS pollution means that individual discharge of effluents cannot be observed. The situation in Southern Florida offers an exciting opportunity to get around this problem. Due to the geographical features of the land, farms have to be hydrologically connected to large canals and drainage systems in order to continue agricultural production. Each farming parcel is surrounded by canals that channel water to one point (sometimes more) where water is then pumped out into the public canal system. When multiple farms share the same pumping infrastructure, then they're said be a part of the same basin and the EFA requirements will apply to that basin as a whole. The reason for the extensive canal system is that the EAA was once a part of the Everglades wetlands but during the early 20th century a large system of canals was developed by both the Army Corps of Engineers and local farmers to reclaim land for agriculture. This infrastructure, depicted in Figure A.3, is largely publicly funded and allows farmers to drain their fields during the wet season and provides irrigation from Lake Okeechobee during the dry season. Without this intricate canal system, agriculture in this region would not be possible (Daroub et al., 2009). The process of drainage and irrigation via canals means that water inflows and outflows from any unit passes through an identifiable point creating this unique situation whereby this runoff problem is actually a point-source pollution problem but is regulated as if it were non-point source.[11]

1.3 Data

Most of the data for farms within the EAA effected by the EFA are taken from the annual Everglades Consolidated Reports and South Florida's Environmental Reports.[12] These reports contain both annual TP load and estimated TP load reduction (relative to baseline), land size, baseline year, whether the farm elected to enroll in the Early Baseline Option, each farm's baseline (pre-BMP) TP loads, acres dedicated to vegetable production, and the EAA wide incentives earned by all farms for each year. The baseline year is the water-year for which the farm established its pre-BMP base period load. Basins (farms) can enroll in the Early Baseline Option which requires farms to fast track their compliance timetables and water quality monitoring efforts and divulge more information such as soil type and other farm specific characteristics. In return, farms who elect to participate in the Early Baseline Option have less regulatory oversight and face less liabilities in the event that non-compliance occurs.[13] Data on individually earned credits (earned based on individual performance) and dates of *potential* BMP changes were ob-

[11]Political and institutional context for how this peculiar pollution management system came to be can be found in Milon (2018).
[12]URL for the reports: https://www.sfwmd.gov/science-data/scientific-publications-sfer
[13]See F.A.C. 40E-63.145(4)(g)

tained through a public records request submitted to the SFWMD. The data starts from 1994 to 2018 and is measured on an annual basis[14]. There are about 221 farms throughout the sample period with only 127 of which are balanced throughout the time period. Other geospatial data such as permit application boundaries and canal networks used to calculate distances from monitoring points were taken from SFWMD's arcgis website.[15]

I also have data from water quality monitoring stations (WQMS) located across the state of Florida which is obtained through the DBHYDRO database which is also owned and maintained by the SFWMD agency. Such data will allow me to create watershed control groups so that I can compare water quality outcomes from the regulated EAA basin with other basins to estimate the overall effect of the EFA policy.

1.4 Did the Everglades Forever Act Work?

In many ways, the policy of the EFA has worked but in other ways it has not. For instance, the main goal of the EFA was to achieve a water quality standard for the water entering the Everglades such that the concentration of phosphorus does not exceed 10 ppb.[16] The strategy was to reduce the phosphorus load flowing out of the EAA by 25% and leave the remainder of the clean up effort to the storm water treatment areas situated south of the EAA. However, between 2007-2017, the outflow phosphorus concentrations averaged over 126 ppb (Milon, 2018) so in that sense, the policy has failed.

However, according to the SFWMD's own internal reports, the EFA has largely suc-

[14] Data for years 1994 through 2000 was also obtained via public records request.
[15] URL: https://sfwmd.maps.arcgis.com
[16] It was originally aimed to achieve a concentration no greater than 50 ppb but was later amended in 2003 to 10 ppb.

ceeded in reducing the phosphorus concentrations flowing out of the EAA with an average annual reduction of 55% far exceeding the 25% reduction goal (Davison et al., 2017). In that sense, the policy was quite successful. Furthermore, the EAA never fell below the 25% reduction target at all except for one year. Unfortunately, percent reduction is based on SFWMD's estimation of the pre-policy phosphorus loads and is subject to unknown but possibly significant error. Therefore, there is value in focusing on the overall trends in the levels themselves which show much more modest improvements (Davison et al., 2017). The downside is that the EAA does not exist in a vacuum and its outflow water quality is subject to, in some degree, the inflow water quality from Lake Okeechobee residing to its north (upstream).

In **??**, I use the synthetic control method to tackle this problem of ignoring upstream changes in water quality. The unit of analysis is the water quality monitoring station and is given treatment if the station is immediately downstream of the EAA and if the year is after the passage of the EFA. There are 2 treated units and about 21 potential donors. Donor stations are from areas either to the north, east, or west of the Lake Okeechobee. All other stations are ignored due to them being down stream of the EAA.

The results are shown in Figures A.1 and A.2 which indicate that the EFA policy had a statistically significant negative effect on overall phosphorus concentration compared to other regions but it's also possible that those donor units also received a separate type of treatment. Namely, projects meant to improve water quality. Even though the estimated effects here may seem quite small and the statistical significance is tenuous at best, this is due to the fact that the counterfactual here for the EAA is a world where the EFA was not passed but instead received similar project investments through the Comprehensive Everglades Restoration Plan. If one somehow found donors that truly were not affected by any water improvement projects at all, then the estimated treatment effect is likely higher. Now I turn to answering what role, if any, the incentive credits played in determining farm runoffs.

1.5 Standard Ambient Subsidy Model

Here, the model for the standard ambient subsidy mechanism is introduced with the goal of arriving at a calculation for the optimal subsidy rate. The standard model makes a few simplifying assumptions. First, I assume that regulated polluters cannot cooperate meaning that each agent simply takes the discharge levels of others as given and chooses their own optimal discharge. Second, agents have full control over their discharges and understand how it will impact ambient pollution[17].

Let s denote the ambient subsidy rate, Y denotes observed ambient pollution, and $\overline{Y}$ denotes the ambient pollution standard. Under the standard ambient subsidy mechanism S_i given in (1.1), if observed pollution Y exceeds the standard $\overline{Y}$, then the polluters would not be in compliance and thus receive nothing. If observed pollution is below the standard, then polluters are in compliance and each receives a subsidy equal to $s(\overline{Y} - Y)$. Profit from farming operations is assumed to be a standard concave function with a satiation point (θ_i) and is given by $\pi_i(y_i) = \pi(y_i, \theta_i)$ where y_i is chosen discharge and θ_i also represents i's business-as-usual (BAU) level of discharge and is used to reflect firm type. Observed ambient pollution is assumed be a linear sum of each farm's total discharge $Y = \sum_{i=1}^{n} y_i$.

[17]Uncertainty in the ambient pollution function will be introduced later.

$$S_i = \begin{cases} s(\overline{Y} - Y) & \text{if} \quad Y < \overline{Y} \\ 0 & \text{if} \quad Y \geq \overline{Y} \end{cases} \tag{1.1}$$

If $\overline{Y} = \widetilde{Y}$, where $\widetilde{Y} = \sum_i \widetilde{y}_i$, then there is a unique Nash on a non-compliant outcome. However, if $\overline{Y} > \widetilde{Y}$, then there can be two Nash equilibria, one where there is compliance ($Y < \overline{Y}$) and one where there is non-compliance ($Y > \overline{Y}$). Each polluter is willing to reduce their emissions by one unit from their business-as-usual level if they are paid s for that reduction. If a farm is pivotal in the determination of compliance, then the lowest level of discharge that is profitable is (henceforth referred to as the minimum profitable pollution level) denoted as $\widetilde{y}_i$ and is defined in (1.2). Said differently, if the only way for the pivotal farm to attain compliance is by reducing discharge below $\widetilde{y}_i$, then the farm would not do so and instead opt to pollute at the BAU level, θ_i (Bao, 2021).[18] However, whether a subsidy is paid out depends on others' actions. There can be two sets of policies, one that satisfies the incentive compatibility constraint for all agents thereby engendering a compliant Nash equilibrium ($Y^{NE} < \overline{Y}$) and a second, more generous one that completely eliminates the non-compliant Nash.

$$\pi'(\widetilde{Y}_i, \theta_i) = s \tag{1.2}$$

To achieve the first policy (henceforth referred to as the compliant Nash) it must be such that the incentive compatibility constraint, given by (1.3), holds for every agent. Note that the left hand side of (1.3) is the same for everyone so the policy need only hold for the agent $k: \; k = \arg\max_j \{\pi_j(\theta_j) - \pi_j(\widetilde{y}_j)\}$. The subsidy rate s is chosen so that the ambient pollution under a compliant Nash achieves the target, $\overline{Y}$, while the

[18]It should be noted that there are two possible Nash Equilibria in general. Either noncompliance occurs where everyone pollutes at their BAU levels or compliance occurs where everyone pollutes at their $\widetilde{y}_i$ levels so that Y is strictly less than $\overline{Y}$.

value $\overline{Y}$ must be chosen so that pivotal agents are incentivized to choose their minimum profitable pollution level (chosen so that (1.3) holds where Y^{NE} is the ambient pollution under compliant Nash).

$$s(\overline{Y} - Y^{NE}) \geq \pi_i(\theta_i) - \pi_i(\widetilde{y}_i) \tag{1.3}$$

Let the profit function be defined as in (1.4).[19] Then one only needs to evaluate the values for θ_i and γ_i (the business-as-usual discharge and the slope of the marginal abatement cost curve, respectively) in order to back out the value for s (the implied static marginal incentive from the incentive credit program) necessary for the compliant Nash to achieve $\overline{Y}$.

$$\pi_i(Y_{it}) = -\frac{\gamma_i}{2}(\theta_i - y_{it})^2 \tag{1.4}$$

Setting the right hand side of (1.2) equal to the subsidy rate s gives i's minimum profitable pollution (1.5), also known as their pollution demanded conditional on price s.

$$\widetilde{y}_i = \theta_i - \frac{s}{\gamma_i} \tag{1.5}$$

Then utilizing the pollution constraint (1.6) we get that the optimal subsidy rate, is given by (1.7)[20].

$$\overline{Y} = \sum_{i=1}^{n} \widetilde{y}_i \tag{1.6}$$

$$s^* = \frac{Y^{bau} - \overline{Y}}{\sum\limits_i \frac{1}{\gamma_i}} = \frac{Y^{bau}\left(1 - \frac{\overline{Y}}{Y^{bau}}\right)}{\sum\limits_i \frac{1}{\gamma_i}} \tag{1.7}$$

[19]Even if the marginal profit curves are not linear, one can use a linear approximation of the function and proceed.

[20]The pollution target in (1.6) is the "true" target.

where $Y^{bau} = \sum_{i=1}^{n} \theta_i$ Adding a command-control policy to the model is straightforward. Simply change θ_i to $\theta_i^{bmp} < \theta_i$ (which implies $Y^{bmp} < Y^{bau}$) and I assume γ_i remains unchanged ($\gamma_i = \gamma_i^{bmp}$) In words, I model command-control as a policy that mandates the adoption of best management practice (BMP) so that, in absence of a market incentive, there will strictly be lower levels of pollution by all individuals. However, I assume that the command-control policy does not change the slope of the pollution demand curve.

Strategic Interactions

An important feature of my empirical setting is now incorporated into the model here. Under the EFA, the mandatory BMPs imposed on polluters is done so in accordance with the goal of reducing phosphorus runoff by 25% relative to estimated baseline levels. In effect, the BMPs alone were intended to reach this pollution standard on its own and the incentive credit program was layered on top in an attempt to induce *additional* abatement. Importantly, the target for both command-control and market incentives were set equal to 75% of BAU levels (without BMPs), i.e., $\overline{Y} = 0.75Y^{bau} = Y^{bmp}$. Setting the pollution target in such a way dissolves the strategic interactions between polluters under an ambient subsidy. So long as polluters do not collectively exceed the ambient pollution level given by Y^{bmp} ($Y^{bmp} = \sum_{i=1}^{n} \theta_i^{bmp}$), then each farmer can be confident that their marginal abatement efforts will always result in a marginal reward because there is no threat of the ambient pollution exceeding the subsidy threshold. In other words, there is no risk of other farms discharging so much that the subsidy will not trigger regardless of own abatement efforts.

Unfortunately, it is not obvious how to translate the marginal incentives that farmers faced under the incentive credit program into an implied s for the static model. Nor is it obvious how one would back out the parameter γ_i under the current policy setting. This is because the incentive credit program under the EFA created a dynamic decision problem for farmers where abatement effort today leads to the accumulation of tax credits that can only be used to reduce *future* tax burdens.

The remainder of this paper will proceed as follows. First, I model the dynamic decision problem farmers faced under the EFA taking their BMP decisions as given. I show that the policy function that arises serves three main purposes in the analysis. First, it allows me to calculate an upper bound on the implied static subsidy rate s. Secondly, it informs my empirical strategy by identifying the relevant economic incentive to be used as my covariate of interest. Lastly, it allows me to interpret the estimates as the slope of the marginal profit curve, γ_i.

Polluter's Decision Problem Under Incentive Credit Program

In this section, I try to model the decision problem that agents *actually* faced under the EFA policy. The incentive credit program under the EFA engendered a dynamic decision problem for the farmers in that tax credits awarded for compliance can be stored for future use, e.g., used to reduce the lump sum tax in future periods. So instead of behavior being governed by (1.2), it is instead governed by (1.8).

$$\pi'(y^*_{it}, \theta_i) = G_{it} \tag{1.8}$$

The term G_{it} is simply the partial derivative of the continuation value with respect to the pollution choice variable (see equation A.11 for the technical expression). To put into words, the incentive credit program made farmers' abatement incentives tied to uncertain future outcomes that are also discounted. The term G_{it} represents the expected present value from reductions in future taxes via a marginal increase in abatement. Said differently, G_{it} represents the partial derivative of the continuation value with respect to pollution choices, y_{it}.

Equation (1.8) implies some value for the privately optimal discharge $y^*_{it}(G_{it}, \theta_i)$. If the ambient incentives induces changes in discharge levels then we would expect that y^*_{it} changes depending on the value of G_{it}. The main goal in the empirical section is to estimate the partial $\frac{\partial y^*_{it}}{\partial G_{it}}$. This estimand is equivalently given by (1.9) which shows how a simple comparative static on the policy function can retrieve the parameter γ_i.[21] This parameter can be construed as the slope of the marginal abatement cost curve, the same as in the standard ambient subsidy model (1.2).

$$\frac{\partial y^*_{it}}{\partial G_{it}} = \frac{1}{\frac{\partial g(y_{it}, \theta_i)}{\partial y_{it}}} = \frac{1}{\pi''\left(y^*_{it}, \theta_i\right)} = -\frac{1}{\gamma_i} \tag{1.9}$$

A Proxy for G_{it}

The problem with using G_{it} directly is that it represents the farmer's expectations about the future values of credits earned today. Additionally we have no way of knowing each farmer's discount factors. One way to proxy for G_{it} is to use something that is conceptually similar. Since the partial derivative of the continuation value hinges on the number of credits left to earn, then I can simply use that as my proxy. Specifically, I will use the proxy defined in (1.10), the number of credits still needed to be earned, as a proxy for G_{it}. The justification of D_{it} is detailed in **??** where I also show that $\left|\frac{\partial y^*_{it}}{\partial G_{it}}\right| > \left|\frac{\partial y^*_{it}}{\partial D_{it}}\right|$.

[21] Abusing terminology a bit here because equation (1.9) is not truly my estimand due to it being individual specific. This is more like the ideal estimand. The empirically feasible estimand, discussed later, is the average of (1.9) across farms.

Therefore, my estimates of slope γ_i using estimates of $\dfrac{\partial y^*_{it}}{\partial D_{it}}$ will be biased away from zero of the true slope term without any BMPs, γ. Consequently, the compliance cost estimates under an ambient subsidy will also be biased away from zero. The term M represents the maximum exercisable credits each period from 1998-2013 and $(T - t + 1)$ represents the number of remaining periods in which credits are relevant, including the present. The product of which represents the maximum level of credits necessary to achieve minimum tax burden for the duration of the policy.[22] The term S_{it} represents the starting balance of credits (a stock variable) for period t.

$$D_{it} = (T - t + 1)M - S_{it} \tag{1.10}$$

If $D_{it} \leq 0$ then S_{it} is *more* than enough to cover current and all future period's credit demands leaving $G_{it} = 0$ because earning more credits today will *not* increase the amount of exercised credits in the future. Alternative, if $D_{it} > 0$, then there are still incentives to reduce discharge because the current stock of credits is not enough to reach the maximum needed level. So as D_{it} increases, G_{it} increases (weakly) as well. Additionally, both terms decrease with the distance between current period t and the credit expiration date T. Said differently, as time nears the end of the incentive program, there is less incentive to abate pollution which is represented by smaller values of G_{it} and D_{it}.

1.6 Effect of the Incentive Credits

The goal of this section is to estimate the effect of incentive credits on farms' phosphorus levels while controlling for BMPs in a coarse manner. The incentive that a farm has to increase their abatement efforts above what is required by the mandatory BMPs

[22] This includes the present so think of it as a starting balance value.

is captured by the variable D_{it} mentioned before. This variable represents the amount of credits that farm i has left to earn at time t and is calculated by subtracting the current stock of credits from the maximum exercisable number of credits over the duration of the policy. I can re-code this variable to be a dummy that equals 1 when firms have already reached their max credits needed and 0 otherwise. This binarized treatment variable separates the sample into cohort groups where each farm within the same cohort stopped needing to earn additional credits at the same time.

Empirically, it is useful to distinguish two effects on discharges that are at play. First, is the effects from the mandatory BMPs (think switching from θ_i to θ_i^{bmp}) and the second is the value of earning tax credits (think $D_{it} \approx G_{it}$). Such credits can come from both group performance and the individual performance. The empirical strategy does not need to distinguish between these effects to estimate farms' pollution in response to credits generally, however. Fortunately, the ability to earn additional credits via individual performance provides the necessary variation in D_{it} needed to estimate our estimand. Otherwise, all farms in our sample would have identical D_{it} values because the credits would only be earned through group performance. Figure A.12 graphs a heatmap of the distribution of D_{it} across time and gives a glimpse at the identifying variation across both N and T.

For further context, see Figures A.13 through A.16 which plot the annual averages of the outcome variable and covariates broken out by cohort. For instance, the 1999 cohort are consists of all farms who, at the start of 1999, no longer needed to earn more credits ($D_{it} = 0$). The figures show that there were significant differences in baseline phosphorus loads across cohorts and that the cohort that earned the most credits had the highest initial levels of phosphorus loads per acre. As might be expected, this decreases with cohort years since farms with lower initial phosphorus loads have less room to reduce their loads and thus, not as able to aggressively abate to earn credits faster. Interestingly, the treatment cohorts differ greatly over all covariates but are relatively similar in terms of the outcome variable after water year 1995. The cohort that earned credits the fastest tends to be farms who had high initial discharges, started operations at the beginning of the policy (Figure A.17), had the most land dedicated to vegetable production, large in size, and located midstream.

The chosen BMPs by each basin (farms) were required to be in place by 1996 for all basins and farms who were in operation in 1994[23]. Thus, I restrict the estimation period to start on 1996 to avoid spurious correlation.[24] Furthermore, I allow for the adopted BMPs to change once every five year cycle. Farms are allowed to adjust their chosen BMPs but only during the permit renewal process which occurs every five years from when they were first issued their permit (different for each farm). I include a categorical variable that represents which cycle each farm is at for each water-year thus creating a unit-specific 5-year fixed effects for all units.

Empirical Methodology

To achieve a consistent estimate of our estimand, the average of (1.9), I rely on the Arellano-Bond two-step estimator also known as the two-step difference GMM estimator. In a perfect world, the estimating equation would be given by (1.11) where Y_{it} is the

[23]Basins are hydrologically connected farms that share the same discharge infrastructure. Essentially, the level of monitoring is at the basin level, not necessarily the farm level. For a breakdown of basins under different management types from single ownership to varying degrees of shared ownership, see (Yoder, 2019; Yoder, Chowdhury and Hauck, 2020)

[24]Some farms came into operation after 1994; the timeline of when BMPs were required to be fully implemented is not known in those cases. I chose to drop the first 2 years of available data for such farms.

phosphorus load attributed to farm i at water year t. The X_{it} term includes time fixed effects, BMP-cycle, land size, interaction between D_{it} and distance from monitoring points, and acres dedicated to vegetable production.[25]

$$Y_{it} = \alpha_i + \alpha_t + \beta_1 D_{it} + \beta_2 X_{it} + \varepsilon_{it} \tag{1.11}$$

The problem with estimating (1.11) is that D_{it} (the credits left to earn) is correlated with the error term leading to bias and inconsistent estimates of β. This correlation is due to the fact that D_{it} is a function of the balance (stock) of credits S_{it} via (1.10). The stock value S_{it} is a function of all past outcomes $(Y_{i1}, \ldots, Y_{i,t-1})$ and thus all past error terms which violates strict exogeneity. A known workaround is to take first differences of (1.11) so that consistency only requires sequential exogeneity (Hansen, 2021; Anderson and Hsiao, 1981). A variable satisfies sequential exogeneity if it is not correlated with current or future period error terms and only past ones, if at all; covariates that satisfy sequential exogeneity are said to be predetermined. Then lagged values of the predetermined variables are suitable IVs for the first differenced predetermined variable. I argue that they are suitable since the relevance condition is satisfied by (1.10) together with the law of motion for credit stock (A.9). The exclusion restriction assumption is satisfied via the sequential exogeneity as seen by first differencing equation (1.10). First differenced values are denoted with a $\triangle$ symbol where $\triangle r_t = r_t - r_{t-1}$. The first differenced version of (1.11) is given by (1.12).

$$\triangle Y_{it} = \beta_1 \triangle D_{it} + \triangle \alpha_t + \beta_2 \triangle X_{it} + \triangle \varepsilon_{it} \tag{1.12}$$

To see how the sequential exogeneity assumption might hold here, first remember that D_{it} is a function of all past Y_{it}'s. Then the challenge is to establish the fact that pre-

[25] Acres dedicated to vegetable production is given special treatment under the EFA.

vious discharges (Y_{it-k}) are uncorrelated with future error terms (ε_{it+k}). The first order condition (1.2) implies that, under a compliant Nash, current period optimal discharge is a function of today's expectations about future credit stock levels, i.e., the G_{it} term which is itself a function of past performance and thus past errors. So long as error terms are not autocorrelated, G_{it} are not be related to future error terms. The assumption of no autocorrelation is already a necessary assumption required for the consistency of the two step difference GMM estimator and so it does not add any additional assumptions. Furthermore, autocorrelation is something that can be readily tested and is done automatically in STATA. The results indicate that there is no autocorrelation in the level errors.

Empirical Results

The result from estimating (1.12) using lagged values of D_{it} as instruments for $\triangle D_{it}$ (limiting lag lengths to 10), is reported in column 1 of Table **??**. The estimation sample is restricted to years 1996 or later to avoid spurious correlation because most farms were transitioning towards full BMP implementation between 1994 and 1996 water years and water year 1996 was the deadline to complete BMP implementation. Some farms were provided exceptions and allowed to complete BMP implementation after 1996 but excluding those farms from the estimation sample only strengthened the results. Both point estimates and corresponding statistical significance results are robust to varying the exogeneity assumptions on the control variables basin acreage and vegetable acreage. Column 1 shows the results from treating such variables as strictly exogenous. Column 2 treats the control variables as predetermined whereas column 3 treats only the vegetable acres as the only other predetermined covariate and is our preferred specification. This reflects the fact that the entire incentive credit program applies only to acres *not* dedicated to vegetable production. Thus, farms could selectively change their acres dedicated to vegetables according to the incentives coming from the credit program. The Hansen test for over-identifying restrictions almost always leads to a fail-to-reject outcome with the corresponding null being that instruments are jointly valid.

At the start of the policy, most farms had a maximum of roughly 180 credits that they needed to earn to reach the minimum tax for every year up to and including 2013. Taking the estimates from column 3 Table **??** at face value would imply that the incentive credit program resulted in an average P load decrease of about 2.11 lbs/acre (.0117 × 180) in 1994 (CY). By water year 2002, on average, firms had roughly 4 credits left to earn meaning that the incentive credits induced 0.047 lbs/acre of phosphorus abatement on average. For context, the median and mean pre-intervention P loads were about 1.8 and 2.96 lbs/acre, respectively. Figure A.12 illustrates the distribution of D_{it} values across time and units. By water year 1999, most farms had less than 5 credits left that they need to earn which is a very insignificant motivation for abatement.

Table A.3 from shows the same estimation results but using estimated percent P load reduction as the outcome variable. Those results indicate that the incentive credit program did not account for any variability in P loads once precipitation was accounted for at the farm level.[26] Importantly, the magnitudes of those coefficients are implausibly large since the maximum credits needed to earn in 1996 was about 180 credits. The results then imply that farms reduced their P loads by more than 100%. However, the standard errors are quite large as well suggesting that using estimated percetn P load reduced as the dependent variable comes with much more noise thus limiting the usefulness of those results considerably.

[26]The percent P load reduction is estimated by SFWMD using precipitation at the farm level as the only covariate.

1.7 Cost Effectiveness

For this section I compare the compliance cost under the mandatory BMPs with that under an ambient subsidy to gauge relative efficiency. Using some back of the envelope calculations, I am able to estimate what the ambient subsidy rate has to be for the compliant Nash to achieve some pollution target. These calculations are based on the assumption that BMPs did not change the slope of marginal profit curves.

Ambient Subsidy Rate under Compliant Nash

The incentive credit program under the EFA is not the standard ambient subsidy mechanism and the task here is to answer the question, what would the standard ambient subsidy look like in our empirical setting? To answer this, I use estimates from the last column of Table **??** to produce the marginal abatement curve per acre (shown in Figure A.19) for the average farmer in the EAA.[27]. To get an estimate of the average discharge under the command-control only scenario (θ_i^{bmp}), I average the TP loads across farms under each period for which farms no longer needed to earn credits (see Figure A.12).

Using the functional form assumptions under the static model for the compliant Nash subsidy rate (not per acre) from Equation (1.7), I can map out what the subsidy rate should be for different targets expressed as a fraction of ambient pollution under command-control only. Without individual level estimates for γ, I approximate the pollution demand (and inverse demand) for the average farmer using estimates from earlier to get (1.13) where tildes represent per acre versions of their original counterparts. Furthermore, the average farm produced about 2.08 lbs/acre (2.23 metric tons or 4925 lbs)

[27]The estimated curve does not seem to be out of the question when one compares this to the profit estimates from Roka et al. (2010).

of phosphorus during the baseline year, the year before the EFA policy kicked in.

$$\begin{aligned} \widetilde{\pi}_i'(\widetilde{y}_i) &= \frac{1}{0.0117}(2.08 - \widetilde{y}_i) \\ \widetilde{y}_i &= 2.23 - 0.0117s \end{aligned} \tag{1.13}$$

Equation (1.14) gives the ambient subsidy rate for various targets for ambient pollution. To estimate $Y^{bau} = \sum_i \theta_i$, I take the baseline data (data pre-EFA intervention) on total lbs of phosphorus discharged and sum that value across farms to get 402.04 metric tons of phosphorus for the average year under business-as-usual.[28]

$$s^* = \frac{402.04\left(1 - \dfrac{\overline{Y}^T}{402.04}\right)}{2.1177} \tag{1.14}$$

Figure A.20 plots Equation (1.14), the estimated subsidy rate necessary for the compliant Nash to achieve various pollution targets (expressed as a fraction of emissions level with only command-control.). In reality, the target loads set forth by the EFA between 2013 to 2017 varied quite a bit ranging from 139 to 213.8 metric tons, as a consequence, the ambient pollution under command-control only would vary too.

The horizontal axis in Figure A.20 is the ambient pollution target expressed as a fraction of the total pollution under command-control (Y^{bmp}). Thus the prediction is that if the regulator wanted to decrease ambient pollution by 25% relative to Y^{bmp}, then the ambient subsidy rate needs to be roughly \$47.46. In other words, without the EFA in place, the regulator could have achieved, at a minimum, a 25% reduction relative to Y^{bau} with an ambient subsidy rate of \$47.46.

[28]Metric tons is unit used in determining compliance by the SFWMD regulator.

The benchmark pollution level for cost comparison is arrived at by estimating the percent abatement under only the command-control component of the EFA. The EAA wide basin averaged an annual reduction of about 55% (Davison et al., 2017). However, this average is the result of both the command-control and the market incentive components. In order to estimate what the average TP reduction would have been under a mandatory BMP only scenario, I use the estimated model from the column 3 of Table **??** to estimate the counterfactual EAA basin-wide TP loads setting $D_{it} = 0$ for all (i, t). The result of this is graphed in Figure A.21. On average, the estimated counterfactual basin-wide TP loads were 47.34% higher when compared to the estimated basin-wide TP loads using the true EFA data. Said differently, I estimate that without the market incentive component of the EFA, the average annual emissions would be 47.34% higher implying that average TP load reductions under a command-control-only regime would have been about 37% rather than 55%. Therefore if the regulator instead opted for a standard ambient subsidy such that the compliant Nash achieves the same abatement level of 37%, a subsidy rate of $70.24 is needed. Taking the relevant area under the marginal abatement cost curve results in an area of about $27.08/acre which represents the estimated compliance cost per acre under the standard ambient subsidy policy for the average farm. Scaling this figure up using the median land size of 1021.5 acres means that the compliance cost for the average farm is almost $27,700/year or roughly 4% of farming costs estimated in Roka et al. (2010).

Cost of Mandatory BMPs

The set of BMPs for which farmers got to choose from were designed by the University of Florida's Institute of Food and Agricultural Sciences who worked with farmers to develop cost-effective management practices meant to reduce phosphorous loads. Coupled with the fact that farmers could choose which of the designed BMPs to actually implement opens up the potential for the mandatory BMPs to achieve pollution goals at very low costs. The cost of implementing the command-control component of the EFA, i.e., the mandatory BMPs, is taken from engineering estimates and validated through data from USDA.

About 80% percent of the EAA, which is the geographical region under regulation, is dedicated to sugarcane production (Daroub et al., 2011). The total operating cost is roughly \$638.88/acre (Roka et al., 2010) the data for which came from calendar years 2008-09 but those estimates do not disentangle the costs from BMPs. Therefore, this number can be interpreted as a farm operating costs for sugarcane under only the mandatory BMPs because farms did not face any need to earn additional credits by 2003. Short of interviewing the farms perfectly to get the truth of behaviors, there is no way of knowing how much the mandatory BMPs actually costed the polluters, separate from the effects from the incentive credit program. The engineering estimate of mandatory BMPs were made ex-ante, i.e., before the passage of the EFA. The BMP cost estimates imply that for the evaluated set of BMPs, the cost would have been \$34.15 per acre in 2009 terms (Johns, 1993) and comes out to about 5% of the total per acre cost.

I validate the ex-ante engineering estimates by using the two-way fixed effects (1.11) model with data from the USDA Quick Stats portal that has annual state level data on total agricultural expenses and total acres operated from 1970-2018. The two-way fixed effects model has two dummies of interest. The first represents the effect from the passage of the EFA (= 1 if Florida and year $\geq$ 1994) and the second represents the effect after the latest break point in our data (= 1 if Florida and year $\geq$ 2003) as an attempt to disentangle the command-control and market incentive programs under the EFA. I find that the EFA increased state agricultural expenditure per acre by about 12% compared to pre-EFA periods whereas the break point dummy saw an increase of only 5% (but not statistically significant). This suggests that the mandatory BMPs *alone* had an increase in cost of about 5% which happens to be identical to the engineering estimates if the cost figure from Roka et al. (2010) is used as the base.

1.8 Results and Conclusion

Two main findings in this paper standout. First, farms did on average respond to the market incentive component of the EFA even after implementing mandated practices under the command-control component. Further, the market incentive was responsible for almost a quarter of the water quality improvements seen since the passage of the EFA in this region. Second, I find that to achieve a benchmark abatement of 37%, the cost of the command-control is about \$34.15/acre compared to the market incentive of \$27.08/acre meaning that the compliant Nash ambient subsidy produces an average compliance cost savings of 20%.[29]

Further, the compliant Nash can be guaranteed if the “target” $\overline{Y}$ is set equal to the business-as-usual (BAU) level Y^{bau} but this is not the true target in the sense that the regulator does not aim to achieve Y^{bau}. The calculation for optimal subsidy rate will still use the true target but the subsidy base $(\overline{Y} - Y)$ will use a “target” equal to the BAU level. Under that simulated ambient subsidy scenario, the regulator would be paying a total subsidy amount of about \$10 million/year in order for the compliant Nash to achieve annual abatement of 37%. This subsidy amount is equal to about 0.3% of 2019

[29]Although this isn’t a comparison with the least cost ideal, i.e., as in a point source regulation, it is a comparison with an analogous second best situation.

sugarcane revenue in the EAA.[30] This is very important result in that even if the regulator pays everyone for each unit of abatement from the BAU level, that cost is seemingly quite small.

The comparison of the BMP cost with the ambient subsidy is not standard in that the ambient subsidy mechanism does not represent the least cost solution. In other words, firms do not make discharge decisions in a socially optimal way. As many have pointed out, ambient mechanisms have the tendency to achieve the pollution target but in a way where some are abating more than socially optimal and others abating less so (Kotchen and Segerson, 2020). Yoder, Chowdhury and Hauck (2020) found that EAA farms had very heterogeneous trends in P loads throughout the policy duration; some had statistically significant negative trends while a lesser number exhibited positive trends. This finding is consistent with the idea that there exists some free-riders.[31]

Furthermore, the comparison relies on the assumption that the estimated slope of the demand curve accurately reflects the true slope with no policy intervention. There may be a number of reasons to doubt this due to the interaction with BMP adoption, the use of a proxy (see equation **??**), and the existence of cooperative behavior. If we relax this assumption, then the compliance cost under only the standard ambient subsidy policy can look quite different. As a result, I provide a table that shows various possibilities for the slope to be different and create a range of numbers shown in Table A.4. Each row of Table A.4 refers to a different value for λ which controls the ratio between slopes under mandatory BMPs and that under the business-as-usual as shown in equation (1.15).

[30]Florida Department of Agriculture and Consumer Services https://www.fdacs.gov/Agriculture-Industry/Florida-Agriculture-Overview-and-Statistics.

[31]Figure 6, Yoder, Chowdhury and Hauck (2020).

$$\gamma^{estimated} = \lambda\gamma^{bau} \tag{1.15}$$

Finally, the author would like to caution those who view this work as evidence that ambient mechanisms can reduce NPSP in the agricultural runoff context for two reasons. First, this paper does not test the assumptions under standard AMM theory but rather assumes they hold and compute the outcomes. Secondly, external validity is limited by the possibility of cooperation/coalition formation and how that may change the way the above findings are interpreted. The level of cooperation/communication among farmers matters because lab evidence corroborates the theory that cooperative behavior often leads to excessive abatement (reduces occurrence of non-compliant Nash) under an ambient subsidy (Suter, Vossler and Poe, 2009; Poe et al., 2004). In all likelihood, the estimated γ comes from at least a partially cooperative setting in which some agents maximize individual payoffs while others form a coalition and maximize sum of members' payoffs. This is because the EFA was the product of a negotiated settlement with great stakeholder involvement (Yoder, 2019). Yoder (2019) interviewed many farmers in the EAA who cited the minimization of regulatory intrusion and the avoidance of in-fighting as reasons for the group liability design. Furthermore, roughly 70% of the EAA land is operated by two companies split nearly evenly.[32] Taken together these facts suggest that average behavior, as indicated by our estimate for γ, is a result of a partially-cooperative setting and likely leaning more towards the full-cooperation side of the spectrum. Therefore, care must be taken to extrapolate this conclusion to settings in which the potential to cooperate/communicate is vastly different than that of the EAA.

[32]Table 1, Yoder (2019).

Chapter 2

Regulating Non-point Pollution with Ambient Tax: Are more monitors better

2.1 Introduction

Much of the environmental economics literature focuses on policies that are based on observable individual emissions such as Pigouvian taxes, tradable permits, and even Coasian bargaining mechanisms. However, there is an entire class of pollution problems that render individual emissions monitoring infeasible or prohibitively costly due to the sources of pollution being diffuse and/or the emissions transfer function being stochastic. Such occurrences are referred to as non-point source (NPS) pollution.

In the U.S., NPS pollution problems represent the last major hurdle to achieving water quality goals with agricultural runoff as the main source of such pollution (U.S. Environmental Protection Agency, 2016). Due to the unobservable nature of NPS pollution, traditional emissions-based policies cannot be applied. Fortunately, there are many alternatives in the policy toolbox from which to choose. The focus of this paper is on ambient taxes.

Basing policies on observable ambient quality can overcome many of the issues seen in other alternatives. First, it gives incentives to abate and it is flexible in regards to the method of abatement, unlike input taxes. Second, ambient-based policies are tied to observable pollution rather than estimates of it, like the emission proxies, making it more parsimonious and accurate. However, ambient-based policies have their own set of problems as well. One important issue is the potential for free-riding to occur since ambient-based policies are group-based incentives. The research goals in this paper are to (1) examine under what conditions free-riding can occur under both NE and SPNE when an ambient tax is imposed, and (2) does adding more monitoring points reduce the potential for free-riding?

Segerson (1988) and Meran and Schwalbe (1987) were the first to suggest ambient-based policies to correct for NPS pollution and showed how an ambient tax/subsidy can induce polluters to collectively choose the socially optimal level of ambient concentration as a Nash Equilibrium. However, their proposed solutions involve charging firm specific tax rates which require knowledge of firms' abatement cost functions thus placing an informationally expensive burden on the regulator. If knowledge about the distribution of types is available, it is possible to achieve first best abatement allocations with a uniform tax rate even with heterogeneous firms (Segerson and Wu, 2006). Without such information readily available, the regulator has two options. First, a damage-based tax can be implemented according to Hansen (1998) which only requires knowledge about the damage function at the socially optimal ambient level; however, even this can be argued as too informationally demanding. Alternatively, Segerson and Wu (2006) develop a regulatory threat mechanism whereby the regulator threatens the NPS polluters with an ambient tax if the polluters do not achieve the standard voluntarily. The ambient tax, if implemented, requires the regulator to invest resources to learn about the firm types in order to optimally set the tax rate. Unfortunately, this mechanism requires that the regulator's threat be credible so it is not a perfect workaround.

Any informational requirement about the damage function or distribution of firm types is, in practice, still a significant hindrance for the regulator even in a point-source pollution setting. This fact has motivated the environmental economics literature to shift its focus towards the second best policy solution which aims to achieve a set pollution target at least cost. The second best arises because of uncertainty about the optimal pollution target.

With NPS pollution however, an ambient tax is not guaranteed to achieve this second best target without the information requirements mentioned earlier. As noted in (Kotchen and Segerson, 2020), it is possible that an ambient tax can achieve its pollution target but with some degree of free-riding (i.e., some polluters discharge more than socially optimal). Thus, in the presence of free-riding, ambient taxes produce an outcome closer to a third best situation where the second best target is achieved but at greater than least cost. In this paper, I characterize the conditions under which free-riding can occur while achieving the pollution target and examine how expanding the monitoring network affects the degree of free-riding.

I find that when the uniform tax rate is set too high relative to the pollution target (i.e., ambient standard), then the possibility of achieving compliance at greater than least cost arises. This occurs because the collective tax gives rise to a minimum profitable pollution level ($\widetilde{X}_i$) for each polluter. This level of discharge is possibly heterogeneous and marks the lowest level of discharge that a firm is willing to commit towards avoiding the known tax penalty that would result from non-compliance. Intuitively, if a firm is pivotal in the determination of compliance, then they would not be willing to pollute below $\widetilde{X}_i$ to avoid the group tax penalty and would instead prefer to pollute at $\widetilde{X}_i$ and pay the tax rather than go below $\widetilde{X}_i$ to avoid the tax. Therefore, $\widetilde{X}_i$ is a decreasing function of the ambient tax rate.

This implies that there is a unique value for t such that the minimum profitable pollution level equals the least cost level for each polluter. Above this unique point for t, the minimum profitable pollution $\widetilde{X}_i$ is less than the least cost level X_i^*. When that happens, a multiplicity of Nash Equilibria (NEs) arises[1]. These NEs all achieve compliance (henceforth referred to as compliance NEs) but creates a situation where some polluters are polluting less than the least cost amount so that others can pollute more than the least cost level. Those who pollute above their least cost level are henceforth referred to as free-riders. This is the fundamental moral hazard problem prevalent in team games that lead to free-riding (Holmstrom, 1982).

The other main contribution of this paper is to examine the impact from adding more monitoring points on the degree of free-riding. The classic model from Segerson (1988) assumes that individual discharge monitoring is prohibitively costly but that group level monitoring is feasible. For example, having one monitoring point downstream of all known polluters. When one such monitoring point is feasible then it is natural to ask

[1]Least cost pollution level is the pollution level that a planner would choose (for the individual polluter) that results from a second best optimization problem.

how many more monitors are feasible? The concept of feasibility here is determined by an implicit cost-benefit analysis. If the regulated body of water were a lake, such additional monitoring points would do little to change outcomes and thereby providing no real benefits. However, under a river network, adding more monitoring points could effectively partition the initial group of polluters into smaller groups, thereby creating less free-riding potential and possibly translating to real welfare benefits. Allowing the number of monitors to be greater than one is the more general model with the classic Segerson (1988) model as one special case in which the network has only one monitoring point at the river's bottom. The other special case is when the number of monitors m equals the number of polluters n in which case the NPS pollution effectively becomes point source.

Such an analysis requires the examination of a particular outcome that can be examined as m increases. However, the presence of free-riding incentives only exists when there are a multiplicity of NEs. Thus, the Subgame Perfect Nash Equilibrium (SPNE) is used as an alternative concept where the player furthest upstream is the first mover and the player furthest downstream is the last mover. Using the SPNE has many advantages to the research goal. First, the SPNE is a refinement of the NE so it is itself an NE and remains unique regardless of the ambient tax rate. Secondly, the SPNE produces the highest cost compliance scenario when firms are homogeneous. Thus, even if there is no way to know which NE will occur, it is at least possible to examine how the highest cost NE would change with m. In this way, the SPNE outcome can be viewed as a measure of the maximum potential for free-riding.

Lastly, many water quality goals encompass rivers/streams which have a flow direction dictated by gravity allowing the possibility of differential "power" among polluters based on their river location. This idea has been studied in the literature on irrigation access as a public good (Bell et al., 2015; D'exelle and Lecoutere, 2012) and has recently been studied in a NPS pollution context (Zia et al., 2020; Miao et al., 2016). Both papers use experimental methods to find that as monitoring locations expand and frequency of measurement increases, upstream players' behavior is more affected relative to downstream players. However, in those models, the differential strategies between players located more upstream and those more downstream arises because of the differences in nutrient transport, specifically the process of nitrification. In this paper, such differences are ignored because the focus of this paper is on free-riding incentives which exist even without heterogeneity.

There are many other issues with ambient policies which are not addressed in this paper. For instance, efficacy of ambient policies requires firms to understand that their actions have effects on measurable ambient quality. This is typically only an issue when the number of polluters is large and thus ambient policies have much greater appeal in settings with few polluters. However, settings with few polluters could exacerbate the collusion issue that can arise under ambient policies (Cabe and Herriges, 1992). Collusion occurs when polluters have the ability to communicate with each other and find it collectively more profitable to over abate at the aggregate level. This paper abstracts away from the collusion issue by focusing on a pure ambient tax which gives no subsidies for over abatement. Combining this with the assumption of no stochasticity in the ambient quality buys us a model where there is no incentive to collude and over abate. This result is confirmed in the experimental literature on ambient policies for NPS pollution (Cochard, Willinger and Xepapadeas, 2005).

I begin with setting up the model for the social planner that tries to achieve an ambient goal at least cost. From this, a least cost policy is derived and used to benchmark against the other pollution outcomes discussed later. I then derive best response functions of firms in both the simultaneous and sequential game settings treating the policy as given and fixed. Then equilibria is discussed in both game types (simultaneous and sequential) and policy types (perfect tax and strict tax) along with the resulting welfare implications. Afterwards, I describe and model the potential for free-riding and examine whether location additional monitors matter and how increasing the number of monitors might impact the potential for free-riding.

2.2 Model Setup

Consider n known polluters (firms) whose discharge all go to the same monitoring point. Firms differ in location and are all situated along a simple linear river network and are allowed to be heterogeneous. I allow firms to freely choose their discharge level (X_i) and I abstract away from both output decisions and the consumer market. For now, I assume the regulator can only feasibly monitor ambient concentrations directly downstream of the last polluter, firm n. Later, I will allow the number of monitors to increase above one. Figure B.4 depicts a two player example of the game tree when the game is assumed to be sequential.

The regulator observes ambient quality X, takes the ambient standard $\overline{X}$ as given and chooses a value for the uniform tax rate t that will induce a compliance outcome. Each firm faces an ambient tax given by (2.1)

$$T_i(X) = \begin{cases} 0 & \text{if } X \leq \overline{X} \\ t(X - \overline{X}) & \text{if } X > \overline{X} \end{cases} \tag{2.1}$$

and firm level payoffs are given by (2.2)

$$\Pi(X_i, X, \theta_i) = \begin{cases} \pi(X_i, \theta_i) & \text{if } X \leq \overline{X} \\ \pi(X_i, \theta_i) - t(X - \overline{X}) & \text{if } X > \overline{X} \end{cases} \tag{2.2}$$

where $\pi()$ is the farm profit for a chosen individual pollution level without tax burden considerations. The model setup will be general enough to allow for heterogeneity but I will invoke the homogeneity assumption to derive many of the results in this paper. Firm types are given by θ_i, the slope of the marginal profit of pollution curve (isomorphic to marginal abatement cost curve) and $\pi_i(X_i)$ is short hand for $\pi(X_i, \theta_i)$. A higher value for θ is assumed to have a positive effect on the marginal profit of pollution ($\frac{\partial^2 \pi_i}{\partial X_i \partial \theta_i} \geq 0$) and thus leading to a (weakly) higher level for X_i^{bau}, the business as usual level of discharge for each firm. The ambient pollution is assumed to be the sum of discharges across all polluters $X = \sum_{j=1}^{n} X_j$. Lastly, $\pi_i(\cdot)$ is assumed to be an upside down parabola where $\pi_i'(X_i^{bau}) = 0$ and $\pi(0) = 0$.

The Social Planner

The goal of this section is to pin down the optimal uniform tax rate. The planner wants to choose pollution allocations $(X_1, \ldots, X_n)$ so that ambient quality reaches the standard $(X \leq \overline{X})$ at least cost. The cost structure is subsumed in the farm profit function so that the planner's problem is framed as in (2.3).

$$\max_{\{X_i\}_{i=1}^{n}} \sum_{i=1}^{n} \pi(X_i, \theta_i) \qquad \text{s.t.} \qquad X \leq \overline{X} \tag{2.3}$$

From equation (2.3), the least cost pollution level for individual i, denoted as X_i^*, is pinned down by (2.4).

$$\pi'(X_i^*, \theta_i) - \lambda^*(\theta_1, \ldots, \theta_n, \overline{X}) \leq 0 \qquad \text{for } i = 1, \ldots, n \tag{2.4}$$

Thus the socially optimal pollution allocation is such that everyone pollutes up to the point where their marginal profit from pollution equals the shadow price of pollution given by the lagrange multiplier, $\lambda^*(\boldsymbol{\theta}, \overline{X})$. The least cost pollution allocation is then given by $(X_1^*, \ldots, X_n^*)$ and this achieves compliance exactly ($\sum X_i^* = \overline{X}$).

Firm Problem

Polluting firms face the following optimization problem

$$\max_{X_i} \Pi(X_i, X_{-i}, \theta_i) \tag{2.5}$$

where the objective function in (2.5) is given by (2.2). And since the tax schedule from (2.1) is piecewise, solving (2.5) requires analyzing the optimum on both sides of the kink (see Appendix for full solution).

Proposition 2.2.1 *For each player i, there exists a minimum profitable pollution level (denoted as $\widetilde{X}_i$) such that player i would never find it profitable to pollute below $\widetilde{X}_i$ to avoid the tax penalty given by $t(X_{-i}+\widetilde{X}_i-\overline{X})$ where X_{-i} denotes the pollution attributable to all but firm i. The minimum profitable pollution level is indirectly given by*

$$\pi'(\widetilde{X}_i, \theta_i) = t$$

Therefore we have $\widetilde{X}_i = \widetilde{X}_i(t)$ and $\widetilde{X}_i'(t) \leq 0$.

Proof: We can rewrite 2.5 as

$$\max_{X_i^c, X_i^d} \left\{ \Pi_i^c, \Pi_i^d \right\} \tag{2.6}$$

where

$$X_i^c = \arg\max_{X_i} \ \pi_i(X_i) \qquad \text{s.t} \qquad X \leq \overline{X} \tag{14.1}$$

$$\Pi_i^c = \pi_i(X_i^c) \tag{14.2}$$

$$X_i^d = \arg\max_{X_i} \ \pi_i(X_i) - t(X - \overline{X}) \qquad \text{s.t} \qquad X > \overline{X} \tag{14.3}$$

$$\Pi_i^d = \pi_i(X_i^d) - t(X_i^d + X_{-i} - \overline{X}) \tag{14.4}$$

$$\widetilde{X}_i : \pi_i'(\widetilde{X}_i) = t \tag{14.5}$$

Here, X_{-i} denotes the pollution level of all other players but i. The strategy of player i can be broken down into two types, a comply strategy and a don't comply strategy. The comply strategy and associated payoffs are represented with a superscript c as in (14.1)-(14.2). The don't comply strategy and corresponding payoff is represented with a d as in (14.3)-(14.4).

Recognize that if $\widetilde{X}_i + X_{-i} \leq \overline{X}$ then $X_i^c \geq \widetilde{X}_i$ by definition. We want to show that $\Pi_i^c \geq \Pi_i^d$ if and only if $\widetilde{X}_i + X_{-i} \leq \overline{X}$. I prove this below.

Suppose that $\Pi_i^c \geq \Pi_i^d$.

$$\begin{aligned}
&\Longleftrightarrow \pi(X_i^c) \geq \pi(X_i^d) - t(X - \overline{X}) \\
&\Longleftrightarrow t(X - \overline{X}) \geq \pi(X_i^d) - \pi(X_i^c) \\
&\Longleftrightarrow t(X_i^d - X_i^c) \geq \pi(X_i^d) - \pi(X_i^c) \qquad \text{(add/subtract by } t(X_i^c) \text{ to LHS)} \\
&\Longleftrightarrow t \geq \frac{\pi(X_i^d) - \pi(X_i^c)}{X_i^d - X_i^c}
\end{aligned}$$

Note that there are only two possibilities, either the "don't comply" (DC) constraint binds $(\widetilde{X}_i + X_{-i} \leq \overline{X})$ or it doesn't $(\widetilde{X}_i + X_{-i} > \overline{X})$. When the DC constraint binds, then we have $\widetilde{X}_i \leq X_i^c < X_i^d$. When it fails to bind, we have $X_i^c < X_i^d = \widetilde{X}_i$.

Since we know that $t = \pi'(\widetilde{X}_i)$, then if $t \geq \dfrac{\pi(X_i^d) - \pi(X_i^c)}{X_i^d - X_i^c}$ holds, it must be the case that the DC constraint binds since both X_i^c and X_i^d are to the right of $\widetilde{X}_i$. When the DC constraint fails to bind, (i.e., $X_i^d = \widetilde{X}_i$ and $X_i^c < \widetilde{X}_i$), then the slope condition will fail to hold also. Thus

$$\Pi_i^c \geq \Pi_i^d \Longleftrightarrow \widetilde{X}_i + X_{-i} \leq \overline{X} \qquad \text{(DC constraint binds)}$$

Therefore, when X_{-i} is small enough so that firm i can pollute at a minimum of $\widetilde{X}_i$ and still achieve $\overline{X}$ then it will do so. However, when X_{-i} is sufficiently large so that when firm i chooses $\widetilde{X}_i$ it would not be compliant, then firm i will still choose to pollute $\widetilde{X}_i$.

■

Nash Equilibrium

Here, I present the setup for the simultaneous game by deriving best response functions and the Nash Equilibrium. From Proposition 2.2.1, we know that no player would choose pollution below $\widetilde{X}_i$ no matter what. Furthermore, all players would like to choose X_i^{bau} if they could do so without incurring a penalty. Thus for all players, their best response function given the pollution level of others (denoted as X_{-i}) is given by (2.7).

$$X_i^{BR} = \begin{cases} X_i^{bau} & \text{if} \quad X_{-i} \leq \overline{X} - X_i^{bau} \\ \overline{X} - X_{-i} & \text{if} \quad \overline{X} - X_i^{bau} \leq X_{-i} \leq \overline{X} - \widetilde{X}_i \\ \widetilde{X}_i & \text{if} \quad X_{-i} \geq \overline{X} - \widetilde{X}_i \end{cases} \tag{2.7}$$

Equation (2.7) is depicted graphically in Figure B.1. If player i knows that they can pollute business as usual without incurring the tax penalty then they will surely do so. However, if they cannot do so without being penalized, then they will cut back on pollution levels to avoid the penalty but only up to a certain point. All firms would rather contribute towards noncompliance rather than pollute below their minimum profitable pollution levels, $\widetilde{X}_i$. This result relies on the fact that polluters know exactly what their tax burden would be in the case of noncompliance and if uncertainty is allowed, firms will then need to know some moments of the distribution for the penalty.

From proposition 2.2.1 and equation (2.4), we see that if the regulator sets the uniform tax rate so that it equals the lagrange multiplier λ^*, then all firms would have their minimum profitable pollution levels be equal to their least cost pollution levels and thus would result in a unique Nash Equilibrium where ambient quality target is met exactly and at least cost (Segerson and Wu, 2006).

However, assuming that the regulator knows the full distribution of $\boldsymbol{\theta}$ is not likely to hold in reality. Though it could be the case that the regulator can incur a cost to learn $\boldsymbol{\theta}$, this cost could easily be prohibitively high. When $\boldsymbol{\theta}$ is unknown, it invites the possibility of having a value $t \neq \lambda^*$ while still maintaining compliance; this occurs if $t > \lambda^*$.

The Effects of t on Nash Equilibria

Here we look at the implications of various levels of t that would induce a compliance NE. From equation (2.4) and proposition 2.2.1, we know that when $t < \lambda^*$, then $\widetilde{X}_i > X_i^*$ for all i since we assume $\pi''() \leq 0$. This inevitably leads to noncompliance because no one is willing to pollute below their minimum profitable pollution levels which happens to be higher than the least cost pollution level for each i.

When $t = \lambda^*$, each player has their minimum profitable pollution level exactly equal to their least cost pollution level. When this happens, the only unique Nash Equilibrium pollution allocation occurs at the point where each firm pollutes exactly $\widetilde{X}_i$ as depicted in Figure B.2. I refer to this value as the "perfectly" set tax rate. This choice of nomenclature captures the idea that when t is set equal to λ^*, players' best response functions intersect at exactly one point in the n-dimensional space. At that point, compliance is met perfectly and at least cost to polluters.

The novel result of this paper focuses attention on the case when t is set "too strictly" so that $t > \lambda^*$. This is shown in Figure B.3 and when this occurs, all players' minimum profitable pollution level now lies below their least cost levels ($\widetilde{X}_i < X_i^*$). In such a setting, all firms are willing to pollute less than X_i^* but no less than $\widetilde{X}_i$ to avoid a tax penalty. Therefore, some firms can get away with polluting above X_i^* and free-ride off of those who are polluting less than what is optimal. This result is a consequence of having a multiplicity of NEs where any allocation outside of $\boldsymbol{X}^* = (X_1^*, \ldots, X_n^*)$ is an inefficient allocation even though all NE's achieve compliance. This is summarized in theorem 2.2.2 and the intuition for the result is very simple.

When $t > \lambda^*$, it creates a gap between $\widetilde{X}_i$ and X_i^*. This creates a potential surplus of implied pollution quotas available for some to pollute beyond X_i^*. The total potential surplus available to a firm i is given by (2.8). When homogeneity is assumed, equation (2.8) becomes $\overline{X} - n\widetilde{X}$.

$$\sum_{\substack{j=1 \\ j \neq i}}^{n} \left(X_j^* - \widetilde{X}_j \right) \tag{2.8}$$

Theorem 2.2.2 *Let λ^* be the shadow price of pollution which is defined as in (4). When $t < \lambda^*$, then the NE is non-compliance such that*

$$X = \sum_{i=1}^{n} \widetilde{X}_i(t) > \overline{X}$$

But when $t = \lambda^*$, compliance is reached exactly (i.e., $\sum_{i=1}^{n} \widetilde{X}_i(t) = \overline{X}$). Lastly, when $t > \lambda^*$ we have

$$\sum_{i=1}^{n} \widetilde{X}_i(t) < \overline{X}$$

and the allocation $(\widetilde{X}_1, \ldots, \widetilde{X}_n)$ is no longer an NE. Instead, the NE is characterized by

$$(X_1^{ne}, \ldots, X_n^{ne}) : \quad \sum_{i=1}^{n} X_i^{ne} = \overline{X}$$

with $X_i^{ne} \in \left[\widetilde{X}_i, X_i^{bau} \right]$ for all i. Therefore, the ability to free ride exists to the extent that $t > \lambda^*$.

Proof: By definition we have

1. $\sum_{i=1}^{n} \widetilde{X}_i(\lambda^*) = \overline{X}$

   or equivalently we can state $\widetilde{X}_i(\lambda^*) = X_i^*$

2. $\widetilde{X}_i(t) = \left(\frac{\partial \pi_i(X_i)}{\partial X_i}\right)^{-1}(t)$

3. $\pi_i'(X_i)$ is convex and weakly decreasing over $\left[0, X_i^{bau}\right]$

By point two and three above, $\widetilde{X}_i(t)$ is also convex and decreasing in t. Therefore, when $t < \lambda^*$ the first point above implies that $\sum_{i=1}^{n} \widetilde{X}_i > \overline{X}$. It also proves the case for $t = \lambda^*$. And when $t > \lambda^*$ we have that $\widetilde{X}_i < X_i^*$. ■

Without introducing any equilibrium selection concepts, there is no way to know which NE will be selected when $t > \lambda^*$. Worse yet, in the two player example with homogeneous types, the allocations $(X_1, X_2) = (\widetilde{X}_1, \overline{X} - \widetilde{X}_1)$ and $(X_1, X_2) = (\overline{X} - \widetilde{X}_2, \widetilde{X}_2)$ produces a compliance outcome at the highest cost. It turns out that under homogeneity and sequential play, then the Sub-game Perfect Nash Equilibrium will produce this "worst case scenario".

SPNE as "Worst Case"

It is helpful for expositional purposes to use the SPNE concept to characterize the "worst case scenario", that is, when compliance is reached at highest cost. Even though it may not be innocuous to assume that downstream players can perfectly observe the quality of water that reaches their own stretch, such an assumption allows us to examine the SPNE for other purposes. The extensive form game tree is depicted in Figure B.4 assuming only two players. Player 1 is the first mover while player n is the last. Following standard procedure, we utilize backward induction and first pin down the last player's strategy.

The n^{th} player's strategy is exactly described by equation (2.7) since they are the last mover in this game. Player $n-1$'s problem will slightly diverge from equation (2.7). Player $n-1$ still has the same value for their minimum profitable pollution level as in the simultaneous game. The difference here is that their compliance goal is not to stay under $\overline{X}$ since they are not the last person in the river. If player $n-1$'s goal is to reach compliance, then they must keep the ambient pollution discharged by everyone upstream of n (denoted as $X_{\uparrow(n)}$) to be weakly less than $\overline{X} - \widetilde{X}_n$ because if player $n-1$ pollutes too much so that $X_{\uparrow(n)}$ is too high, then player n will still choose $\widetilde{X}_n$ and thus push the group to be out of compliance. The best response function for player $n-1$ is then given by (2.9).

$$X_{n-1}^{BR} = \begin{cases} X_{n-1}^{bau} & \text{if} \quad X_{\uparrow(n-1)} \leq \overline{X} - X_{n-1}^{bau} - \widetilde{X}_n \\ \overline{X} - \widetilde{X}_n - X_{\uparrow(n-1)} & \text{if} \quad \overline{X} - X_{n-1}^{bau} - \widetilde{X}_n \leq X_{\uparrow(n-1)} \leq \overline{X} - \widetilde{X}_n - \widetilde{X}_{n-1} \\ \widetilde{X}_{n-1} & \text{if} \quad X_{\uparrow(n-1)} \geq \overline{X} - \widetilde{X}_n - \widetilde{X}_{n-1} \end{cases} \tag{2.9}$$

The term $X_{\uparrow(n-1)}$ denotes the pollution amount attributable to polluters upstream of $n-1$ and is not to be confused with $X_{-(n-1)}$ which is the pollution amount attributable to all polluters excluding $n-1$. Equation (2.9) essentially translates equation (2.7) to the sequential context so that now player $n-1$ takes only upstream pollution ($X_{\uparrow(n-1)}$) as given and their compliance goal explicitly takes the next player's strategy into account.

Player $n-1$ knows that player n will never choose to pollute below their minimum profitable pollution level ($\widetilde{X}_n$). Therefore, if player $n-1$ wants to achieve a compliance outcome, she must ensure that the water received by n does not exceed $\overline{X}-\widetilde{X}_n$. However, if the water received by $n-1$ is too polluted so that $n-1$ must pollute below her own minimum profitable pollution level to achieve the compliance goal, then she will surely not do so resulting in overall non-compliance. Equation (2.10) extends the best response function to all players j where j is upstream of n ($j < n$). For (2.10) to apply to Player 1, simply set $X_{\uparrow(1)} = 0$.

$$X_j^{BR} = \begin{cases} X_j^{bau} & \text{if} \quad X_{\uparrow(j)} \leq \overline{X} - X_j^{bau} - \sum_{k=j+1}^{n} \widetilde{X}_k \\ \overline{X} - X_{\uparrow(j)} - \sum_{k=j+1}^{n} \widetilde{X}_k & \text{if} \quad \overline{X} - X_j^{bau} - \sum_{k=j+1}^{n} \widetilde{X}_k \leq X_{\uparrow(j)} \leq \overline{X} - \widetilde{X}_j - \sum_{k=j+1}^{n} \widetilde{X}_k \\ \widetilde{X}_j & \text{if} \quad X_{\uparrow(j)} \geq \overline{X} - \widetilde{X}_j - \sum_{k=j+1}^{n} \widetilde{X}_k \end{cases} \tag{2.10}$$

Welfare in Equilibrium

There is a well known result that the SPNE is a subset of the set of NE's and so when t is set perfectly, there is a unique NE and is thus identical to the SPNE. When t is set too strictly (high), however, the SPNE results in one of the extremes from the set of NE's. Take Figure B.3 as an example. Assuming that Player 1 is upstream of 2, the SPNE would produce the point $(\overline{X} - \widetilde{X}_2, \widetilde{X_2})$ as the pollution allocation[2]. This is because Player 1 can exert its first mover advantage over Player 2 by producing more pollution and forcing Player 2 to pick up the slack. Player 2 is happy to do this because of Proposition 2.2.1. This intuition is captured in Corollary 2.2.3 and Theorem 2.2.4.

Theorem 2.2.3 *If all firms are identical in all but location, then the SPNE resulting*

[2] Assuming that $\overline{X} - \widetilde{X}_2 < X_1^{bau}$

from the policy $(t, \overline{X})$ *where* $t > \lambda^*(\boldsymbol{\theta}, \overline{X})$ *produces a pollution allocation that is non-increasing downstream. That is*

$$X_h^{spne} \geq X_\ell^{spne}$$

where $h < \ell$ *(so that* h *is upstream of* ℓ*).*

Proof: The proof follows directly from Equation (2.10). For example, take the first line from the piecewise function and compare this for two different players, h and ℓ where h is upstream from ℓ. Player h will pollute X^{bau} if $X_{\uparrow(h)} \leq \overline{X} - X_h^{bau} - (n-h)\widetilde{X}$ and Player ℓ will also pollute X^{bau} if $X_{\uparrow(\ell)} \leq \overline{X} - X_\ell^{bau} - (n-\ell)\widetilde{X}$. Since we have

$$X_{\uparrow(\ell)} > X_{\uparrow(h)}$$

and

$$\overline{X} - X_\ell^{bau} - (n-\ell)\widetilde{X} > \overline{X} - X_h^{bau} - (n-h)\widetilde{X}$$

it is hard to tell which player is more likely to play their BAU levels at the moment. However, we can establish that

$$X_{\uparrow(\ell)} - X_{\uparrow(h)} > (\ell - h)\widetilde{X}$$

since players in between h and ℓ would, at a minimum, produce $\widetilde{X}$. This then allows us to claim that the condition for h to play their BAU level is more likely to hold than the condition for ℓ to play their BAU level. A similar process can be done for the remaining pieces from (2.10) to fully establish the proof. ■

Corollary 2.2.4 *Suppose all firms are homogeneous except location and that* $t > \lambda^*$. *Define* $k = \lfloor \widetilde{k} \rfloor > 0$ *where* $\widetilde{k} = max\{B\}$ *and* $B = \left\{ \overline{k} \in \mathbb{R}_0^+ : \ \overline{k} X^{bau} + (n - \overline{k})\widetilde{X} = \overline{X} \right\}$.

Then the SPNE would produce the following result

$$(X_1^{spne}, \ldots, X_k^{spne}, \ldots, X_n^{spne}) = (\underbrace{X^{bau}, \ldots, X^{bau}}_{k}, X_R, \underbrace{\widetilde{X}, \ldots, \widetilde{X}}_{n-k-1})$$

and compliance is met exactly so that

$$\overline{X} = kX^{bau} + (n-k-1)\widetilde{X} + X_R$$

where $X_R \in \left(\widetilde{X}, X^{bau}\right)$ *and* $k = \left\lfloor \dfrac{\overline{X} - n\widetilde{X}}{X^{bau} - \widetilde{X}} \right\rfloor$.

Proof: The SPNE pollution allocation follows directly from the definition of k and equation (8). To see that $X_R \in \left(\widetilde{X}, X^{bau}\right)$, notice that we have

$$\begin{aligned}
&\Longrightarrow \widetilde{k}X^{bau} + (n-\widetilde{k})\widetilde{X} = kX^{bau} + (n-k-1)\widetilde{X} + X_R \\
&\Longrightarrow (\widetilde{k}-k)X^{bau} + \left(1 - \left[\widetilde{k}-k\right]\right)\widetilde{X} = X_R \\
&\Longrightarrow \sigma X^{bau} + (1-\sigma)\widetilde{X} = X_R \qquad \text{(where } \sigma \in (0,1))
\end{aligned}$$

■

Note that $\lfloor \quad \rfloor$ is the floor function/operator.

Theorem 2.2.4 simply says the SPNE would be so that the first k players will choose BAU levels, player $k+1$ will pollute some amount between BAU and minimum profitable level (henceforth referred to as the residual polluter), and the remaining downstream players pollute the minimum profitable pollution level. This formalizes the arguments made in the previous section and shows that the SPNE does indeed produce the most extreme allocation possible when $t > \lambda^*$.

The result from theorem 2.2.4 above and theorem 2.2.5 below implies that the SPNE still achieves compliance but at the highest possible cost. This result relies heavily on the homogeneous firm assumption which limits its value somewhat.

Theorem 2.2.5 *The SPNE allocation in Corollary 2.2.4 produces the lowest welfare possible among all other compliance NE's.*

Proof: The welfare from Proposition 2.2.5 is given by

$$W_0 = k\pi(X^{bau}) - (n-k-1)\pi(\widetilde{X}) + \pi(X_R) - D(\overline{X})$$

but since all NE's result in compliance, the damage function will be same when comparing across different NE's and there is no tax incurred. Thus, the only relevant comparison is done on producer welfare, W_0^p given by

$$W_0^p = k\pi(X^{bau}) - (n-k-1)\pi(\widetilde{X}) + \pi(X_R)$$

The only possible reallocation will be one in which a free rider will pollute ε less while a contributor will pollute ε more. Such a reallocation produces welfare W_1^p where

$$W_1^p = (k-1)\pi(X^{bau}) + (n-k-1)\pi(\widetilde{X}) + \pi(X^{bau} - \varepsilon) + \pi(X_R + \varepsilon)$$

Since it would increase welfare marginally more if we give the ε to a polluter at the level of $\widetilde{X}$ over one at X_R. Then evaluating $W_0^p - W_1^p$

$$\begin{aligned} W_0^p - W_1^p &= \pi(X^{bau}) - \pi(X^{bau} - \varepsilon) + \pi(X_R) - \pi(X_R + \varepsilon) \\ &= \pi(X^{bau}) - \pi(X^{bau} - \varepsilon) - \Big[\pi(X_R + \varepsilon) - \pi(X_R)\Big] \\ &\leq 0 \qquad \text{(since } \pi() \text{ is concave or } \pi'(x) \text{ is decreasing in } x \text{ for } x \leq X^{bau}) \end{aligned}$$

■

When we start to consider the more realistic scenario where firms are heterogeneous, the welfare consequences of a too strict t value in an SPNE becomes more complicated. In particular, the SPNE no longer coincides with the "worst case scenario" which is occurs when the lowest θ types are free-riding off of the highest θ types. In other words, the "worst case" occurs when those who stand to gain the least from free-riding, free-ride off of those who stand to gain the most from free-riding.

2.3 Optimal Location of Additional Monitors

The regulatory structure of applying an ambient tax on NPS polluters along a river will change as m, the number of monitoring points, changes. How that changes may depend on where those monitors are located. Towards that end, I will invoke the assumption that firms are homogeneous in all but location and this includes each firm's marginal damage of pollution. When an additional monitor is placed upstream of player $\ell+1$, then it would effectively split the group of n polluters into two groups; the upstream group would have size ℓ while the downstream group has size $n-\ell$.

It is assumed that the regulator only cares about total pollution downstream of player n so that the resulting two groups are regulated independently. Since homogeneity is assumed here, the ambient tax rate that is applied to each section are the same. The ambient standard for each section will depend on where the second monitor is located. The ambient standard for the upstream section is

$$\overline{X}_u = \frac{\ell}{n}\overline{X}$$

and the standard for the downstream section is

$$\overline{X}_d = \frac{n-\ell}{n}\overline{X}$$

so that the sum of the two standards equals the original standard for the case $m = 1$. It should be noted that the process of determining the appropriate standard for each section is extremely simplified here where each section gets a representative share of the total original standard. Under homogeneity, this arbitrary process happens to be the optimal choice for the regulator since $X_i^* = \frac{\overline{X}}{n}$ for all i. But when heterogeneity is allowed, this simple process no longer corresponds to the optimal standard for each section. The corresponding total profits for both upstream (subscript u) and downstream (subscript d) groups are given in (2.11).

$$\begin{aligned} \Pi_u &= k_u\pi(X^{bau}) + (\ell - k_u - 1)\pi(\widetilde{X}) + \pi(X_{R_u}) \\ \Pi_d &= k_d\pi(X^{bau}) + (\ell - k_d - 1)\pi(\widetilde{X}) + \pi(X_{R_d}) \end{aligned} \tag{2.11}$$

The values (k_h, X_{R_h}) are defined similarly to (k, X_R) from theorem 2.2.4 but are derived from $\overline{X}_h$ for $h = \{u, d\}$. Thus welfare is given by (2.12).

$$W = \Pi_u + \Pi_d - D(\overline{X}) \tag{2.12}$$

Equations (2.11) and (2.12) indicate that the choice in location (ℓ) affects welfare through two channels: (1) how it affects total number BAU polluters ($k_u + k_d$) and how it affects the amount that the two residual polluters discharge (X_{R_u} and X_{R_d}).

Theorem 2.3.1 *Initially let $m = 1$. Under homogeneity, the welfare maximizing location for the second monitor is $\ell = \frac{n}{2}$.*

Proof: First I show that the choice of ℓ doesn't change the value $k_u + k_d$ and then I show that the choice $\ell = \dfrac{n}{2}$ maximizes $\pi(X_{R_u}) + \pi(X_{R_d})$.

By definition we have $k_u + k_d = \lfloor \widetilde{k}_u \rfloor + \lfloor \widetilde{k}_d \rfloor$. We can decompose $\widetilde{k}_h$ for $h \in \{u, d\}$ as

$$\widetilde{k}_h = \lfloor \widetilde{k}_h \rfloor + b_h$$

where $b_h \in (0, 1)$. Then we have

$$\lfloor \widetilde{k}_u + \widetilde{k}_d \rfloor = \lfloor \widetilde{k}_u \rfloor + \lfloor \widetilde{k}_d \rfloor + \lfloor b_u + b_d \rfloor$$

and since

$$\lfloor b_u + b_d \rfloor = \begin{cases} 0 & \text{if} \quad b_u + b_d < 1 \\ 1 & \text{if} \quad b_u + b_d \geq 1 \end{cases}$$

then

$$\lfloor \widetilde{k}_u \rfloor + \lfloor \widetilde{k}_d \rfloor = \begin{cases} \lfloor \widetilde{k}_u + \widetilde{k}_d \rfloor & \text{if} \quad b_u + b_d < 1 \\ \lfloor \widetilde{k}_u + \widetilde{k}_d \rfloor - 1 & \text{if} \quad b_u + b_d \geq 1 \end{cases}$$

Now that we have this expression, we see that

$$\arg\min_{\ell} \lfloor \widetilde{k}_u \rfloor + \lfloor \widetilde{k}_d \rfloor = \arg\min_{\ell} \lfloor \widetilde{k}_u + \widetilde{k}_d \rfloor$$

But since

$$\lfloor \widetilde{k}_u + \widetilde{k}_d \rfloor = \left\lfloor \frac{\frac{\ell}{n}\overline{X} - \ell\widetilde{X}}{X^{bau} - \widetilde{X}} + \frac{\frac{n-\ell}{n}\overline{X} - (n-\ell)\widetilde{X}}{X^{bau} - \widetilde{X}} \right\rfloor = \left\lfloor \frac{\overline{X} - n\widetilde{X}}{X^{bau} - \widetilde{X}} \right\rfloor$$

Thus, the location of the second monitor does not change $k_u + k_d$.

The only channel in which location affects welfare then is through the sum

$$\pi(X_{R_u}) + \pi(X_{R_d})$$

Denote ℓ^* as the location that maximizes the above sum. Suppose that ℓ^* is such that $X_{R_u} \neq X_{R_d}$. Then this contradicts the definition of ℓ^* because by shifting some pollution from the higher X_R to the lower X_R it would increase the join profit since $\pi()$ is concave. Thus, the necessary condition for ℓ^* to be the argmax of the joint profits is that $\ell^*: \ X_{R_u} = X_{R_d}$.

By definition we have that

$$X_{R_u} = \frac{\ell}{n}\overline{X} - \left\lfloor \frac{\frac{\ell}{n}\overline{X} - \ell\widetilde{X}}{X^{bau} - \widetilde{X}} \right\rfloor X^{bau} - \left(\ell - \left\lfloor \frac{\frac{\ell}{n}\overline{X} - \ell\widetilde{X}}{X^{bau} - \widetilde{X}} \right\rfloor - 1\right)\widetilde{X}$$
$$X_{R_d} = \frac{n-\ell}{n}\overline{X} - \left\lfloor \frac{\frac{n-\ell}{n}\overline{X} - (n-\ell)\widetilde{X}}{X^{bau} - \widetilde{X}} \right\rfloor X^{bau} - \left(n - \ell - \left\lfloor \frac{\frac{n-\ell}{n}\overline{X} - (n-\ell)\widetilde{X}}{X^{bau} - \widetilde{X}} \right\rfloor - 1\right)\widetilde{X}$$

Therefore, the only ℓ that satisfies the necessary condition for maximization is $\ell = \dfrac{n}{2}$. By equations 2.11 and 2.12, this is also the location that maximizes total welfare. ■

Theorem 2.3.1 suggests that the optimal location for the additional $m-1$ monitors would be so that the entire river is partitioned evenly. Without a formal proof of this, for now I treat this as more of a simplifying assumption.

Optimal Number of Monitors

Now that it is established where the additional $m-1$ monitors will be located, the question that remains is how should m be determined so that the potential for free-riding is minimized? There will be m sections that are partitioned along the river (the number of sections equals the number of monitors) and homogeneity means that each section is regulated the same and thus behaves the same (has the same pollution outcome). The welfare under an m monitor regime is given by equation (2.13).

$$W_m = m\left[k_m\pi(X^{bau}) + (n_m - k_m - 1)\pi(\widetilde{X}) + \pi(X_{R_m})\right] - D(\overline{X}) \tag{2.13}$$

The bracketed term is the profits to each section so that (k_m, n_m, X_{R_m}) are respectively, the number of BAU polluters, number of total polluters, and the discharge level of the residual polluter for each identical section or group. By construction, $n_m = \frac{n}{m}$ and it is assumed that it is an integer. Further, the number of BAU polluters for each section is given by (2.14).

$$\begin{aligned}
k_m &= \left\lfloor \widetilde{k}_m \right\rfloor \\
\widetilde{k}_m &= max\{B_m\} \\
\widetilde{k}_m &= \frac{\overline{X} - n\widetilde{X}}{m(X^{bau} - \widetilde{X})} = \frac{\widetilde{k}}{m} \\
B_m &= \left\{\overline{k}_m \in \mathbb{R}_0^+ :\ \overline{k}_m X^{bau} + (n_m - \overline{k}_m)\widetilde{X} = \overline{X}_m\right\}
\end{aligned} \tag{2.14}$$

The number of BAU polluters per section (weakly) decreases with m but the number of sections increases with m. This begs the question of whether increasing the number of evenly space monitors actually affects the potential for free-riding in the manner that is socially desirable. The potential for free-riding is measured by the sum of all individual differences between the least cost pollution level and their minimum profitable pollution level. This is stated in the definition of k from theorem 2.2.4 when you recognize that the least cost pollution level for each polluter equals $\frac{\overline{X}}{n}$ under homogeneity. Figure B.5 depicts the intuition for where the potential for free-riding comes from in a more general way that allows for heterogeneity.

As a starting point, consider the case in which everyone is producing at their minimum profitable levels, $\widetilde{X}_i$. This is not an NE because there are unused implied pollution quotas left, i.e., $\sum_{i=1}^{n} \widetilde{X}_i < \overline{X}$; specifically, there would be $\overline{X} - \sum_{i=1}^{n} \widetilde{X}_i$ many unused implied quotas. How many BAU polluters that this unused implied quotas can support depends on the distance between X_i^{bau} and $\widetilde{X}_i$ for each i. Therefore, under homogeneity we see that theorem 2.2.4 defines the maximum BAU polluters for a compliance NE to be $k = \left\lfloor \frac{n\left(\frac{\overline{X}}{n} - \widetilde{X}\right)}{X^{bau} - \widetilde{X}} \right\rfloor$.

When we allow for $m > 1$, then the free-riding potential within each section depends on the distance between $\overline{X}_m$ and $n_m \widetilde{X}$. Since $\overline{X}_m$ is decreasing faster with m than $n_m \widetilde{X}_m$ does, then the free-riding potential within a section decreases as well. The total number of BAU polluters for the entire river, denoted as k_m^T is given by (2.15). At a glance, it is unclear whether total free-riding potential measured by (2.15) increases or decreases with m. Certainly when $m = n$, the potential for free-riding vanishes which would seem to indicate that the total free-riding potential will decrease with the number of monitors. However, this is not the case and I show how that works formally below and try to provide intuition along the way.

$$k_m^T = m k_m \tag{2.15}$$

Equation (2.15) implies that

$$k_1^T = \left\lfloor \frac{\overline{X}_1 - n_1 \widetilde{X}}{X^{bau} - \widetilde{X}} \right\rfloor \tag{2.16}$$

where $\overline{X} = \overline{X}_1$ and $n = n_1$. Intuitively, when $m = 1$ the resulting number of total BAU polluters is at its maximum ($k_1^T = \max_m\{k_m\}$) and when $m = n$ then that number is now at its minimum ($k_n^T = \min_m\{k_m\}$). But theorem 2.3.2 shows that the function k_m^T does not in generaly change in a monotone fashion. Instead, there is a condition for which k_m^T

actually increases with m, though never above k_1^T as stated in corollary 2.3.3.

Theorem 2.3.2 *Let k_m and k_m^T be the maximum number of BAU polluters within a section and the total maximum BAU polluters along the river, respectively. Then for $m_1 < m_2$ we have that $k_{m_1}^T > k_{m_2}^T$ if and only if equation (2.17) holds.*

$$\frac{k_1 - k_2}{k_1} > \frac{m_2 - m_1}{m_2} \tag{2.17}$$

Proof: Let $m_1 < m_2$. We seek to find the conditions under which $k_{m_1}^T > k_{m_2}^T$. Suppose that it's true and let $m_1 = m_2 - c$.

$$\begin{aligned}
& k_{m_1}^T > k_{m_2}^T \\
\iff & m_1 k_1 > m_2 k_2 \\
\iff & m_2 k_1 - c k_1 > m_2 k_2 \\
\iff & \frac{m_2(k_1 - k_2)}{k_1} > c \\
\iff & \frac{k_1 - k_2}{k_1} > \frac{m_2 - m_1}{m_2}
\end{aligned}$$

■

Corollary 2.3.3 *Increasing m may increase k_m^T but never more than k_1^T. In other words, a maximum (not necessarily unique) for k_m^T is k_1^T.*

Proof: Equations 2.14 and 2.15 imply that

$$k_m^T = m \left\lfloor \frac{\overline{X}_m - n_m \widetilde{X}}{X^{bau} - \widetilde{X}} \right\rfloor$$

which we want to compare with equation 2.16. This comparison of these two values can be boiled down to comparing

$$\lfloor ab \rfloor \text{ with } \lfloor a \rfloor b$$

for some positive value a and positive integer b. Using Hermite's identity, it is apparent that

$$\lfloor ab \rfloor \geq \lfloor a \rfloor b$$

which means that

$$k_1^T \geq k_m^T \qquad \forall m \in \mathbb{N}$$

because $\lfloor m\widetilde{k}_m \rfloor = \left\lfloor m\frac{\widetilde{k}_1}{m} \right\rfloor = \lfloor \widetilde{k}_1 \rfloor$. ■

In general, equation (2.17) is not guaranteed to hold which means that the total maximum number of BAU polluters along the entire river, is not guaranteed to decrease with increases in the number of evenly spaced monitors. Its important to clarify that we are referring to the maximum possible number of BAU polluters that could result from a simultaneous game since there are so many possible NEs when $t > \lambda^*$. Under a more sequential type game, which is more plausible in a river setting as opposed to a lake, the result from theorem 2.3.2 is a proper prediction of a behavioral outcome.

Intuitively, theorem 2.3.2 says that an increase in monitors from m_1 to m_2 would decrease the potential for free-riding *for the entire river* if and only if the percent decrease in the potential for free-riding *within a section*, is greater than the percent increase in monitors (i.e., number of sections) relative to the new value, m_2. Restating this graphically, turn to figure B.6. The result from theorem 2.3.2 means that the distance between the values $\overline{X}_m$ and $n_m\widetilde{X}$ must decrease faster than m is increasing in order for an increase in m to decrease the total potential to free-ride[3].

2.4 Discussion

The results suggest that when the regulator can calibrate t perfectly for $\overline{X}$, then there is no difference in the NE and SPNE results. However, if the regulator overshoots λ^* even slightly, then the NE and SPNE diverge. For the case in which polluters are homogeneous in all but location, the SPNE will always produce the worst compliance outcome in terms of welfare. This is because if t is set too strict (i.e., $t > \lambda^*$), then firms' minimum profitable pollution level ($\widetilde{X}_i$) is lower than the individual least cost discharge, X_i^*. This gap gives rise to the potential for free-riding leading to a wide range of pollution allocations that can both achieve compliance exactly and is individually rational. But when $t = \lambda^*$, firms' minimum profitable pollution level is exactly equal to the socially optimal individual discharge. This situation leads to no potential for free-riding and thus a unique NE would result.

Under homogeneity, the SPNE outcome being the highest cost compliance NE serves as a useful measure for the potential for free-riding under a simultaneous game. The main contribution of this shows that when the potential for free-riding exists, additional monitoring points may not necessarily decrease that potential. The degree to which additional monitors decreases that potential, depends on the extent in which the relative decrease in the potential for free-riding within each section is higher than the relative increase in the number of sections.

[3]To see that the distance between $\overline{X}_m$ and $n_m\widetilde{X}$ does decrease with m, simply take the derivative of both values with respect to m and compare.

Advances in water quality monitory technology has made this line of questioning more relevant than ever, reducing the cost of implementing more complex monitoring networks. Understanding the benefits of additional monitoring locations is thus a crucial component analysis in determining the benefits of such an investment. The policy implication of this paper's results is that if a regulator seeks to achieve a NPS pollution goal in a river-like system through the implementation of an ambient tax, they can do so but at an unknown cost a priori. The regulator can increase the number of monitoring points, but doing so does not guarantee that the resulting outcome is closer to the least-cost outcome. However, additional monitoring locations is more likely to achieve an outcome closer to the least-cost outcome when the level increase in the number of monitors is large as is apparent from equation 2.17.

Lastly, our theoretical results are consistent with the laboratory results from Miao et al. (2016) and Zia et al. (2020) though for different reasons. Those studies sought to examine the effects on polluter behavior under an ambient tax of changes in the information structure such as additional monitoring points or increase in monitoring frequency. This paper addresses the former directly providing a proper theoretical framework for that line of analysis. However, those two papers only went as far as one additional monitoring point which limits the effect on behavior somewhat.

Chapter 3

Indemnity Payments in PES Programs: Practical Implications

Joint with Chris Costello

3.1 Introduction

Ecosystem services (sometimes referred to as environmental services) are the aspects of an ecosystem (or environment) that provide benefits to humanity, directly or indirectly (Millennium Ecosystem Assessment, 2005; Fisher, Turner and Morling, 2009).[1] A majority of ecosystem services (ES) fall within the realm of public goods therefore are supplied at suboptimal levels. Worse yet, early assessments indicate that these services are degrading at rapid rates (Millennium Ecosystem Assessment, 2005). One solution for this market failure that has gained popularity among scholars and practitioners is known as payments for ecosystem services (PES) (Salzman et al., 2018). PES programs

[1]Direct benefits could include eco-tourism, pollination for agriculture, carbon sequestration, and general ecosystem health to prevent desertification. Examples for indirect benefits include non-use value from biodiversity, predator populations to prevent deer overpopulation, etc.

facilitate the creation of contracts between ES beneficiaries (or their representative such as the government or regulator) and ES suppliers where the beneficiary agrees to pay the supplier for their provision of ES. PES contracts are voluntary programs where agents have to opt into participation which is in contrast to Pigouvian taxation. Around the world, there are now 550 PES programs with a combined annual payment of around $36 billion USD (Salzman et al., 2018).[2]

PES schemes are essentially an application of the Coase Theorem and can be contracted on either ES outputs (like lower atmospheric CO2) or ES inputs (like carbon sequestering land uses) and which one to contract on is still an active area of research (White and Hanley, 2016). PES contracts based on outputs are sometimes referred to as performance-based contracts while input-based ones are also known as action-based contracts. One central tradeoff between these two types is that contracting on outputs reduces the uncertainty of benefits from higher ES. However, because of the variability in nature, the ES production function is inherently stochastic which means that contracting on ES outputs could put significant risk on the agent. Further, it is typically much harder to monitor ES outputs compared to ES inputs (Burton and Schwarz, 2013; Derissen and Quaas, 2013).[3] Consequently, many PES programs are contracted on ES inputs rather than outputs (Jack, Kousky and Sims, 2008) with the majority of European PES programs being input-based (Wuepper and Huber, 2022).

The PES literature has acknowledged the important role that risk plays in agents'

[2]In this paper, we abstract away from concerns about the precise definitions of ES (Fisher, Turner and Morling, 2009) and PES (Schomers and Matzdorf, 2013) where there are disagreements on how narrow or broad each definition should be. Throughout this paper, both ES and PES will be used to refer to the broadest definitions of both.

[3]Though remote sensing is making monitoring environmental factors at large more and more accessible, it is still quite difficult to attribute individual contributions to aggregate environmental quality measures.

PES related decisions but rather than formalizing its role, it has chosen to mostly sidestep the issue by narrowing its focus on input-based PES. We argue that risk ought to have a larger consideration in the design of PES programs, regardless of whether it is output or input based. This paper contributes to a small set of papers that analyze the role of risk in PES payments by offering an alternative to increased payments, that is, offering indemnity instead. Our goals with this paper is to (i) define the necessary and sufficient conditions for when it is optimal for the regulator to offer positive indemnity payments and what that optimal indemnity is, (ii) offer an approach to evaluate how large such gains could be, (iii) define further conditions for when it is optimal to pursue the dual objective of additionality and poverty alleviation.[4]

The model tasks the regulator with representing the beneficiaries of the ES. Their objective is to maximize the gross social benefit given a fixed budget by choosing both payment (or subsidy) level and an indemnity level. The typical PES contract is known as linear pricing contracts which defines a measurable and verifiable ES input and pays a subsidy for each unit of input supplied.[5] The typical linear PES contract chooses the optimal payment level conditional on the indemnity being zero which will henceforth be referred to as the pure payment contract. In contrast, the optimal contract is arrived at by allowing the regulator to freely choose both the payment and indemnity levels.

We find that the pure payment contract always offers full indemnity whenever agents are risk averse but that when agents are risk neutral, the optimal and pure payment

[4]Indemnity simply means protection against financial loss/burden. Insurance is a subset of indemnity in that it specifically requires the indemnitee to pay the indemnitor for indemnity.

[5]Linear pricing contracts are in contrast to optimal contracts from the mechanism design literature. Those contracts are optimal in the sense that it maximizes social welfare by explicitly accounting for the asymmetric information about agent's counterfactual ES input supply (i.e., additionality). They are a menu of pairs of ES input levels and the corresponding payment, carefully designed to create a separating equilibrium that maximizes expected welfare (Mason and Plantinga, 2013).

contracts provide the same social benefits per government dollar spent. The reason for this has been well understood from the insurance literature which is that the regulator is effectively risk neutral so that the cost of bearing the risk of ES provision is equal to the mean of the cost shock. However, a risk adverse agent would value the cost from risk at the mean cost shock plus some risk premium. Thus, the regulator can always arbitrage this by offering indemnity and "charging" a higher price than it costs to insure. The risk neutrality on the part of the regulator can be justified on the grounds of having a large number of beneficiaries Arrow and Lind (1970). Further, the value gained from implementing the optimal contract, relative to the pure payment contract, increases with the coefficient of relative risk aversion. Following Chetty (2006), we show how to estimate a lowerbound for this parameter using estimates of relevant elasticities and moments of the ES cost function. We also conduct a numerical exercise that illustrates the relationship between the magnitude of risk aversion and the value added from implementing the optimal contract. Lastly, we find that the pursuit of the dual objective of maximizing ES benefits with minimizing poverty is optimal only when a particular comparative static is below some threshold. Specifically, the condition states that the business-as-usual level of ES provision must increase with wealth at a sufficiently high rate.

Section3.2 will briefly discuss the context and literature review up which this paper hopes to contribute. Section 3.3 outlines the model detailing both agents' and principal's problems The next section deals with additionality and outlines conditions in which it is optimal for the regulator to pursue the dual objective of additionality and poverty alleviation.

3.2 Literature on Risk in PES

This paper relates closely with the literature on risk associated with payments for ecosystem services (PES) which has since established that the required linear payment needed to induce a certain "risky green" action is higher if agents are risk averse compared to being risk neutral (Benítez et al., 2006; De Pinto, Robertson and Obiri, 2013). Benítez et al. (2006) derived the optimal payment needed to induce the adoption of farming practices/technologies that improve soil carbon sequestration and find that such payment increases with risk aversion. De Pinto, Robertson and Obiri (2013) does something similar for the adoption of farming practices that help with climate change mitigation as well uses Ghana as a case study. The risks faced by agents in each of those papers are related to revenue risk associated with the desirable "green" practices or technologies. However, loss protection, also known as indemnity, is rarely brought up as a potential tool to address risk averse behavior.

There are many other instances in which the participation into PES programs introduces risk to the agent's bottom line. Another example of risks within input based PES is payments to encourage coexistence with predators where agents are paid to avoid revenge killing of a predator that caused damage to either property (livestock) or human life (Dickman, Macdonald and Macdonald, 2010). Many times, these payments are in conjunction with either payments for or requirements to provision ES inputs such as using guardian dogs to minimize conflicts with predators. It is in the predation context that the literature has explicitly analyzed the role of insurance in conservation and find success in preserving carnivore populations and habitats (see Dickman, Macdonald and Macdonald (2010) for a review). There are also case studies that find that such indemnity schemes lead to moral hazard (Bautista et al., 2019). Other examples of risk associated with PES participation include the risk that payments will not be received due to institutional mistrust (Jack et al., 2022), risks associated with stochasticity of nature within output based PES contracts, and the risk from habitat maintenance which can cause damages to livestock through disease transmission from increased wildlife (Rhyan et al., 2013).

To the best of our knowledge, the literature has not yet addressed what role that "insurance" or, more precisely, indmenity, can play in achieving ES goals under an economic optimality standpoint.[6] Only Graff-Zivin and Lipper (2008) suggest insurance as a tool to be used in conjunction with the standard linear PES contract. However, those authors mentioned it casually as part of a general discussion rather than giving it a formal treatment. This paper hopes to bring everything together by thinking about the issue that risk poses in PES schemes generally and how a regulator should account for this in its design of linear pricing PES contracts.

3.3 Model

The linear PES contract is characterized by (1) an indemnity rate $I \in [0, 1]$ that is paid out for each dollar of loss ($x_i \epsilon_i$) that occurs and (2) the ES input payment rate p which is paid for each unit of ES input x_i (henceforth referred to as the pay rate). There is a cost shock ϵ_i that is distributed $(\mu_\epsilon, \sigma_\epsilon^2)$ and has support over $[0, e]$ and when multiplied with x_i produces the loss that an agent faces for choosing x_i. I assume that only one ES input x_i is being contracted and that the input is continuous over $[0, \infty]$ so that if a cost shock occurs, the PES participant's loss equals $x_i \epsilon_i$ but receives $x_i \epsilon_i I$ in indemnity

[6] The main difference between insurance and indemnity is that insurance implies that there is an insurance premium whereas indmenity is a much more general sense of protection against loss and does not require the insuree to pay a premium or cost of insurance.

payments. If the agent does not participate in the PES program, then $x_i = 0$. Potential enrollees all have heterogeneous initial wealth ω_i and are heterogeneous in their known input cost function $g_i(x_i, \omega_i)$ and for brevity, subscripts i will be henceforth omitted when risk of confusion is low.[7]

Agents have Bernoulli utility $u(c)$ over consumption c and a budget constraint defined in (3.1). Thus, consumption is only stochastic when opting into the PES program by choosing $x > 0$ and deterministic if $x = 0$.[8] For any given policy level (I, p), there will be X units of ES input supplied in the aggregate which then engenders ES output $ES(X)$. This ES output then leads to some level of social benefit $\widetilde{B}(ES(X))$ which may be random as well. From here on, denote $B = \widetilde{B} \circ ES$ as the expected social benefit and is a function of the aggregate ES inputs provided, X.

3.3.1 Agent's Problem

Agents are expected utility maximizers who take contract (I, p) as given and chooses ES input level.

$$\begin{aligned} &\max_x \mathbb{E}\left[u(c)\right] \\ \text{s.t.} \qquad & c = \omega + xp - g(x, \omega) - x\epsilon(1 - I) \qquad (3.1) \\ & x \geq 0 \end{aligned}$$

The ES input cost function is assumed to be increasing and convex ($g_x(x, \omega) > 0$, $g_{xx}(x, \omega) > 0$.[9] The first order condition is given by (3.2) which implicitly defines the

[7]Small letters will denote individual level values and big letters denoting aggregate values.

[8]There is no loss of generality since one could simply treat ω as a random variable as well.

[9]One could allow agents to derive positive benefits from provision of x and include a second argument into the utility. Then the RHS of (3.2) would instead be equal to $\mathbb{E}[u_x(c, x)]$. Further, one would have to follow more closely to Chetty (2006) in order to account for the role of complementarity between x and c in the application stage of this paper.

interior solution x^*.

$$\mathbb{E}\left[u'(c^*(x^*,\omega))\frac{\partial c^*}{\partial x}\right] = 0 \tag{3.2}$$

Using monotone comparative statics, it is possible to sign $\dfrac{\partial x^*}{\partial p}$ and $\dfrac{\partial x^*}{\partial I}$.

Lemma 3.3.1 *Given contract (I, p), the provision of ES inputs is non-decreasing in indemnity payment rate I nor is it decreasing in the payment rate p, i.e.,* $\dfrac{\partial x_i^*}{\partial I} \geq 0$ *and* $\dfrac{\partial x_i^*}{\partial p} \geq 0$.

Proof: To show that x^* is non-decreasing in I, we can invoke the Milgrom-Shannon Monotonicity by simply showing that $\mathbb{E}\left[u\Big(c(x,I)\Big)\right]$ is single crossing in (x, I). Suppose $x' > x$ and $I' > I$. Want to show that (i) $\mathbb{E}\left[u\Big(c(x',I)\Big) - u\Big(c(x,I)\Big)\right] \geq 0$ implies $\mathbb{E}\left[u\Big(c(x',I')\Big) - u\Big(c(x,I')\Big)\right] \geq 0$ and that (ii) $\mathbb{E}\left[u\Big(c(x',I)\Big) - u\Big(c(x,I)\Big)\right] > 0$ implies $\mathbb{E}\left[u\Big(c(x',I')\Big) - u\Big(c(x,I')\Big)\right] > 0$.

Let $\mathbb{E}\left[u\Big(c(x',I)\Big) - u\Big(c(x,I)\Big)\right] \geq 0$.

$$\iff \qquad \mathbb{E}\left[c(x',I) - c(x,I)\right] \geq 0 \tag{3.3}$$

since $u()$ is a monotonic transformation of $c()$. Rewriting gives

$$\iff \qquad \omega + x'p - g(x') - x'\mu_\epsilon(1-I) - [\omega + xp - g(x) - x\mu_\epsilon(1-I)] \geq 0$$

$$\iff \qquad p(x'-x) - [g(x') - g(x)] - \mu_\epsilon(1-I)(x'-x) \geq 0$$

Thus we have

$$\implies \qquad p(x'-x) - [g(x') - g(x)] - \mu_\epsilon(1-I')(x'-x) \geq 0$$

$$\iff \quad \mathbb{E}\left[u\Big(c(x', I')\Big) - u\Big(c(x, I')\Big)\right] \geq 0$$

The proof for part (ii) is almost identical to that of (i) except with strict inequalities.

To show that x^* is non-decreasing in p follows an almost exact procedure. ■

Lemma 3.3.1 says that an agent's supply of ES inputs weakly increases with both the pay and indemnity rates. This implies that there must necessarily be a trade off faced by the regulator with a fixed budget G who maximizes expected social benefit, $B(X)$. The natural question then arises, when is it optimal for such a regulator to offer a positive indemnity rate at the expense of offering higher p?

3.3.2 Planner's Problem

The social planner takes government budget G as fixed and seeks to maximize aggregate supply of ES input $X = X(x_1^*, \ldots, x_n^*) = \sum_i x_i^*$. Note that the formulation of (3.4) excludes the welfare of the ES suppliers since the goal is not to achieve a first best outcome, rather the objective is to maximize the benefit of a public good given a fixed budget. If the regulator's budget constraint is not binding then the regulator's solution is isomorphic to the Coasean bargaining outcome and will actually achieve first best.

$$\max_{(I,p)} B(X) \qquad \text{s.t.} \quad X(p + \mu_\epsilon I) \leq G \tag{3.4}$$

With the inclusion of indemnity payments, the government expenditure for any given PES contract (I, p) is now stochastic meaning that there are multiple ways to formulate a budget constraint for the regulator. Equation (3.4) formulates the budget constraint in terms of expectations where μ_ϵ is the expected value of the cost shock which can be justified on the grounds of having a large beneficiary population (Arrow and Lind, 1970). Alternatively, the budget constraint can be formulated in probabilistic or extreme terms, e.g., the probability that the regulator's expenditure exceeds G is less than some threshold or the budget constraint can be formulated to ensure that the budget will not be exceeded in the event of an extreme shock (where all agents experience shock $\epsilon_i = e$).

3.4 When are indemnity payments optimal?

The formulation of (3.4) differs slightly from the standard linear pricing PES contracts. The standard linear pricing PES contract takes $I = 0$ as given, i.e., there is never any indemnity payments and is usually so for exogenous reasons rather than a result of the regulator behaving optimally. As a reminder, this is referred to as the pure payment contract while the optimal contract refers to the case where the regulator optimally chooses both I and p. The central question here is whether the regulator can achieve a higher indirect social benefit function when the constraint $I = 0$ is relaxed. In other words, when is it optimal for the regulator to share the risk of supplying ES inputs with the ES input suppliers?

Proposition 3.4.1 *Given the ES supply function $X = \sum_i x_i^*$, where x_i^* is the solution to (3.2), it is optimal for the regulator to offer a positive indemnity rate ($I > 0$) if and only if agents are risk averse.*

Proof: The goal is the show that the planner can achieve a higher level of indirect social value when $I = 0$ is relaxed. First, let I be a parameter in the planner's problem. The planner then solves the Lagrangian (3.5) where ψ is the multiplier (distinct from the multiplier λ in (3.4)).

$$\mathcal{F} = \max_{p} \quad B(X) + \psi(G - X(p + \mu_\epsilon I)) \tag{3.5}$$

The goal can be equivalently stated as wanting to show that $\frac{\partial \mathcal{F}}{\partial I} > 0$. We can use the Envelope Theorem to characterize this partial.

$$\begin{aligned} \frac{\partial \mathcal{F}}{\partial I} &= B'(X)\frac{\partial X}{\partial I} - \psi\left(\frac{\partial X}{\partial I}(p + \mu_\epsilon I) + X\mu_\epsilon\right) \\ &= \frac{\partial X/\partial I}{\partial X/\partial p}\left[B'(X)\frac{\partial X}{\partial p} - \psi\frac{\partial X}{\partial p}(p + \mu_\epsilon I)\right] - \psi X\mu_\epsilon \end{aligned} \tag{3.6}$$

The first order condition in (3.5) is given by $B'(X)\frac{\partial X}{\partial p} - \psi\frac{\partial X}{\partial p}(p + \mu_\epsilon I) = \psi X$ so then we can write

$$\frac{\partial \mathcal{F}}{\partial I} = \left(\frac{\partial X/\partial I}{\partial X/\partial p} - \mu_\epsilon\right)\psi X \tag{3.7}$$

Since every term is positive, then we have that $\frac{\partial \mathcal{F}}{\partial I} > 0$ if and only if $\left(\frac{\partial X/\partial I}{\partial X/\partial p} - \mu_\epsilon\right) > 0$. Next, we show that this always holds when agents are risk averse.

We first show that the ES supply response to indemnity ($\frac{\partial x}{\partial I}$) can be expressed as in (3.8 by taking derivative of the FOC wrt to I.[10]

$$\frac{\partial x}{\partial I} = \frac{\mu_{u'\epsilon} + x\mu_{u''\Gamma\epsilon}}{\mu_{u'}g_{xx} - \mu_{u''\Gamma^2}} \tag{3.8}$$

Where $\mu_z \equiv \mathbb{E}[z]$ and $\Gamma = \frac{\partial c}{\partial x} = p - g_x(x) - \epsilon(1 - I)$. Then using the fact that

$$\mathbb{E}[u'(c)\epsilon(1 - A\Gamma x)] = Cov(u'(c)(1 - A\Gamma x), \epsilon) + \mathbb{E}[u'(c)(1 - A\Gamma x)]\mu_\epsilon$$

[10]Note that small x denotes individual ES input while big X denotes aggregate ES input.

and using (3.9) gives (3.10).

$$\frac{\partial x}{\partial p} = \frac{\mu_{u'} + x\mu_{u''\Gamma}}{\mu_{u'}g_{xx} - \mu_{u''\Gamma^2}} \tag{3.9}$$

$$\begin{aligned} \frac{\partial x/\partial I}{\partial x/\partial p} &= \frac{\mathbb{E}[u'\epsilon(1 - A\Gamma x)]}{\mathbb{E}[u'(1 - A\Gamma x)]} \\ &= \frac{\widetilde{\sigma}}{\mathbb{E}[u'(c)(1 - R\delta)]} + \mu_\epsilon \end{aligned} \tag{3.10}$$

Where $\widetilde{\sigma} = Cov\Big(u'(c)(1 - A\Gamma x), \epsilon\Big)$ and $\delta = \frac{\Gamma x}{c} = \frac{xp - g_x x - x\epsilon(1-I)}{w + xp - g(x) - x\epsilon(1-I)}$ and A and R are the coefficient of absolute and relative risk aversion, respectively. We can rewrite $\widetilde{\sigma}$ as

$$\widetilde{\sigma} = Cov(u'(c)(1 - R\delta), \epsilon)$$

Note that $\mathbb{E}[u'(c)(1 - A\Gamma x)] = \mathbb{E}[u'(c)(1 - R\delta)]$ is then numerator in (3.9) which is always positive according to Lemma 3.3.1. Then (3.10) implies that (3.7) is positive if and only if $\widetilde{\sigma} > 0$. Since $u'(c)$ is increasing in ϵ and δ is decreasing in ϵ then $\widetilde{\sigma} > 0$. However, when agents are risk neutral ($R = 0$), then (3.7) equals zero, i.e., $\Big(\frac{\partial x}{\partial I} = \frac{\partial x}{\partial p}\mu_\epsilon\Big)$. Then according to (3.7), risk neutrality implies that there is never any change in regulator's objective function for any change in I. ■

Under both optimal and pure payment contracts, the regulator's budget will always be exhausted. If the regulator wanted to increase the indemnity rate I from zero, then their expenditure will increase by $X\mu_\epsilon$ (assuming no supply responses) but then the pay rate p must be reduced which lowers their expenditure by X. However, increasing I and decreasing p will lead to countering effects on the supply of ES inputs X which has further impacts on the budget. Thus, (3.7) from the proof of Proposition 3.4.1 simply says that in order for this budget reshuffling to be optimal, the increase in X in response to an increase in I must outweigh the decrease X in response to the required decrease in p.

This point can be further illustrated by looking at (3.11) where (3.11a) shows that increasing I increases regulator's expected expenditure (i) through an increase in supply X and (ii) through increasing the amount paid on existing supply $X\mu_\epsilon$ in expectation. Then to re-balance the budget, a decrease in p is needed leading to lower spending on existing supply X and by lowering the total ES offered. Suppose that the condition from Proposition 3.4.1 holds with equality ($\partial X/\partial I = \partial X/\partial p \cdot \mu_\epsilon$). Then a one unit increase in I requires p to decrease by μ_ϵ for budget balance. This woulds result in zero change in ES input. If the condition from Proposition 3.4.1 holds with strict inequality, then the pay rate p would have to decrease by more than μ_ϵ to balance the budget but will still result in a higher X. For instance, suppose $\partial X/\partial p \approx 0$ so that the required decrease in p equals $\mu + Z$ since it would have to compensate for increasing I which increases expenditure through two channels. However, the X would clearly be higher and so this reshuffling is optimal for the regulator.

$$\frac{\partial G}{\partial I}dI = \left[\frac{\partial X}{\partial I}(p + I\mu_\epsilon) + X\mu_\epsilon\right] dI \tag{3.11a}$$

$$\frac{\partial G}{\partial p}dp = \left[\frac{\partial X}{\partial p}(p + I\mu_\epsilon) + X\right] dp \tag{3.11b}$$

Proposition 3.4.1 is quite important as it shows that the regulator can always extract more social value given a fixed budget G by offering indemnity payments when agents are risk averse. This may leave the reader wondering, when does the condition from Proposition 3.4.1 hold?

3.5 Optimal Indemnity Under Risk Aversion

After establishing the fact that it is always optimal for the regulator to offer positive indemnity when agents are risk averse, one important question still remains. What is the optimal level of indemnity that the regulator should offer? As it turns out, the intuition in the above section suggests that it is optimal to offer full indemnity ($I = 1$) when the curvature around point A is sufficiently steeper than around B.

Proposition 3.5.1 *When agent's are risk averse then it is optimal for the regulator to offer full indemnity, i.e., $I^* = 1$.*

Proof: The proof follows directly from looking at the proof for Proposition 3.4.1 and noting the fact that $\frac{\widetilde{\sigma}}{\mathbb{E}[u'(c)(1-R\delta)]} > 0$ holds at all levels of $I < 1$ and that at $I^* = 1$, the FOC from (3.7) fails to hold with equality meaning that the solution is at a corner one of which is ruled out by Proposition 3.4.1, hence $I^* = 1$. ■

One way to visualize the result from Proposition 3.5.1 is to look at the iso-G (iso budget) and iso-X (iso supply) curves in Figure C.1. The slope of the iso-G curve can be found by total differentiating the budget equation in (3.4) and total differentiating $X(I,p)$. In Appendix C.2 I show that the slope of the iso-X curve is always steeper than that of the iso-G curve when the condition from Proposition 3.4.1 holds implying that the solution always occurs at $I = 1$.

3.5.1 Graphical Argument

The graphical intuition for Proposition 3.4.1 can be illustrated with a simple example. Consider the case where the choice variable x is binary either 0 or 1, the cost shock is also binary either 0 or e, and agents differ only in their cost of provisioning, g. Then the pivotal agent's decision problem can be summarized by graphing their indifference curve over state-contingent consumption space (c_b, c_g) as in Figure C.2 where c_b and c_g are consumption levels under bad and good states.

When agents are risk neutral ($R = 0$), their indifference curve is a straight line with slope $\frac{\pi}{1-\pi}$ where $\pi = \mathbb{P}(bad\ state) = \mathbb{P}(\epsilon = e)$. Point A_0 would be the pivotal agent's consumption bundle under the PES with no indemnity where $a_0 = \omega + p_0 - g$ and $b_0 = \omega + p_0 - g - e$. By definition, the pivotal agent is indifferent between A_0 and C which implies that $p_0 = \mu_\epsilon + g = \pi e + g$. Now imagine the regulator decides to switch from $I = 0$ to $I = 1$ while holding $p = p_0$. This then pushes the pivotal agent's consumption bundle under PES participation to the 45 degree line (going from A_0 to B_0) which is a horizontal shift equal to e. If the regulator stays at this policy point $(1, p_0)$, then the increase in ES supply is proportional to the distance CB_0. But budget balancing requires a reduction in p which moves the consumption bundle towards the origin along the path of the 45° line.[11] Proposition 3.4.1 says that, at B_0, if the decrease in p_0 required for budget balancing is higher than μ_ϵ, i.e., need to go from B_0 to P_1, then it is not optimal to provide any indemnity. This is because the ES supply at P_1 is strictly less than that at A_0. Whereas if the budget balancing decrease in p_0 is less than μ_ϵ, i.e., need only go form B_0 to P_0, then it is optimal for the regulator to offer positive indemnity since the regulator will always achieve budget balance and being at P_0 offers higher ES supply than A_0. It turns out though that the going from B_0 to C will exactly balance the budget and thus, there is no value added or lost from offering full indemnity which is consistent with Proposition 3.4.1.

However, when agents are risk averse ($R > 0$), then the pay rate under the pure payment contract p_1 has to be greater than that under the optimal contract $p_0 = \mu_\epsilon + g$

[11] Any change in p shifts agents' bundles towards the origin on a path parallel to the 45° line. Changes in I shift bundles horizontally.

in order for the same agent to be indifferent between the consumption bundles from not participating (C) and from participating (A_1). Now if the regulator decides to go from no indemnity to full indemnity (from A_1 to B_1), then the ES supply increase is much higher relative to the risk neutral scenario as B_1 is much further up on the 45° line than B_0. However, the ES supply response to changes in p is always the same no matter the risk averse behavior. Consequently, the budget balancing required reduction in p_1 is the same as the required reduction in p_0 from the risk neutral case.

3.6 Value Added from Indemnity

One may still be wondering how big is the value added from having optimal indemnity alongside the standard linear pricing PES contracts? In both contracts, the regulator's budget constraint will hold with equality in expectation so that the value added V is given by (3.12) where $X_1 = X(1, p(1))$ represents the aggregate ES input supply under the optimal contract and $X_0 = X(0, p(0))$ represents the aggregate ES input supply under the pure payment contract.

$$V = B(X_1) - B(X_0) \tag{3.12}$$

Equation (3.12) implies that the gain from optimal indemnity PES relative to the pure payment PES is a function of two determinants. First, if the curvature of the expected social benefit function around the neighborhood of X_0 and X_1 is high, then the value added would be higher. Second, if the difference $X_1 - X_0$ is high then so too would be the value added. What makes the difference between these two ES input supplied great has to do with risk tolerance. This boils down to how much can offering indemnity payments allow the regulator to relax $p(I)$, the conditionally optimal pay rate? To see this, note that equation (3.10) is an increasing function of A and R. Not only that, increasing the risk aversion increases the ratio in (3.10) everywhere over I. Hence being able to estimate risk aversion allows researchers to estimate the proper policy and the magnitude of the gain.

Table C.1 shows simulation results using estimates of risk aversion from Elminejad, Havranek and Irsova (2022) and assuming CRRA utility. Using the parameters from Table C.1 and randomly generated ES supply costs and initial wealth values (distributions shown in Figure C.3), we numerically solve the planner's problem in (3.5) once for $I = 0$ and another for $I = 1$ which then allows the calculation of value added. This is then repeated for each risk aversion parameter in Table C.1. The results show that the value added from the optimal contract relative to the pure payment contract increase with risk aversion and can range from 5.56% to 42.5% increase in ES supply.

3.6.1 Estimating R

Table C.1 is only useful for practitioners if there is a way to estimate risk aversion for any given PES setting with which to compare with the value added figures in the table. In Appendix C.3, I show that $\frac{\overline{A}_\Gamma}{\mu_\Gamma} < \overline{A} < R$ where $\overline{A}_\Gamma = \frac{-\mu_{u''\Gamma}}{\mu_{u'}}$ is *some* metric for absolute risk aversion and $\overline{A} = \frac{-\mu_{u''}}{\mu_{u'}}$ is the absolute risk aversion coefficient, loosely speaking. Therefore, estimating $\overline{A}_\Gamma$ is equivalent to estimating the lower bound for risk aversion R and thus a lower bound on the value added from implementing the optimal.

To estimate $\overline{A}_\Gamma$, we follow a similar procedure outlined in Chetty (2006) to derive a formula for $\overline{A}_\Gamma$ which I expressed as a function of the price elasticity of Hicksian ES input supply and the income elasticity of ES input supply. The intuition behind this approach is outlined in Chetty (2006) which utilized various labor supply elasticities to compute upperbounds for the coefficient of relative risk aversion with the idea being that labor supply responses to wage changes implies the curvature of the utility function which then gives rise the risk aversion parameter.

First, agents' choices on x (assuming an interior optimum) must satisfy the first order condition (3.2). Taking derivatives of their FOC and rearranging algebraically gives (3.13).

$$\frac{\partial x}{\partial p} = \frac{\mu_{u'} + x\mu_{u''\Gamma}}{\mu_{u'}g_{xx} - \mu_{u''\Gamma^2}} \tag{3.13a}$$

$$\frac{\partial x}{\partial w} = \frac{(1-g_{\omega})\mu_{u''\Gamma} - \mu_{u'}g_{x\omega}}{\mu_{u'}g_{xx} - \mu_{u''\Gamma^2}} \tag{3.13b}$$

Using Slutsky's decomposition (shown in Appendix C.4) for compensated ES input supply (h)

$$\frac{\partial h}{\partial p} = \frac{\partial x}{\partial p} - \frac{\partial x}{\partial \omega}x \tag{3.14}$$

then the ratio of the substitution effect and income effect is given by (3.15)

$$\frac{\partial h/\partial p}{\partial x/\partial \omega} = \left(\frac{\partial x/\partial p}{\partial x/\partial \omega} - x\right) \tag{3.15}$$

Then combining (3.13) with (3.15) and some algebraic manipulation gives our equation for the desired risk aversion metric (3.16).

$$\overline{A}_{\Gamma} = \frac{1 + g_{x\omega}\left(x + \frac{\varepsilon_{hp}}{\varepsilon_{x\omega}}\frac{\omega}{p}\right)}{(g_{\omega}-1)\left(\frac{\varepsilon_{hp}}{\varepsilon_{x\omega}}\frac{\omega}{p}\right) + x(g_{\omega}-2)} \tag{3.16}$$

Where ε_{hp} and $\varepsilon_{x\omega}$ are the price elasticity of Hicksion supply and income elasticity of supply, respectively. Thus to estimate R, one can simply estimate (3.16) and treat the estimate of $\frac{\overline{A}_\Gamma}{\mu_\Gamma}$ as the coefficient of relative risk aversion R. One downside is that estimate (3.16) is quite informationally demanding as it requires the researcher to estimate not only the substitution and income elasticities, but also various aspects of the ES cost function, g_ω and $g_{x\omega}$. However, if one is able to establish that the cost function does not change with income $g_\omega \approx 0$, then by Young's Theorem, the marginal cost will not change either $g_{x\omega} \approx 0$ which will simplify (3.16) to (3.17). Note that $g_\omega = 0$ implies that $\varepsilon_{x\omega} < 0$ which makes (3.17) much easier to estimate.

$$\overline{A}_\Gamma = \left[-\frac{\varepsilon_{hp}}{\varepsilon_{x\omega}}\frac{\omega}{p} - 2x\right]^{-1} \tag{3.17}$$

3.7 Additionality and Poverty Alleviation

In practice, private agents may produce strictly positive levels of the ES input in the absence of a PES program and therefore there is considerable interest in the literature and policy arena on the idea of additionality. That is, researchers and policy makers want to make sure that the ES inputs being contracted for are *additional* and hence would not have been procured in the absence of a PES program. It is often very costly to monitor additionality for all program applicants which could render simple linear contracts, like the one proposed above, inefficient. There are many papers that try to create a mechanism to generate a separating equilibrium that is efficient (Mason and Plantinga, 2013). However, this is only necessary when the regulator cannot observe types which is something of the opposite extreme. There are characteristics of households that are cheaply observable such as income or wealth. Then a natural question is when does additionality decrease (or increase) with wealth? Policy makers are often interested in this as this directly answers the question of when is it optimal to have the dual objective of increasing ecosystem services and providing poverty alleviation. Additionality can be defined as

$$\alpha_i = x_i^* - x_i^{bau} \tag{3.18}$$

It is clear from (3.18) that additionality decreases with wealth if and only if (3.19) holds.

$$\frac{\partial x_i^*}{\partial \omega_i} \leq \frac{\partial x_i^{bau}}{\partial \omega_i} \tag{3.19}$$

Without functional form assumptions, however, evaluating (3.19) is quite difficult. Instead, Proposition 3.7.1 relies on the intuition that in order for additionality to decrease in wealth, the slope of the x^{bau} curve, when plotted against ω, cannot be too flat (shown in Figures C.4 and C.5). A sufficient condition for (3.19) to hold is for the x^* curve to be decreasing in ω while the x^{bau} curve is increasing. However, neither curve is necessarily required to be increasing or decreasing. What is necessary is for the difference between the two to be decreasing in ω, hence the restriction the slope of the x^{bau} curve.

Proposition 3.7.1 *Take PES contract (I, p) as given. Additionality decreases in wealth (poorer households have higher additionality) if the change in the business-as-usual level of ES input in response to a change in wealth is above some lower bound. Specifically, $\frac{\partial \alpha}{\partial \omega} < 0$ if and only if*

$$\frac{\partial x^{bau}}{\partial \omega} > \frac{\mu_{A\Gamma}(h_\omega - 1) - h_{\alpha\omega}}{\mu_{A\Gamma} h_\alpha + \mu_{A\Gamma^2}}$$

where $A = -\frac{u''(c)}{u'(c)}$ is the coefficient of absolute risk aversion, $\Gamma = p - h_\alpha - \epsilon(1 - I)$ is the random marginal return from chosen additionality α, $h(\alpha, \omega)$ is the deterministic cost function in terms of additionality α so that h_α, h_ω, and $h_{\alpha\omega}$ are all the partials with respect to the subscripts. The terms μ simply denote the expectation of the subscripted *variables.*

Proof: For the comparative statics on additionality α, it is easier to start with a reframing of the model where the agent's choice variable is $\alpha = x - x^b$ instead of x where $x^b = x^{bau}$ for simplicity. Thus consumption is given by

$$c = w + p(\alpha + x^b) - h(\alpha, \omega) - (\alpha + x^b)\epsilon(1 - I)$$

where $h(0, \omega) = g(x^b, \omega)$ and $h(\alpha^*, \omega) = g(x^*, \omega)$. Then the optimal additionality α^* is pinned by

$$\mathbb{E}\left[u'(c)\Gamma\right] = 0$$

where $\Gamma \equiv \dfrac{\partial c}{\partial \alpha}$. Then using the Implicit function theorem, we can differentiate this FOC WRT ω to get

$$\frac{\partial \alpha}{\partial \omega} = \frac{\mu_{A\Gamma}(1 - h_\omega + \frac{\partial x^b}{\partial \omega} h_\alpha) + \mu_{A\Gamma^2}\frac{\partial x^b}{\partial \omega} + h_{\alpha\omega}}{-\mu_{A\Gamma^2} - h_{\alpha\alpha}}$$

and since the denominator is negative, then $\frac{\partial \alpha}{\partial \omega} < 0$ if and only if the numerator is positive. ■

Proposition 3.7.1 states that in order for additionality to decrease in wealth, i.e., poorer agents having higher additionality, the business-as-usual ES input supply must increase in wealth beyond some threshold. In other words, the ES input supplied for poorer agents, in the absence of PES incentives, must be lower than those of wealthier agents and this difference must exceed a threshold. The reason for why a bound is neeed on the slope of x^{bau} only is because $\partial x^*/\partial \omega$ has the exact same functional form as $\partial x^{bau}/\partial \omega$ but the two are evaluated at different values for both x and (I, p). One important take away is that it is not sufficient for the marginal cost of ES input supply to be simply decreasing in wealth in order for additionality to decrease in wealth. That is because the if the marginal cost decreases in wealth, then both the business-as-usual and the PES input supplied will decrease in wealth too leaving the additionality ambiguous.

Lastly, the bound on $\partial x^{bau}/\partial \omega$ in Proposition 3.7.1 can be estimated if one could estimate aspects of the cost function and relevant elasticities from (3.16). However, one would still need to be able to gather sample data on x^{bau} which is often the difficult part. At the very least, the approach outlined in this paper can be used to motivate such an effort to gather this data. Doing so can go a long way to answer the question of when it is optimal for the regulator to pursue the dual objectives of promoting environmental quality and poverty alleviation.

3.8 Discussion

This paper shows that a regulator should couple indemnity payments with a standard linear pricing PES whenever the ES supply function is sufficiently more responsive to indemnity than it is to pay rate. Further, this condition (that ES supply function is sufficiently more sensitive to I relative to p) always holds when agents are risk averse but not when agents are risk neutral in which case, there are no gains or losses to the regulator from offering indemnity. This result is due to the fact that the risk neutral regulator can supply indemnity at a cost equal to μ_ϵ while risk averse agents are willing to pay more than that to get full indemnity. Lastly, the optimal level of indemnity with risk averse agents is full indemnity when agents exhibit risk aversion and is consistent with the insurance literature. Additionally, the social gain from switching to the optimal contract is increasing in the risk aversion and can range anywhere from 5% to 40% gain in ES supply. Finally, the theoretical results indicate that targeting low wealth households with a PES contract as a means achieving both poverty alleviation and environmental improvement can be optimal if the slope of the business-as-usual ES supply curve (plotted against wealth) is sufficiently steep.

For practitioners, I show how one could estimate a lowerbound on the value added by estimating a lowerbound on the risk aversion parameter R and certain moments of the ES input cost function, $g_{x\omega}$ and g_{ω}. The procedure is similar to Chetty (2006) and one important advantage of the approach outlined in this paper is that one can estimate the indemnity response of ES supply without needing to first have indemnity implemented in practice. Although it may still be demanding for researchers to estimate this lowerbound, the informational requirement is reduced greatly if it is possible to establish that the ES cost function is independent of wealth so that one need only estimate (3.17) rather than (3.16).

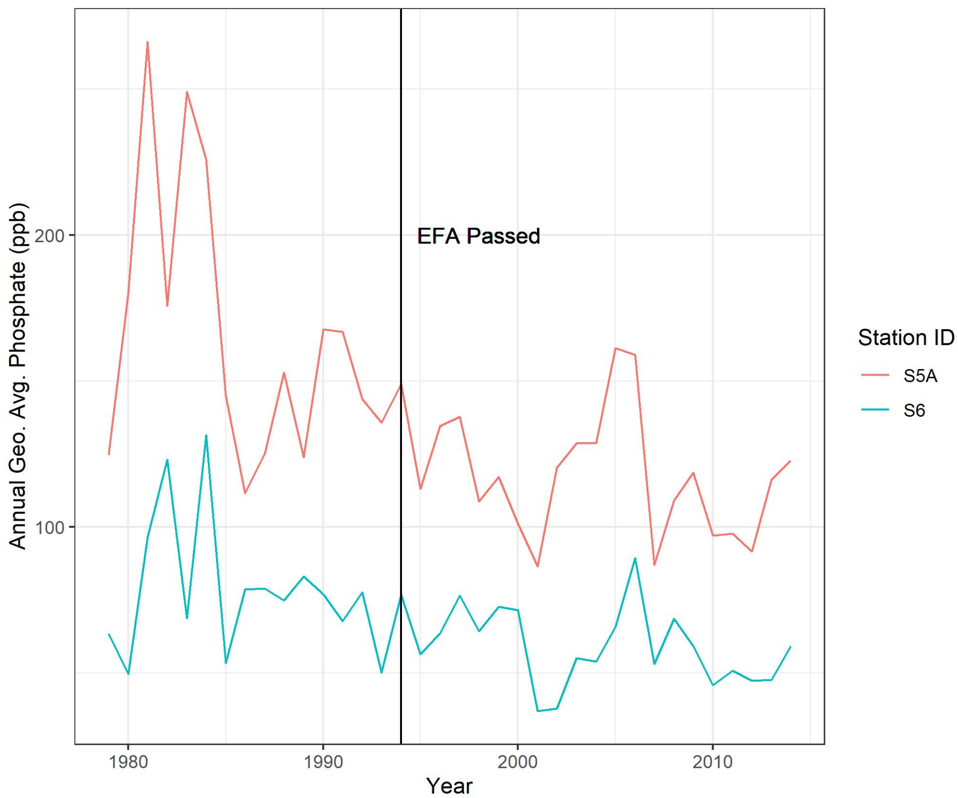
It is important to note that these results do not depend on the specific functional forms for utility, cost functions, nor the stochastic structure of the cost shock. Furthermore, these insights can easily be applied to output-based PES programs where indemnity can be linked to some environmental index similar to index insurance. However, we leave considerations of moral hazard for future studies but note that moral hazard can manifest itself in numerous ways. One of which is a "scale" response, i.e., the loss protection increases the risky activity which means increasing ES supply. This response works in favor of the regulator but it hurts a third party private insurer. On the other hand, indemnity may discourage activities that reduce the probability and/or the magnitude of a loss but do not affect ES supply. In the predation context, indemnity against depredation may decrease incentives to employ guardian dogs which negatively impact both the regulator and the private insurer's objectives.

Appendix A

Chapter 1 Appendix

A.1 Synthetic Control Method

In this section, I attempt to show that overall the EFA did reduce average total phosphorus loads attributable to the EAA. First, I plot a simple time series of the water quality readings from stations within the EAA before and after the EFA implementation shown in Figure A.1. This is suggestive evidence indicating that the policy did reduce phosphorus loads based on the apparent downward trend but it fails to take into account other different factors. Namely, that the state of Florida had implemented a host of other water quality improvement projects that directly impact the water received by our EAA region and elsewhere. In essence, the simple time series plot fails to capture the impacts of water quality improvement projects that occurred upstream of our EAA region but operated independently of the EFA. Such projects were done under the Comprehensive Everglades Restoration Plan that the state adopted which is a culmination of various court decrees, legislation, and directives from the EPA. A naive time series analysis would incorrectly attribute decreases in phosphorus concentrations downstream of the EAA soley to the EFA policy. In reality, only a fraction of that decrease can be attributable to the EFA while the remainder is a result of efforts of upstream constituents. To account for this, I conduct a synthetic control analysis using water quality monitoring stations from other regions in Florida (excluding parts down stream of our treated EAA region) as the potential control (donor) pool.[1]



The unit of analysis is at the water quality monitoring station level with a total of 21 potential donors and 2 treatment units (map of locations of donors and hydrological flow is shown in Figures A.4 and A.5 found in **??**). A station is assigned to be in the treated group if it resides immediately downstream of the EAA area and is used to monitor water quality coming out of the EAA.[2] Units in the treated group are only assigned the treated

[1]I exclude stations that lie downstream of the EAA region from being in the donor pool as well as stations that appear to lie in mostly urban areas.

[2]There are two other stations used to monitor water coming out of the EAA but they lie on the northern border adjacent with Lake Okeechobee. These stations are mostly used to measure quality of water that gets back pumped back into the lake during the wet season and can be a very noisy measure

status for years 1994 and after. I follow the approach from Cavallo et al. (2013) and Kreif et al. (2015) to run the synthetic control method with multiple treated units. The outcome variable is the annual geometric average of measured total phosphorus (ppb) and only one covariate is used which is the annual geometric average of measured nitrate (ppb).

The optimal weights (w_i) are chosen so that equation (A.1) is minimized over the pre-treatment periods between 1979 and 1993. Here I am assuming that only $i = 1$ belongs in the treatment group with $i = 2, \ldots, J + 1$ belonging to the donor group. However in this setting, there are two treated units and so (A.1) is done separately for both treated units.

$$\frac{1}{15} \sum_{t=1979}^{1993} (X_{1t} - w_2 X_{2t} - \cdots w_{J+1} X_{J+1,t})^2 \tag{A.1}$$

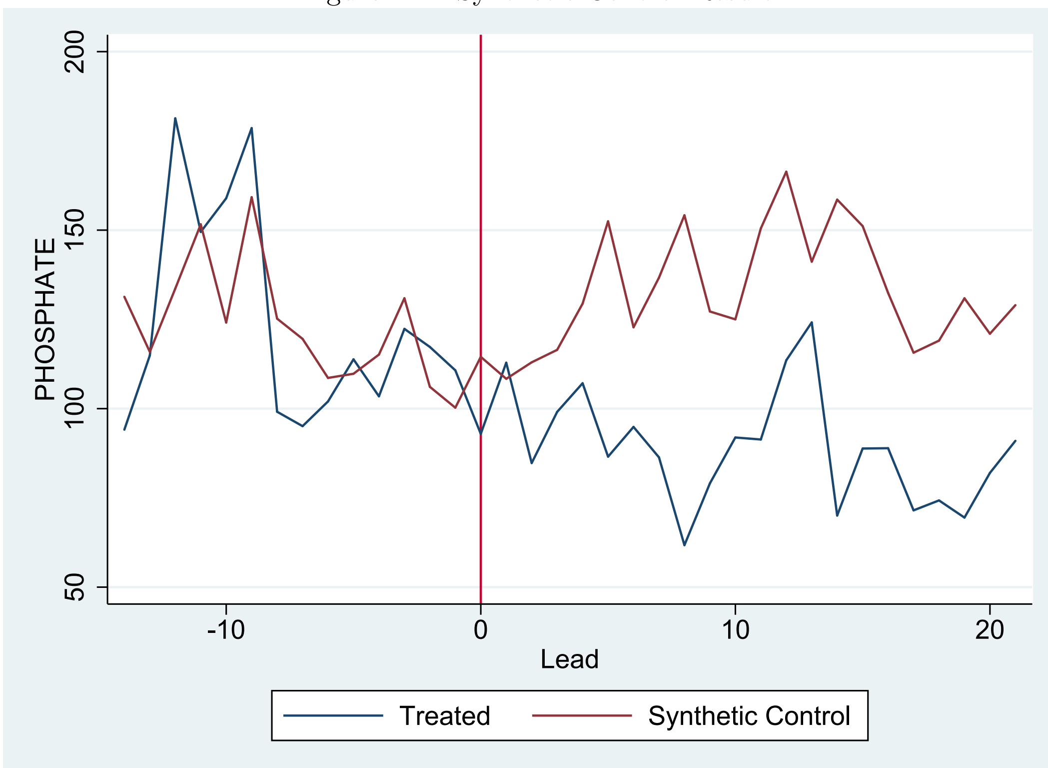
X_{it} denotes the annual geometric average phosphorus levels for station i and no other covariates are used.[3] Once the optimal weights are computed, average treatment effect, α_t, is calculated via (A.2) and the results of which are implicitly shown in Figure A.1.

$$\widehat{\alpha}_t = \frac{1}{2} \sum_{i=1}^{2} \left(X_{it} - \sum_{j=2}^{J+1} w_{ij}^* X_{jt} \right) \tag{A.2}$$

of overall trends in the EAA since only a few farms contribute to the readings of those stations.

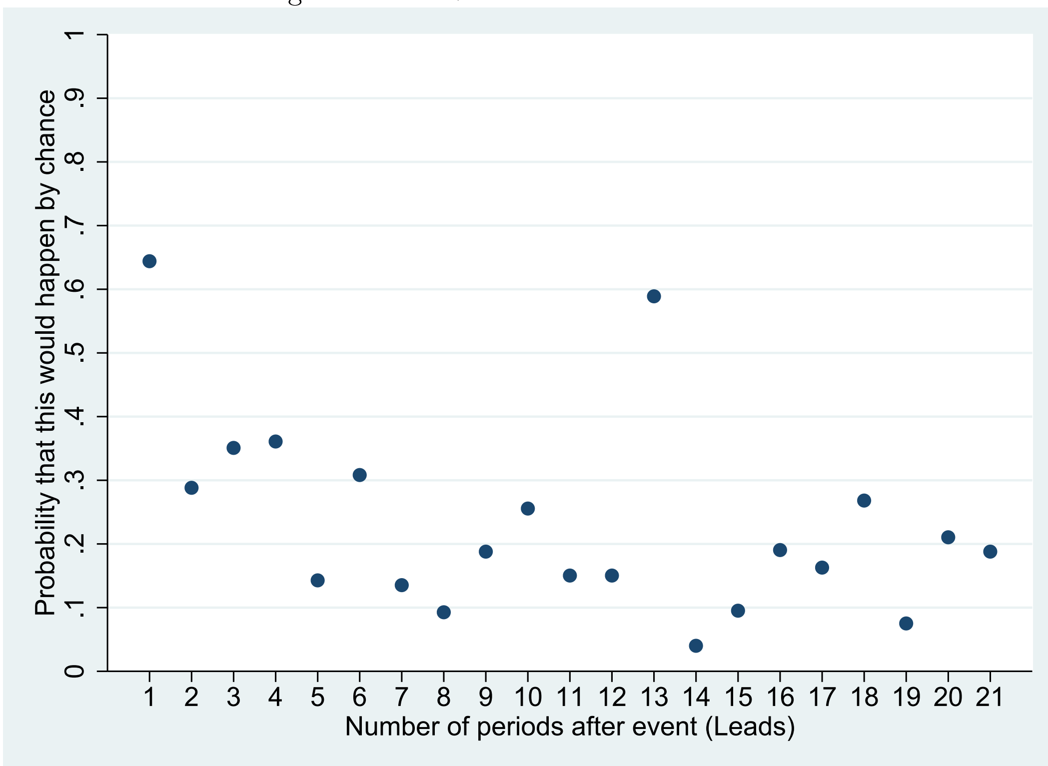
[3]Geometric average is used because measured phosphorus is a flow measure and in such instances, geometric averages provides a more accurate summary of the occurrences over time.

Figure A.1: Synthetic Control Result



Inference is done by using a permutation-placebo test where a control unit is randomly sampled from the donor pool with replacement. The randomly chosen control unit is then assigned as "treated", synthetic control weights are calculated and the corresponding estimated treatment effect is then calculated. This is done about 10,000 times until a distribution of treatment effects is available so that p-values can be calculated and the results are shown in Figure A.2. For some randomly chosen control units, the pre-treatment period matches may be quite poor resulting in large estimated treatment effects which ultimately leads to conservative p-values. Following Abadie, Diamond and Hainmueller (2010), control units with pre-treatment root mean squared prediction errors (RMSPE) greater than 10 times the RMSPE of the highest RMSPE from the actual treatment group, are excluded from this process. The attractive feature of calculating p-values in this way is that they are valid even if the treatment status is not randomly assigned.

Figure A.2: P-Values for Treatment Effects



There are a number of robustness I have implemented and the results are shown in Appendix A. First, I try to incorporate anticipatory effects by treating the "effective" policy implementation date as *if* it were in 1992. The actual policy implementation date was 1994 but the policy is a culmination of legal proceedings that occurred with public attention starting in 1992. The results of changing the intervention date are shown in Figures A.6 and A.7. I also try to follow the advice from Ferman and Pinto (2021) which suggests demeaning the data using pre-treatment means before running the weight computation in situations with poor pre-treatment fit (shown in Figures A.8 through A.11 in **??**). The results seem to be largely unaffected in these checks except for the demeaned version with captured anticipatory effects. Another explaination for the poor pre-treatment fit is that the outcome variable itself is a very noisy measure and applying some noise filtering can help improve pre-treatment matching and improve other qualities of the estimator but this is saved for future work.

A.2 General Figures and Tables

Table A.1: EAA Agricultural Privilege Tax Schedule

Calendar Year	Tax Per Acre	Per Acre Credit Rate	% Reduction Required for Individual Credits	Max Exercisable Credits (per acre)
1994-1997	$24.89	$0.33	30	0.00
1998-2001	$27.00	$0.54	35	3.91
2002-2005	$31.00	$0.61	40	10.02
2006-2013	$35.00	$0.65	45	15.55
2014-2026	$25.00	Tax Credits No Longer Available		
2027-2029	$20.00			
2030-2035	$15.00			
2036-after	$10.00			

Source: Florida CS/HB 7065 and Fl. St. 373.4592

Figure A.3: EAA Area with Canals/Drainages

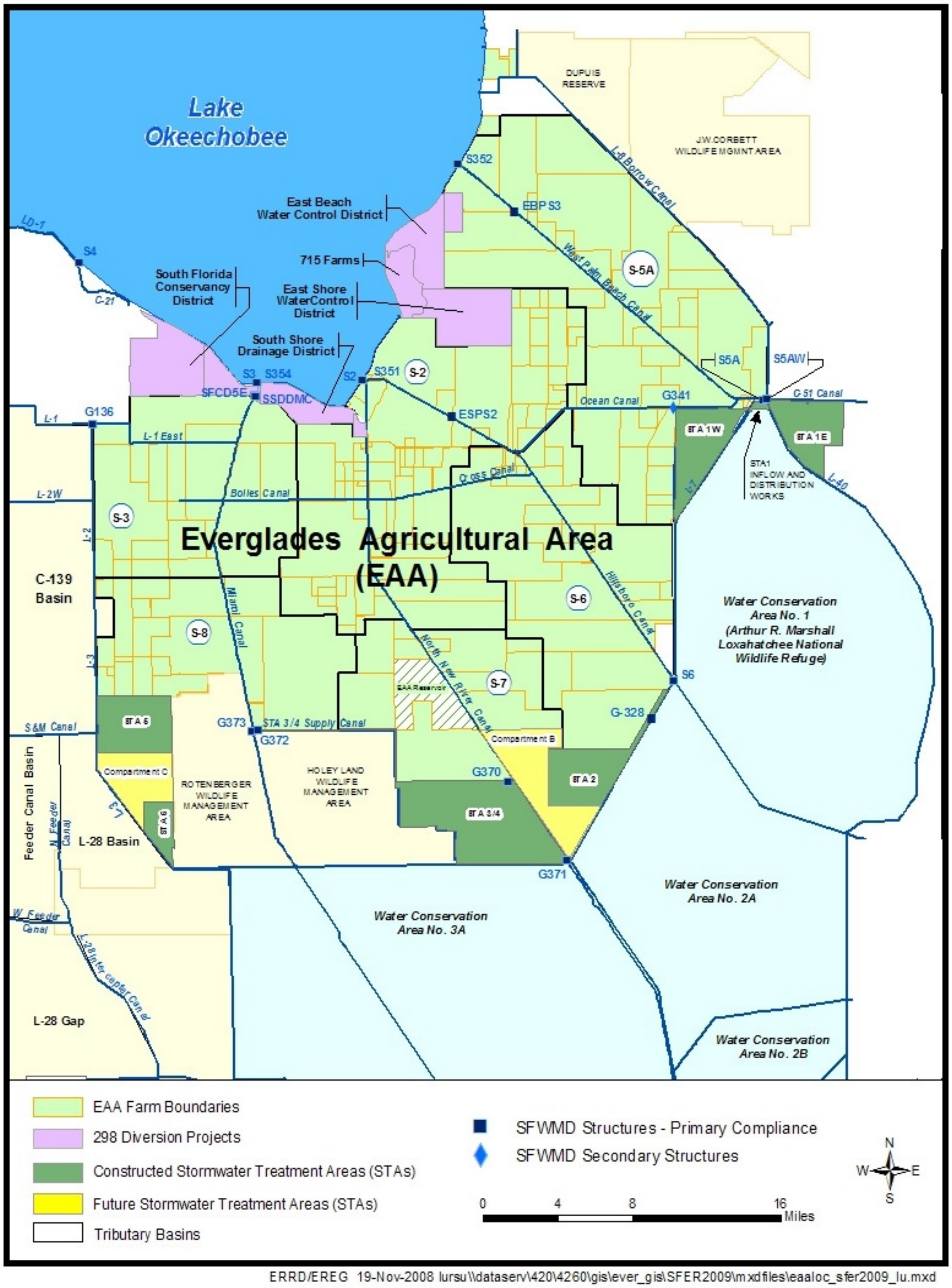


Figure A.4: Map of Donors for Synthetic Ctrl

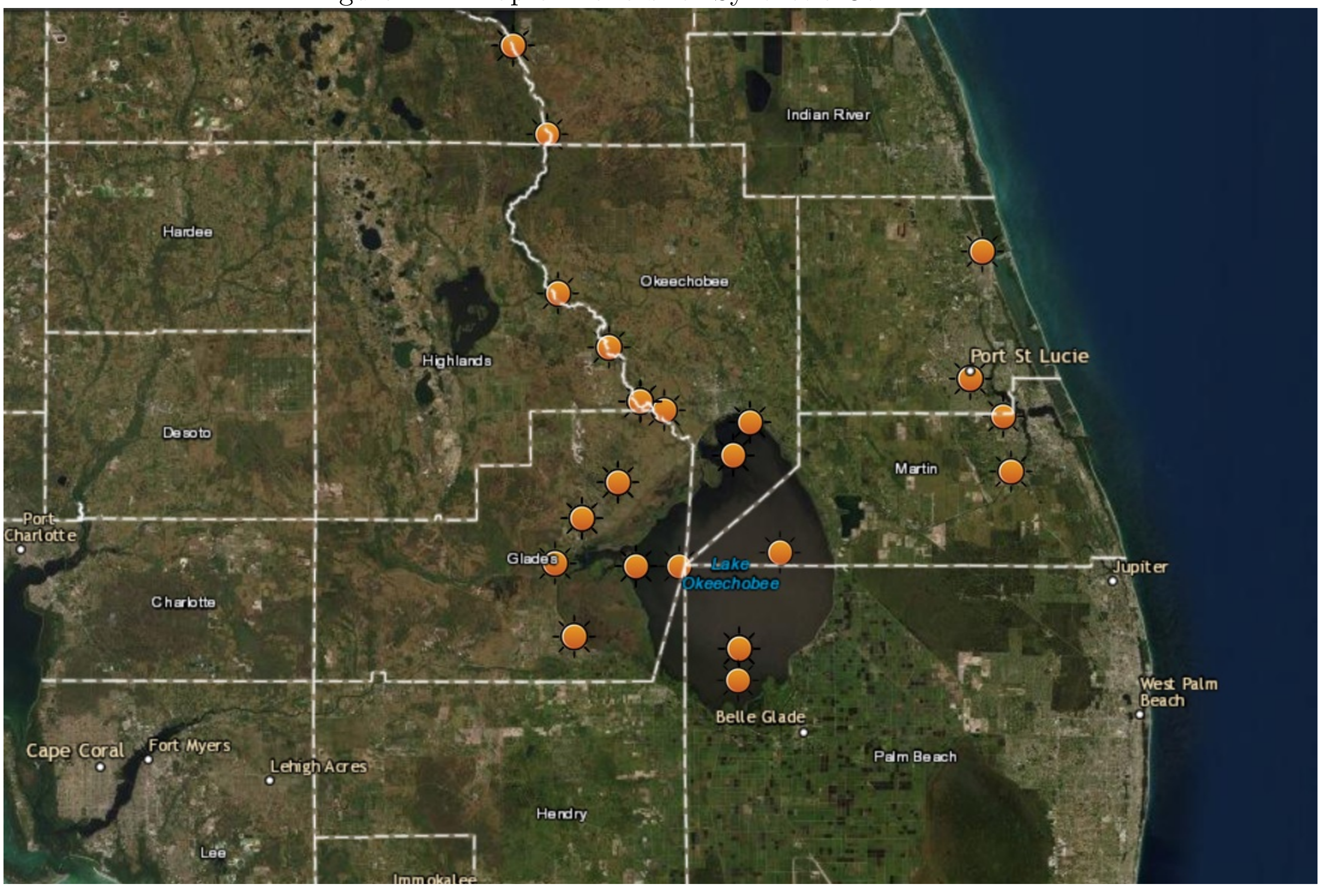


Figure A.5: Hydrological flow in Southern Florida

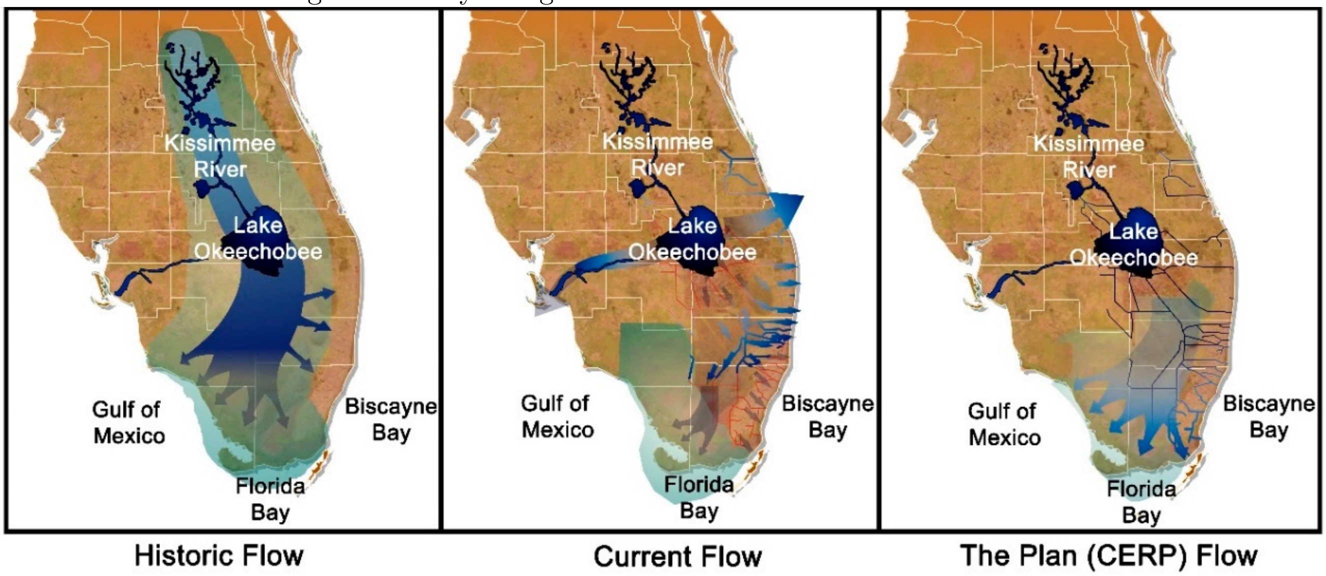


Figure A.6: Synthetic Control Result: Robustness to Anticipatory Effect

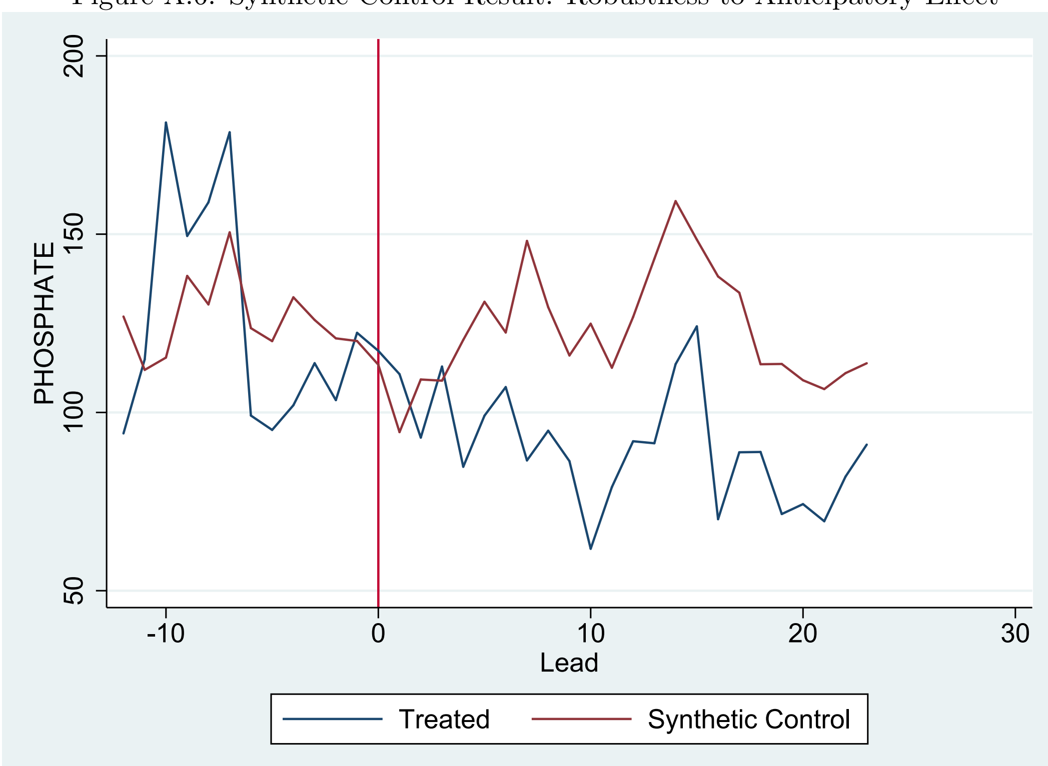


Figure A.7: P-Values for Treatment Effects: Robustness to Anticipatory Effect

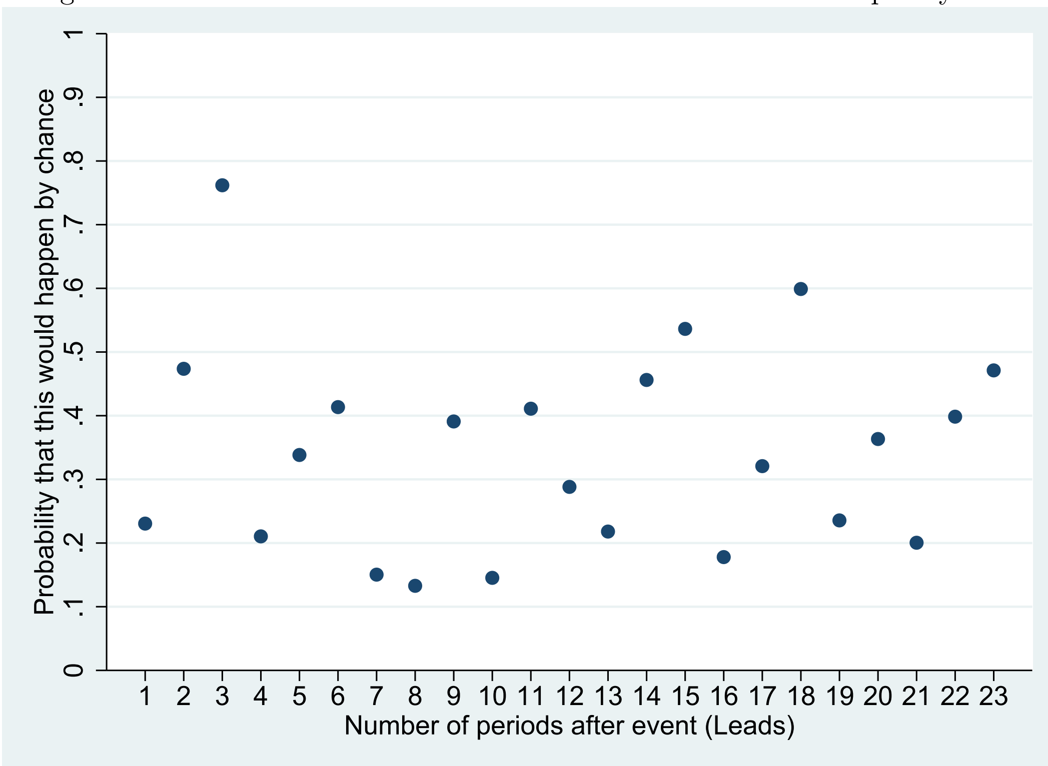


Figure A.8: Synthetic Control Result: Robustness to Demeaning

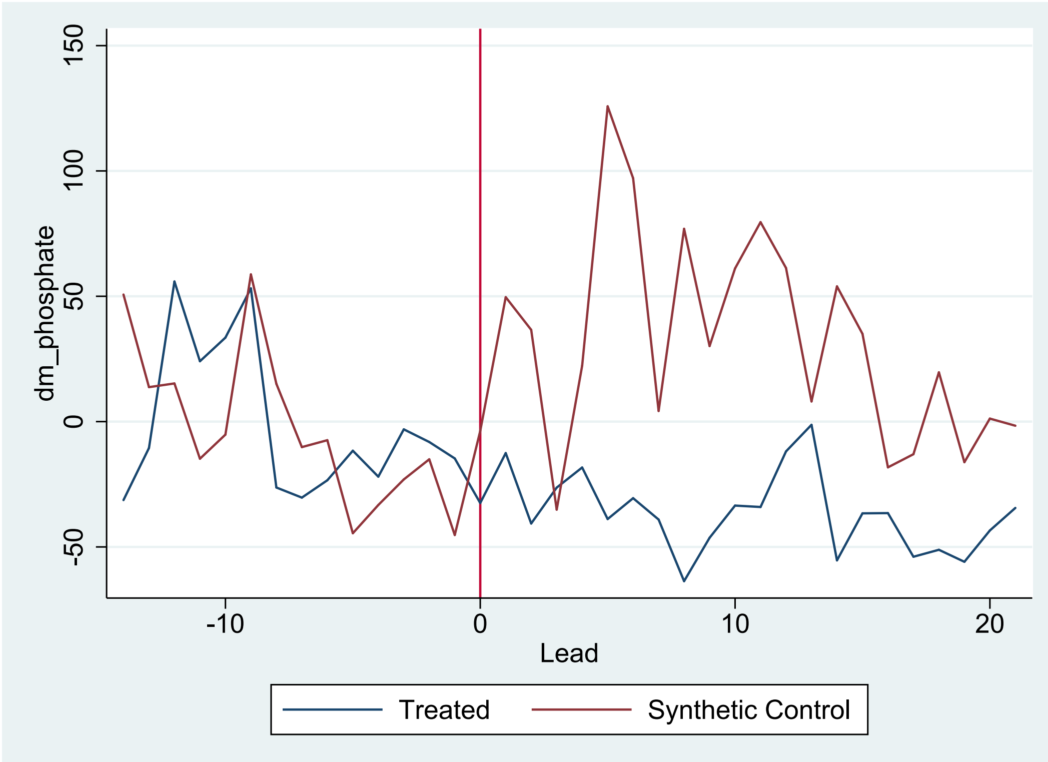


Figure A.9: P-Values for Treatment Effects: Robustness to Demeaning

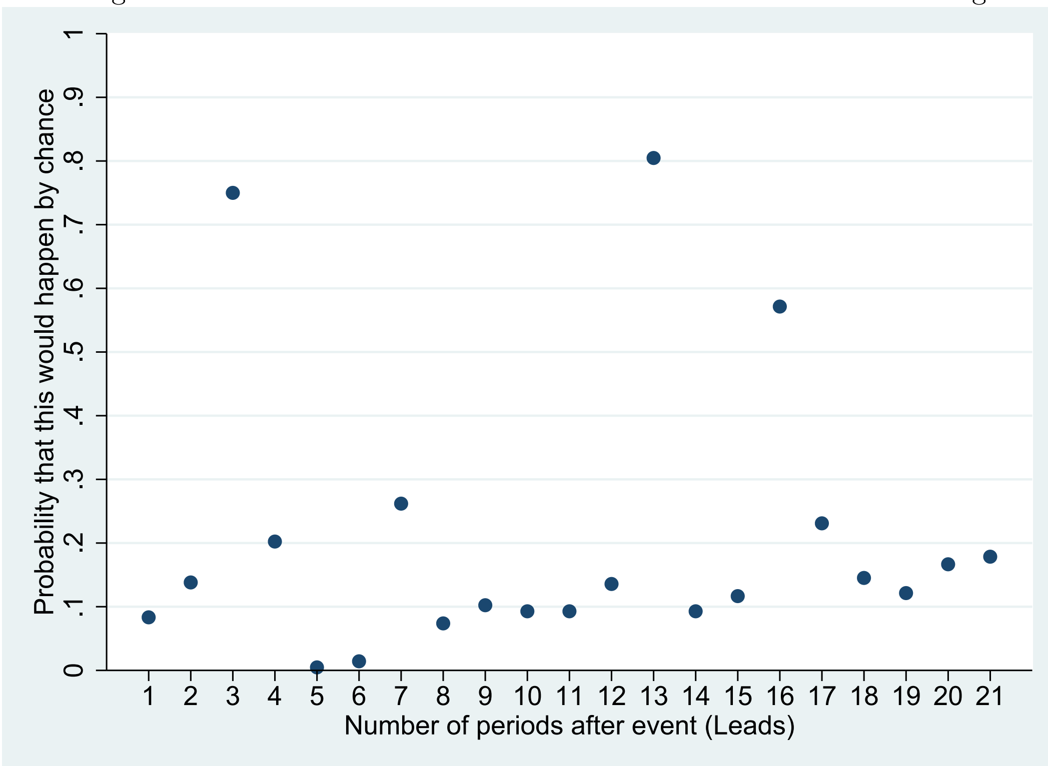


Figure A.10: Synthetic Control Result: Robustness to Anticipatory Effect & Demeaning

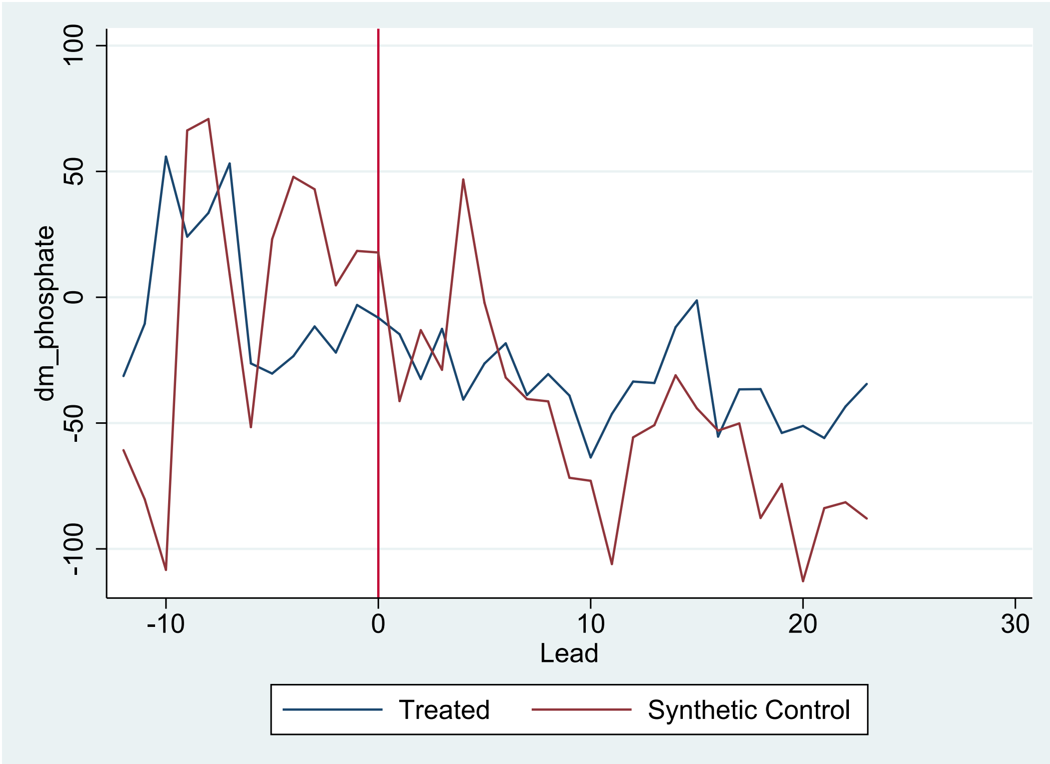


Figure A.11: P-Values for Treatment Effects: Robustness to Anticipatory Effect & Demeaning

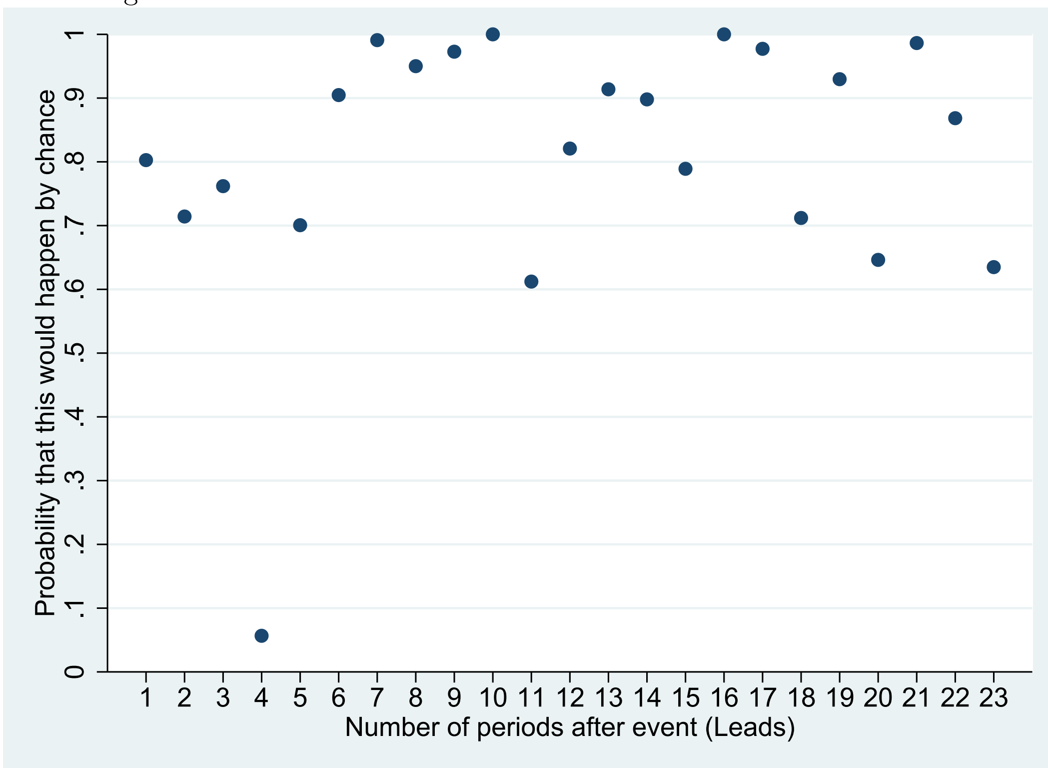


Figure A.12: Heatmap Distribution of D_{it}'s

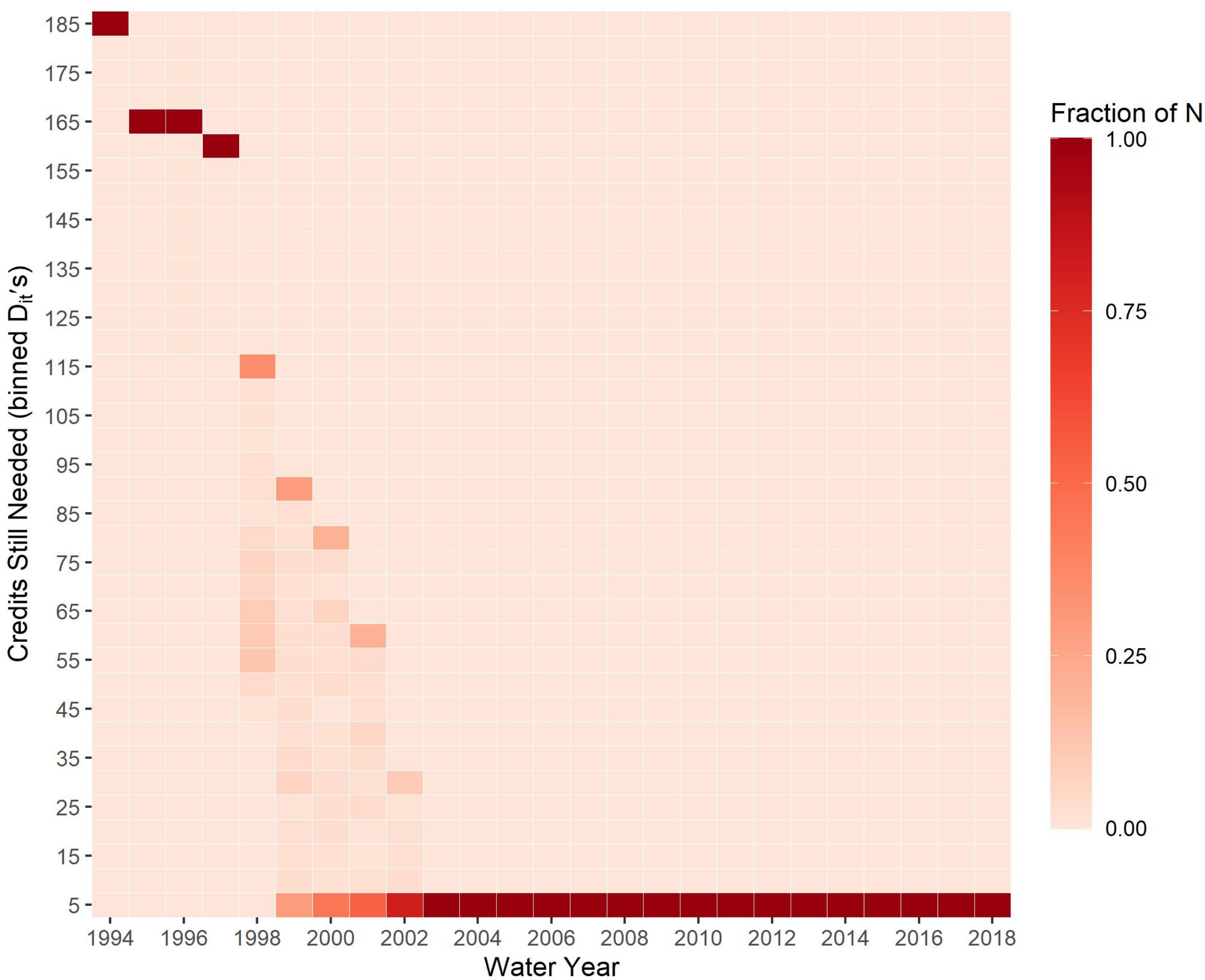


Figure A.13: Annual Average Phosphorus Loads by Cohort

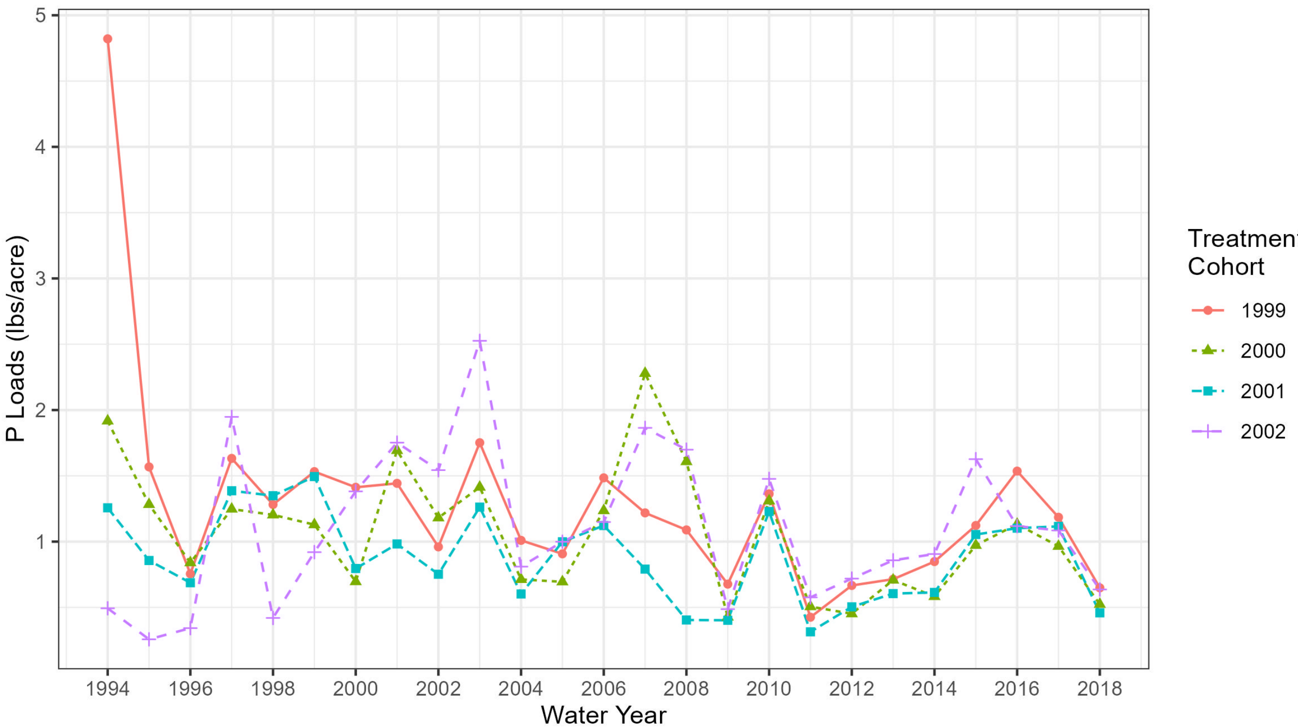


Figure A.14: Annual Average Land Size by Cohort

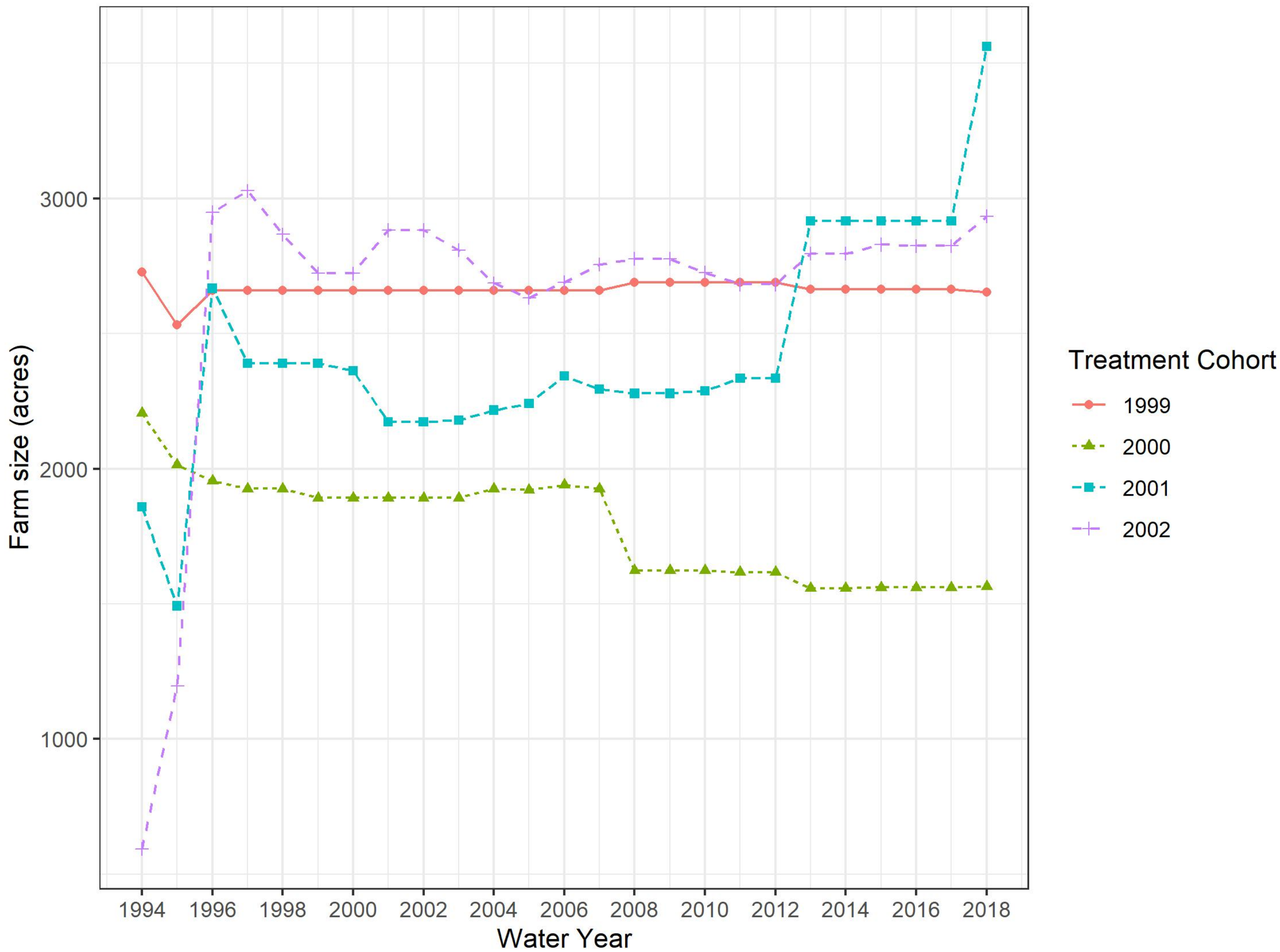


Figure A.15: Annual Average Acres Dedicated for Vegetable Production by Cohort

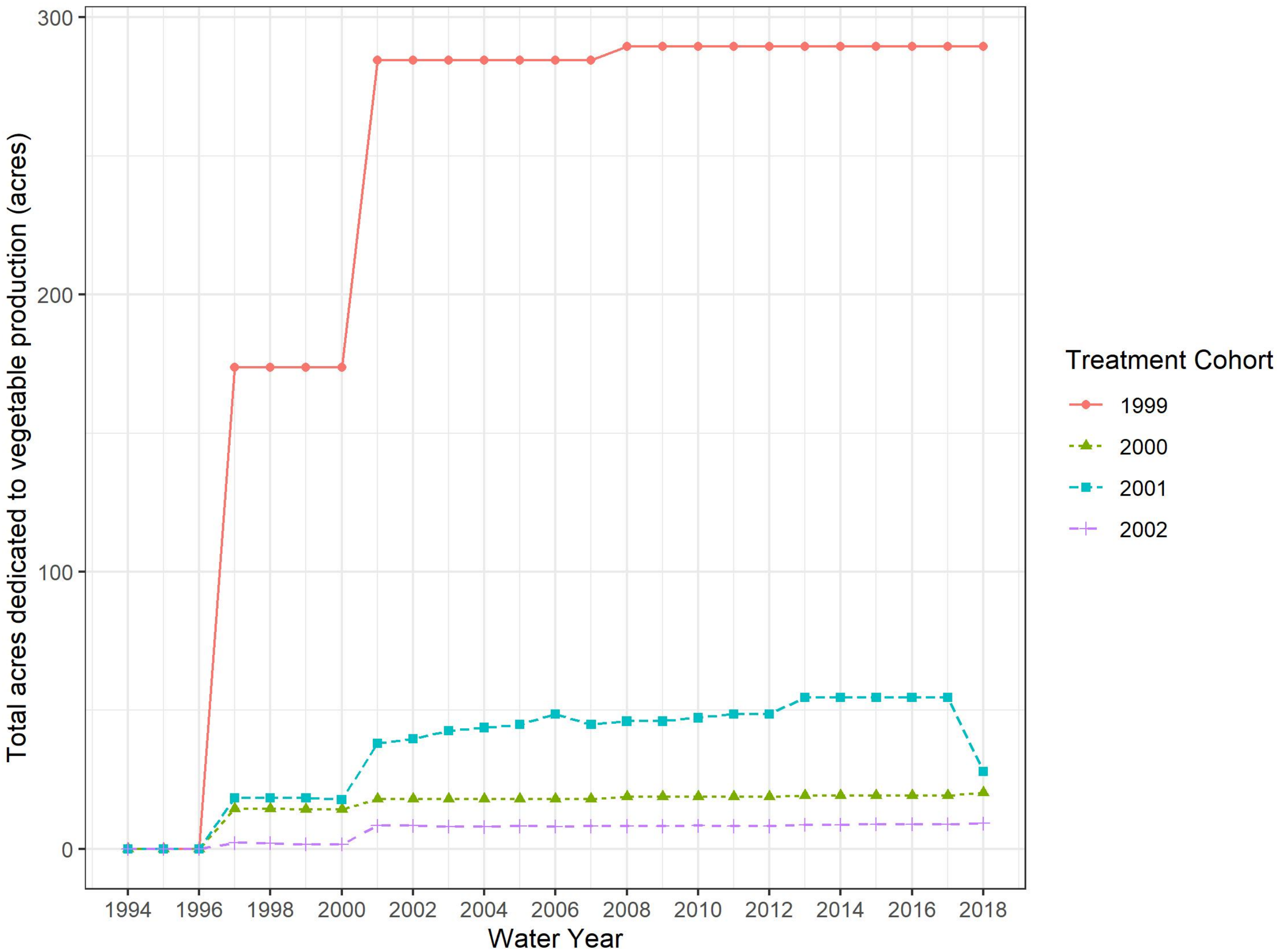


Figure A.16: Annual Average Distance from Lake Okeechobee by Cohort

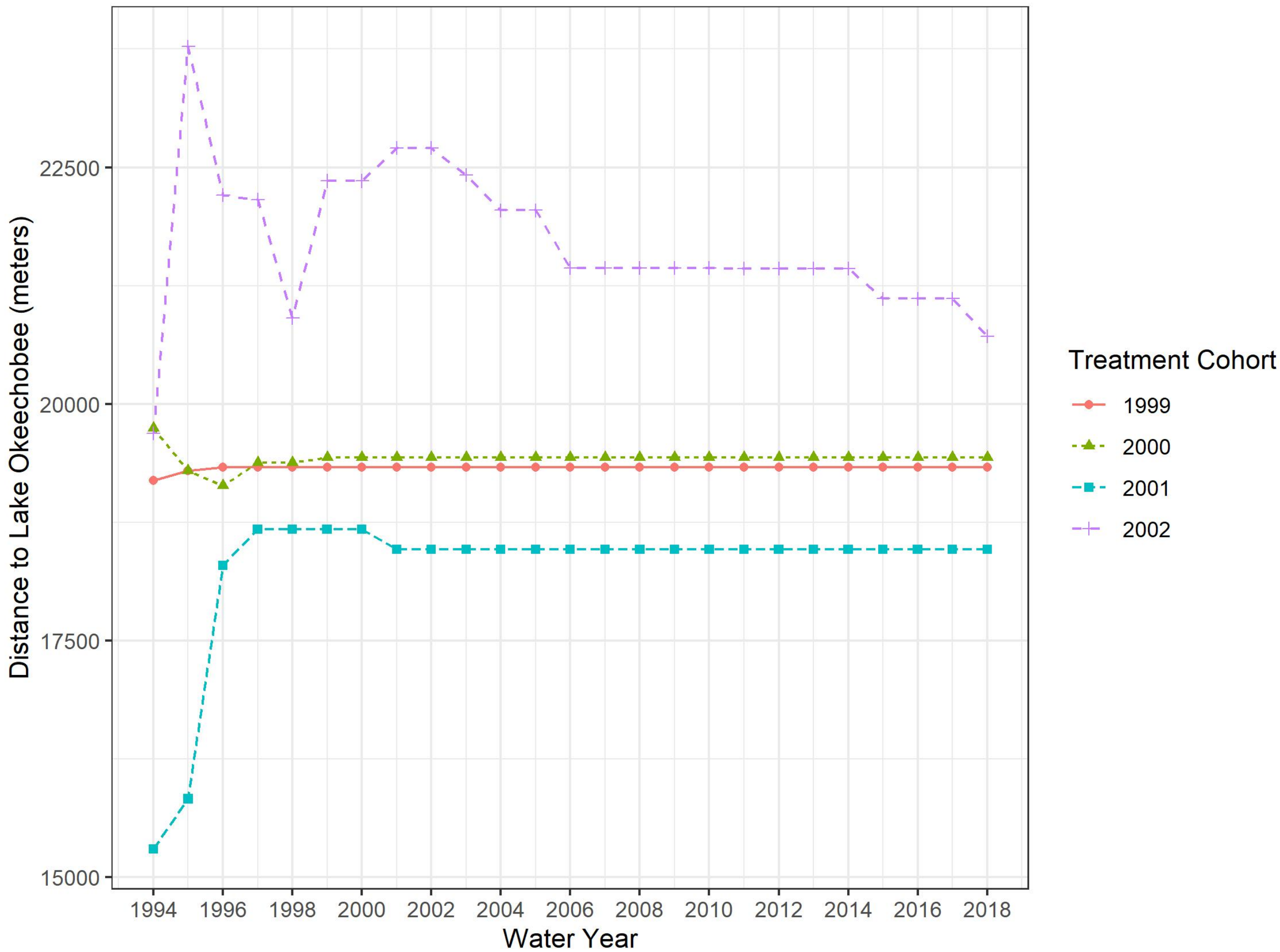


Figure A.17: Distribution of Baseline Year by Cohort

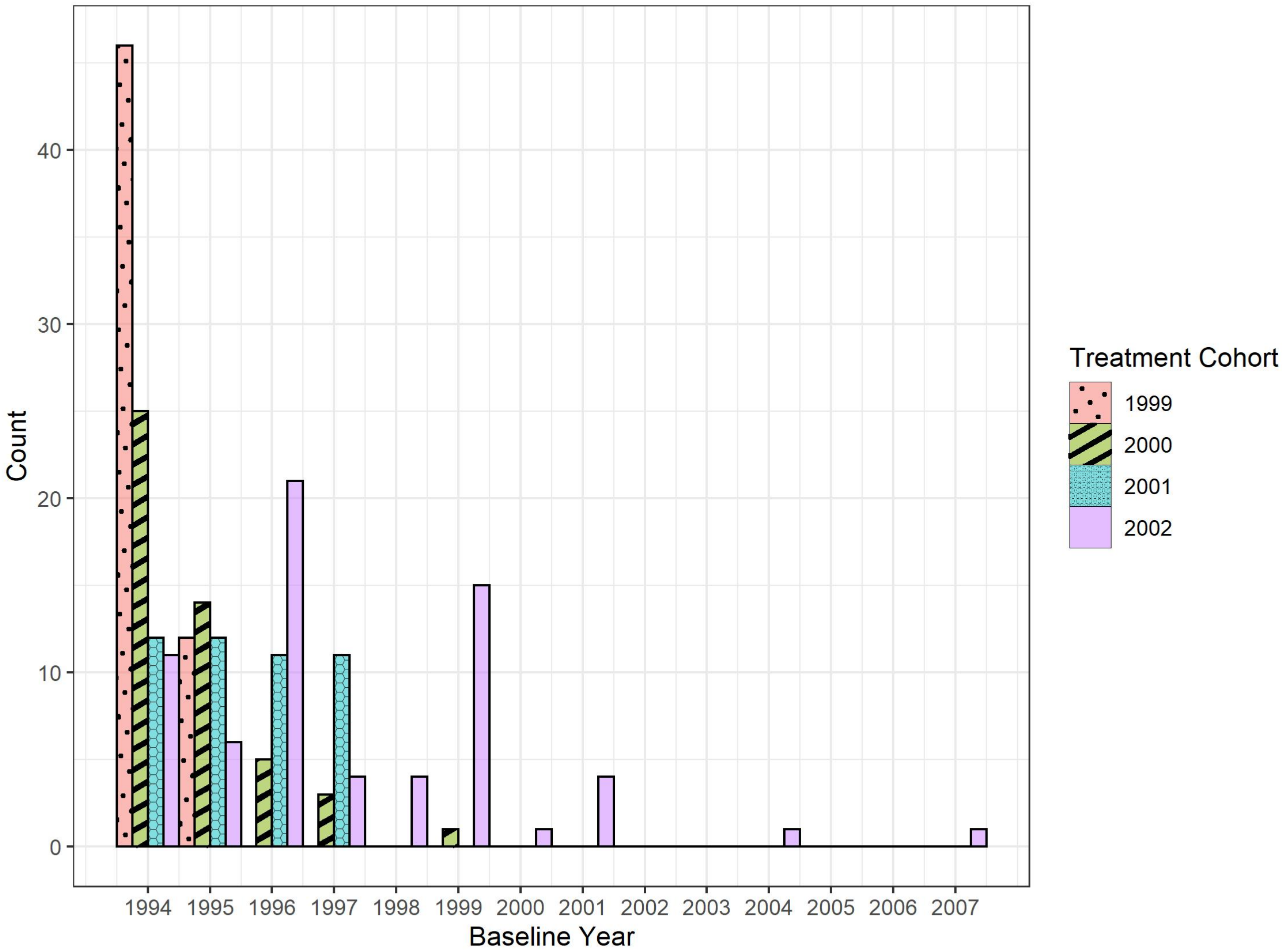


Table A.3: Two-step Difference GMM Results: Outcome is Estimated TP Reduction (%)

	exogenous controls	predetermined controls	Veg Acres Predetermined
rolling_incentives2	1.670	1.922	1.675
	(0.285)	(0.267)	(0.279)
interact2	-0.0000343	-0.0000334	-0.0000345
	(0.141)	(0.121)	(0.128)
Total Acres Dedicated to Vege	0.0226	0.0529	0.0142
	(0.231)	(0.423)	(0.468)
Basin Acreage	-0.00107	-0.00640	-0.00106
	(0.692)	(0.394)	(0.685)
BMP Cycle (categorical)	-1.109	-4.345	-2.277
	(0.973)	(0.832)	(0.941)
N	2503	2503	2503
F-stat			
p-val_Fstat			
Sargan_Test_Pval	0.000186	0.996	0.00895
Hansen_Test_Pval	0.120	1	0.543
AR1_pval	0.264	0.264	0.264
AR2_pval	0.354	0.354	0.354
Instrument_count	169	430	193
Included_farms	170	170	170

p-values in parentheses

Standard errors are robust to Hete and Autocor; Windmeijer's correction applied

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A.18: Histogram of Permuted $\widehat{\beta}$'s

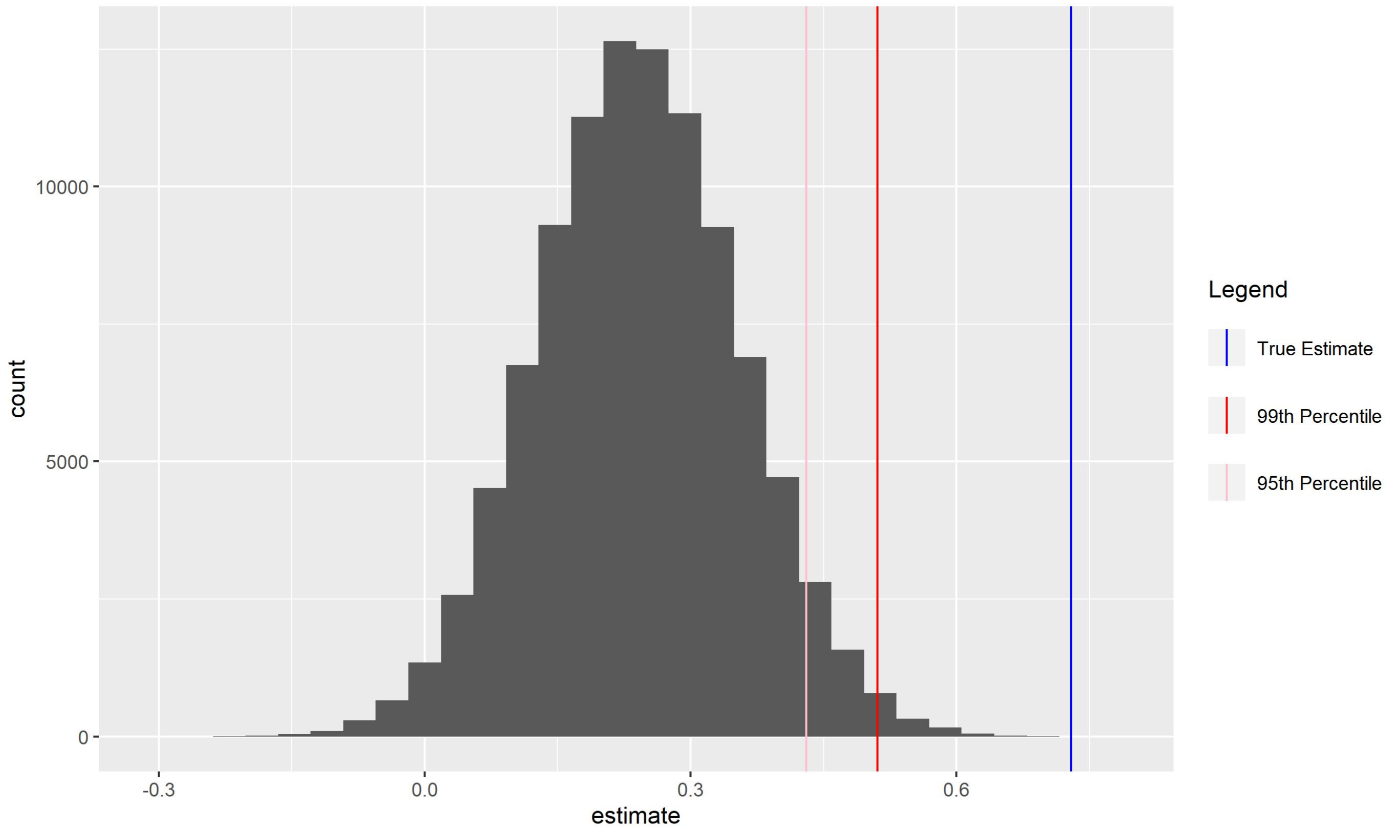


Figure A.19: Estimated Marginal Profit Curve for the Avg. Farm

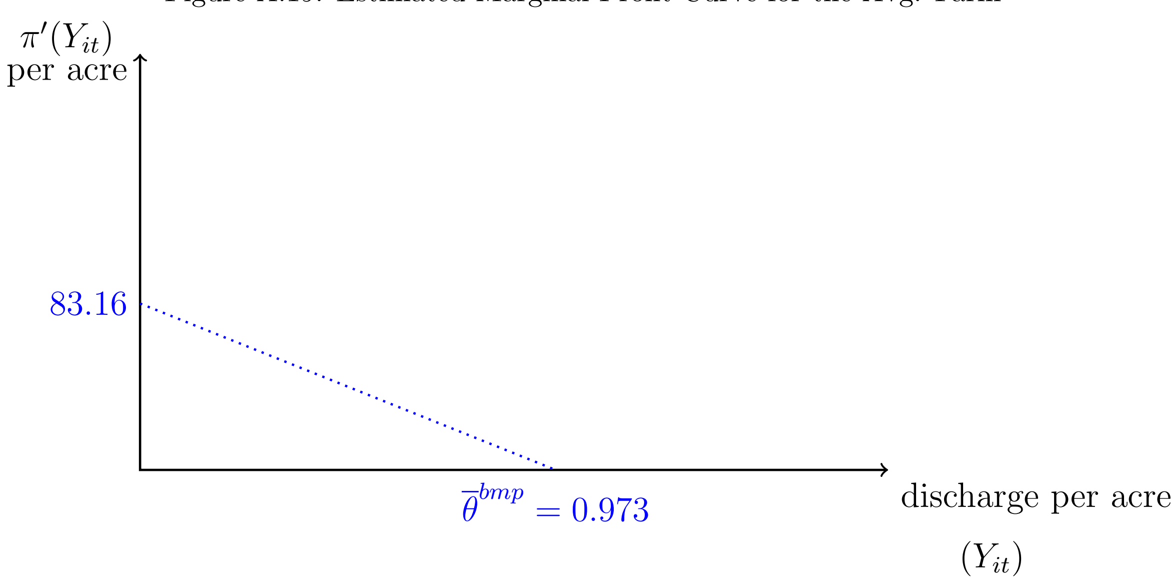


Figure A.20: Compliant Nash Subsidy as a Function of Ambient P Target

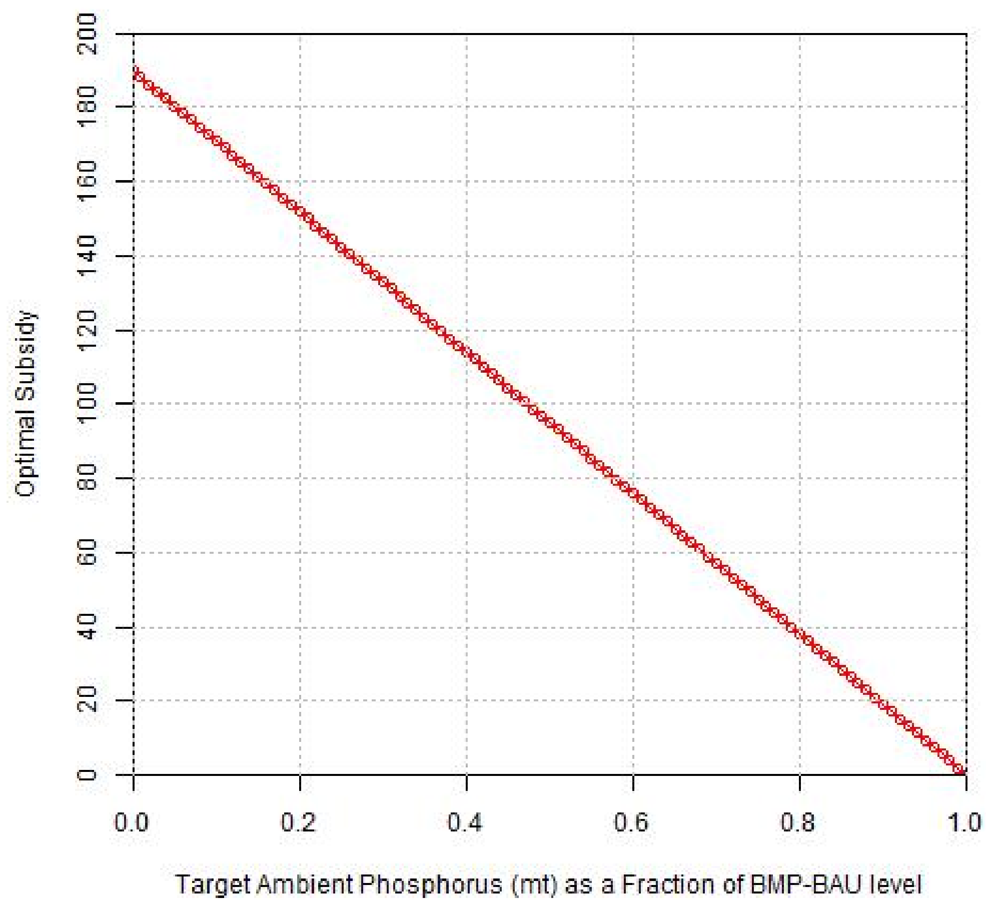


Figure A.21: Estimated and Counterfactual TP Loads

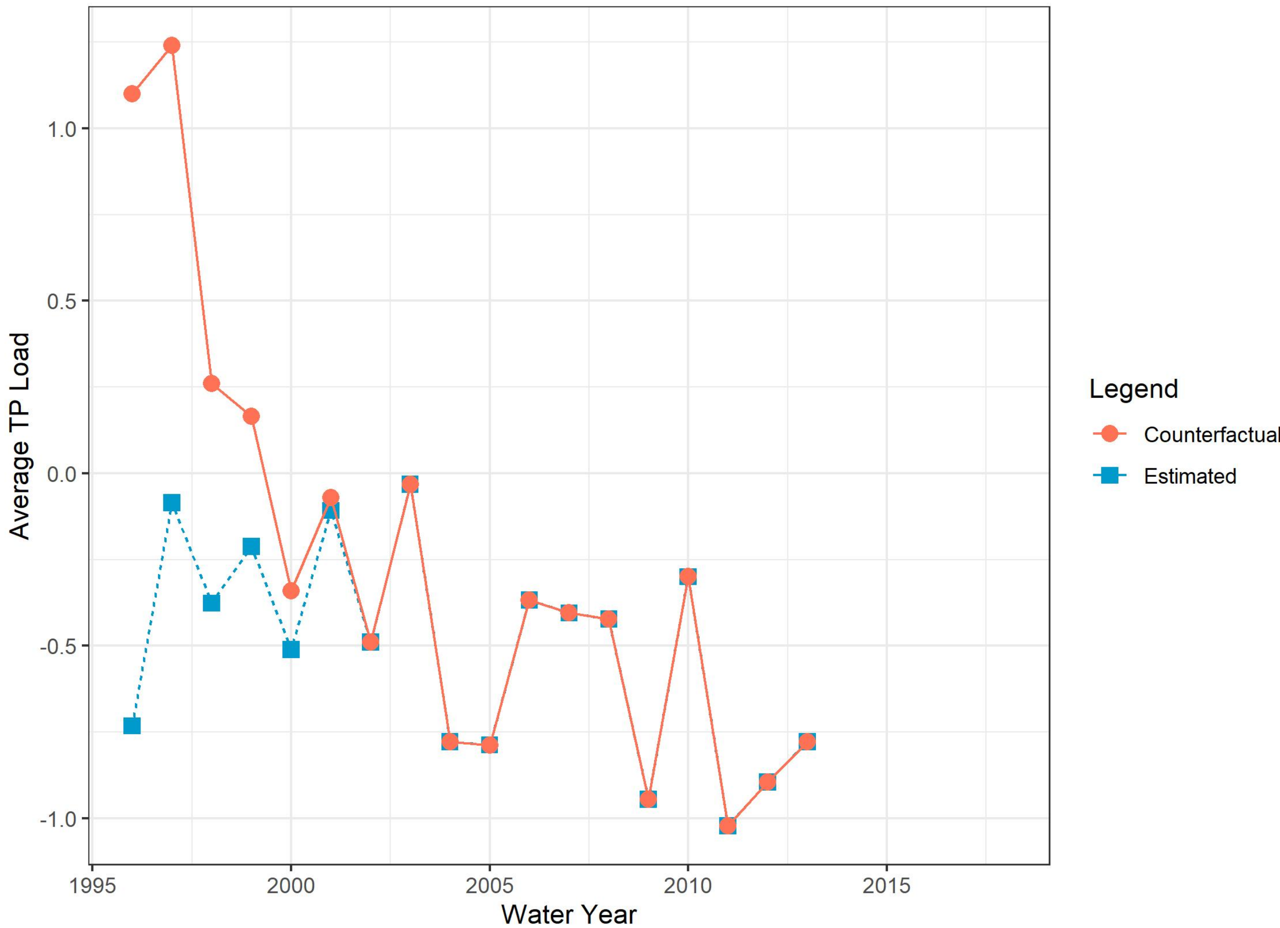


Table A.4: Compliance Cost For Various MAC Slopes under Ambient Subsidy: Set to Achieve 37% Reduction

λ	γ^{bau}	s	Compliance Cost per acre
0.1	854.70	702.44	270.77
0.2	427.35	351.22	135.39
0.6	142.45	117.07	45.13
1.0	85.47	70.24	27.08
1.4	61.05	50.17	19.34
1.8	47.48	39.02	15.04
5.0	17.09	14.05	5.42
10.0	8.55	7.02	2.71

A.3 G to D

Dictionary

- S_{it} is the starting credit balance for i at the start of t
- M is the maximum exercisable credits each period
- Q^*_{it} is the chosen amount of credits exercised each period and is assumed to always be the maximum possible amount.
- G_{it} is the partial derivative of the continuation value wrt the pollution choice variable, Y_{it}
- δ is the discount factor

Justifying the Proxy D_{it}

The point here is to show that $\left|\frac{\partial Y_{it}^*}{\partial G_{it}}\right| > \left|\frac{\partial Y_{it}^*}{\partial D_{it}}\right|$ and that the two partials have the same sign. First, via chain rule, we have (A.3).

$$\frac{\partial Y_{it}^*}{\partial D_{it}} = \left(\frac{\partial Y_{it}^*}{\partial G_{it}}\right)\left(\frac{\partial G_{it}}{\partial S_{it}}\right)\left(\frac{\partial S_{it}}{\partial D_{it}}\right) \tag{A.3}$$

Define $D_{it} = (T - t + 1)M - S_{it}$ and rearrange to get that $\frac{\partial S_{it}}{\partial D_{it}} = -1$. Now we need to find $\frac{\partial G_{it}}{\partial S_{it}}$. First, we must recognize that G_{it} can be alternatively expressed as in (A.4) instead of (A.11).

$$G_{it} = -\frac{d}{dY_{it}}\delta\mathbb{E}\big[V_{t+1}(S_{it+1})\big] \tag{A.4}$$

Then we can apply Young's Theorem and standard regularity conditions to get (A.5).

$$\frac{\partial G_{it}}{\partial S_{it}} = -\frac{d}{dY_{it}}\delta\mathbb{E}\left[\frac{\partial V_{t+1}(S_{it+1})}{\partial S_{it}}\right] \tag{A.5}$$

Now we can find $\frac{\partial V_t(S_{it})}{\partial S_{it-1}}$ and push forward one period. Here, we can invoke the Envelop theorem so long as the relevant partial of the objective function exists (which it does). The theorem then gives the following since $\frac{\partial S_{it}}{\partial S_{it-1}} = 1$.

$$\frac{\partial V_t(S_{it})}{\partial S_{it-1}} = \frac{\partial Q_{it}^*}{\partial S_{it}} = \mathbb{1}\{S_{it} < M\}. \tag{A.6}$$

Since $Q_{it}^* = \min\{M, S_{it}\}$. Thus (A.5) becomes (A.7)

$$\frac{\partial G_{it}}{\partial S_{it}} = -\frac{d}{dY_{it}}\delta\mathbb{P}(S_{it+1} < M) \tag{A.7}$$

We can plug in the equation for the law of motion for credits and rearrange to isolate the shock variable (α_t) so that we have (A.8).

$$\frac{\partial G_{it}}{\partial S_{it}} = -\frac{d}{dY_{it}}\delta\mathbb{P}(\alpha_t > \Gamma_t) = \frac{\partial\mathbb{P}(\alpha_t \leq \Gamma_t)}{\partial\Gamma_t} \tag{A.8}$$

Since $\Gamma_t \equiv S_{it} - Q^*_{it} + \overline{Y} - M - \sum_i Y_{it}$, then $\frac{\partial G_{it}}{\partial S_{it}} \in [-1, 0]$ because the partial of a CDF returns a PDF that is bounded between 0 and 1. Therefore, from (A.3), we finally get that $\frac{\partial Y^*_{it}}{\partial G_{it}}$ has the same sign as $\frac{\partial Y^*_{it}}{\partial D_{it}}$ and that the former has a higher magnitude than the latter. Q.E.D.

A.4 Solving Farmer's Dynamic Decision Problem

In this section, I model the farmer's decision problem as a dynamic optimization problem with no strategic interactions. I assume that the mandatory BMPs do not change over time so that the choice of abatement technology is baked into the firm type parameter, θ_i, which also represents the business as usual level of discharge *after* BMPs are adopted (aka, θ_i^{bmp} which will henceforth be referred to as BMP-BAU or θ_i).[4] The $\overline{T}$ term denotes the lump sum tax (values of this are shown in column 2 of Table A.1), Q^*_{it} is the optimal level of tax credits used, S_{it} is the stock of tax credits per acre entering period t, δ is the discount factor, and M indicates the maximum level of credits that can be exercised each period (shown in column 5 of Table A.1). Farms' decision over how much credits to exercise each period is trivial because they will always choose to exercise as much as they can in each period (under discounting). The farm's discharge decision

[4] In reality, farms are allowed to change BMPs once every 5-year cycle and each farm can be on different cycles. I explicitly control for this in the empirical section.

after optimally deciding Q_{it} is given by the Bellman equation (A.9).[5]

$$
\begin{aligned}
V_t(S_{it}) &= \max_{Y_{it}} \ \pi(Y_{it}, \theta_i^{bmp}) - \left(\overline{T} - Q_{it}^*\right) + \delta \mathbb{E} V_{t+1}(S_{i,t+1}) \\
\text{s.t.} \qquad S_{i,t+1} &= S_{it} - Q_{it}^* + \left(\overline{Y}^P - Y_t\right) \\
Y_t &= \alpha_t + \sum_i Y_{it} \\
\overline{Y}^P &\geq \alpha_t + \sum_i \theta_i^{bmp} \\
\alpha_t &\overset{iid}{\sim} F(0, \sigma_\alpha^2) \\
Q_{it}^* &= \min\{M, S_{it}\}
\end{aligned}
\tag{A.9}
$$

The timing of events in this dynamic problem is as follows: farms first make decisions about discharge (Y_{it}), then uncertainty parameter α_t is resolved and ambient quality Y_t is observed.[6] Then credits owed can be calculated and issued out for use in the next period. I solve (A.9) backwards under finite time with T being the terminal date and normalizing the terminal value to zero. The FOC is given by (A.10).

$$
\pi'(Y_{it}^*, \theta_i^{bmp}) = G_{it} \tag{A.10}
$$

The G_{it} term captures the expected present value of exercising credits in the future which are earned today by marginally reducing discharge Y_{it} and is defined by (A.11).

$$
G_{it} = -\sum_{k=t+1}^{T} \delta^{k-t} \mathbb{E}\left[\frac{\partial Q_{ik}^*}{\partial Y_{it}}\right] \tag{A.11}
$$

Note that since Y_{it} denotes discharges, the partials in (A.11) are weakly negative. The G_{it}

[5] The model presented in (A.9) intentionally ignores the rates presented in column 3 of Table A.1 for notational simplicity.

[6] The uncertainty is in regards to the final observed ambient quality and its variability comes from weather uncertainty. I could have similarly assumed polluters have perfect foresight.

term is analogous to the ambient subsidy rate s for the static model since it represents the pecuniary incentive to abate an additional unit of Y_{it} as evidenced by (1.2) and (A.10). Further, because (i) G_{it} cannot be observed by the researcher, (ii) it changes over time and (iii) it changes with S_{it} (shown later) I instead choose to focus on a proxy for G_{it} in the empirical portion later on. The policy function can be written in general as

$$Y_{it}^* = g^{-1}(G_{it}, \theta_i^{bmp}) \tag{A.12}$$

where $g(\cdot) = \pi'(\cdot)$. Solve this in finite time via backward induction and normalizing terminal value so that

$$V_{T+1}(S_{i,T+1}) = \sum_{k=0}^{\infty} \delta^k \pi(\theta_i^{bmp}, \theta_i^{bmp}) = 0 \tag{A.13}$$

means that

$$\begin{aligned} V_T(S_{iT}) &= \max_{Y_{iT}} \ \pi(Y_{iT}, \theta_i^{bmp}) - (\overline{T} - Q_{iT}^*) \\ \text{FOC:} &\quad \pi'(Y_{iT}^*) = 0 \\ \implies &\ Y_{iT}^* = \theta_i^{bmp} \\ \implies &\ V_T(S_T) = -(\overline{T} - Q_{iT}^*) \end{aligned} \tag{A.14}$$

Then next iteration we have

$$\begin{aligned} V_{T-1}(S_{i,T-1}) &= \max_{Y_{i,T-1}} \ \pi(Y_{i,T-1}, \theta_i^{bmp}) - (\overline{T} - Q_{i,T-1}^*) - \delta \mathbb{E}(\overline{T} - Q_{iT}^*) \\ \text{s.t.} &\qquad S_{iT} = S_{i,T-1} - Q_{i,T-1}^* + (\overline{Y} - Y_{T-1}) \\ \text{FOC:} &\quad \pi'(Y_{i,T-1}^*, \theta_i^{bmp}) = -\delta \mathbb{E}\left[\frac{\partial Q_{iT}^*}{\partial Y_{iT-1}}\right] \\ \implies V_{T-1}(S_{i,T-1}) &= \pi(Y_{i,T-1}^*, \theta_i^{bmp}) - (\overline{T} - Q_{i,T-1}^*) - \delta \mathbb{E}(\overline{T} - Q_{iT}^*) \end{aligned} \tag{A.15}$$

Then the next iteration

$$
\begin{aligned}
V_{T-2}(S_{i,T-2}) = \max_{Y_{i,T-2}} \; & \pi(Y_{i,T-2}, \theta_i^{bmp}) - (\overline{T} - Q^*_{i,T-2}) + \delta \mathbb{E}\left[\pi(Y^*_{i,T-1}, \theta_i^{bmp}) - (\overline{T} - Q^*_{i,T-1}) - \delta(\overline{T} - Q^*_{iT})\right] \\
\text{s.t.} \quad & S_{i,T-1} = S_{i,T-2} - Q^*_{i,T-2} + (\overline{Y} - Y_{T-2}) \\
& S_{i,T} = S_{i,T-1} - Q^*_{i,T-1} + (\overline{Y} - Y_{T-1}) \\
\text{FOC:} \quad & \pi'(Y^*_{i,T-2}, \theta_i^{bmp}) = -\delta \mathbb{E}\left[\frac{\partial Q^*_{i,T-1}}{\partial Y_{i,T-2}}\right] - \delta^2 \mathbb{E}\left[\frac{\partial Q^*_{iT}}{\partial Y_{iT-2}}\right]
\end{aligned}
\tag{A.16}
$$

A pattern starts to emerge where FOC at any period t is

$$
\pi'(Y^*_{it}, \theta_i^{bmp}) = - \sum_{k=t+1}^{T} \delta^{k-t} \mathbb{E}\left[\frac{\partial Q^*_{ik}}{\partial Y_{it}}\right] \tag{A.17}
$$

Thus we have (A.11). Q.E.D.

Appendix B

Chapter 2 Appendix

B.1 General Figures and Tables

Figure B.1: Best Response Function for Pollution

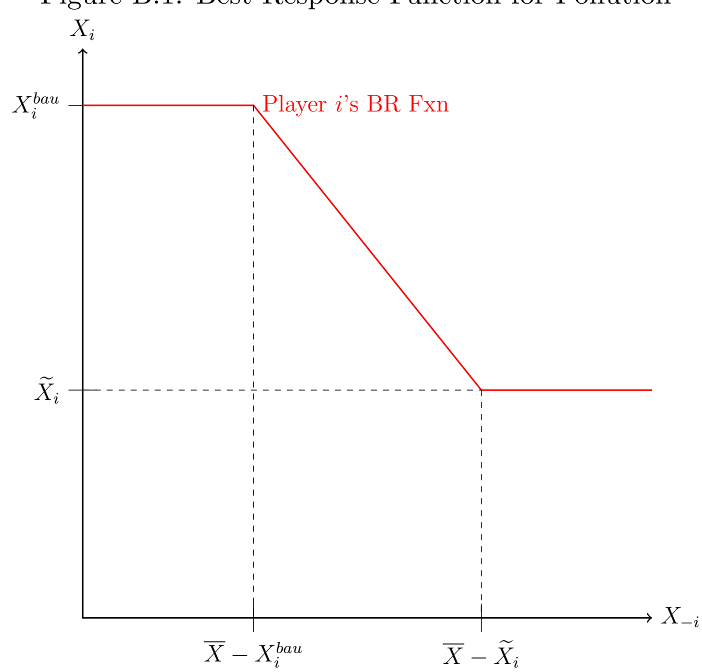


Figure B.2: Two-Player Best Response Functions (perfectly set t)

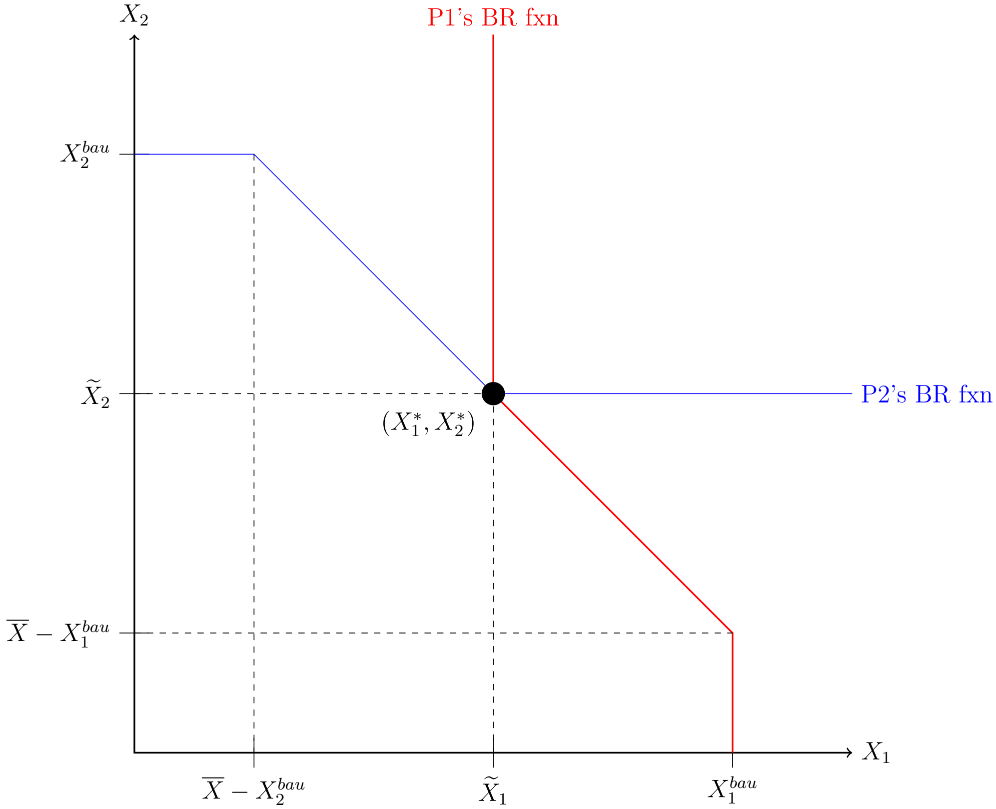


Figure B.3: Two-Player Best Response Functions (too strict of t)

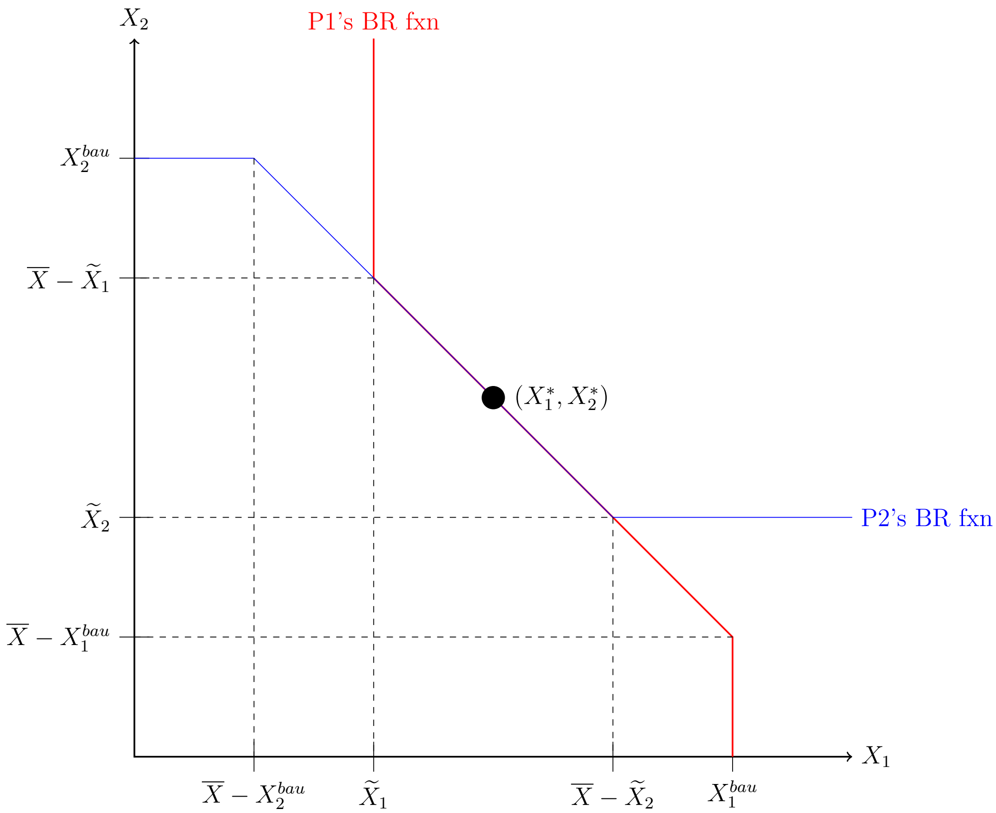


Figure B.4: 2 Player Example Model

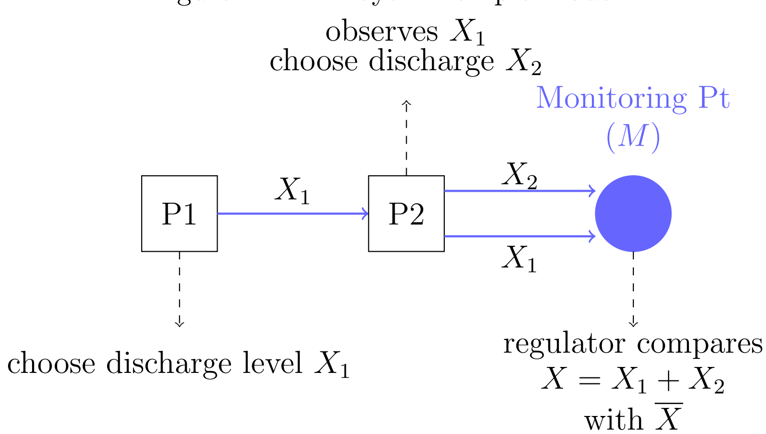


Figure B.5: Free-Riding Potential, $m = 1$ and Heterogeneity Case

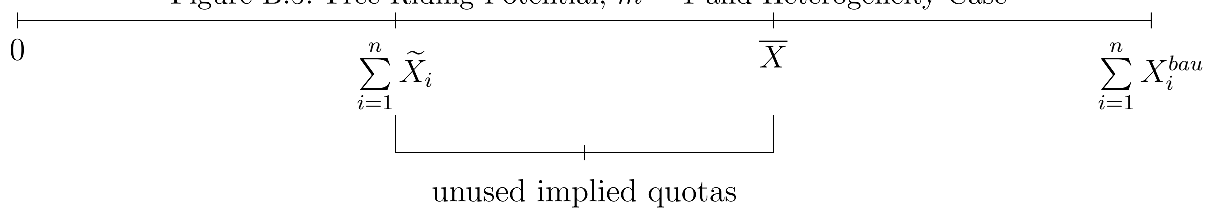
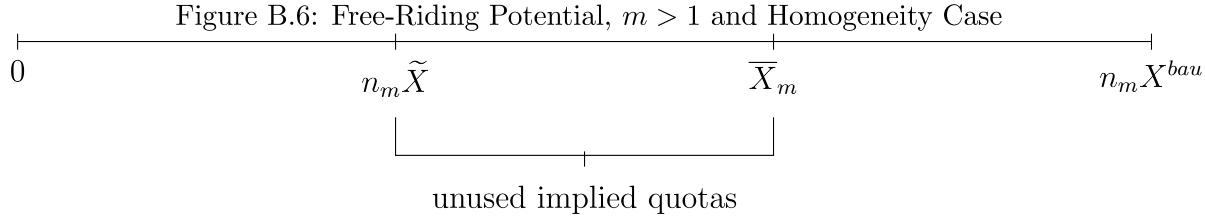


Figure B.6: Free-Riding Potential, $m > 1$ and Homogeneity Case



Appendix C

Chapter 3 Appendix

C.1 General Figures

Figure C.1: Iso-G and Iso-X Curves

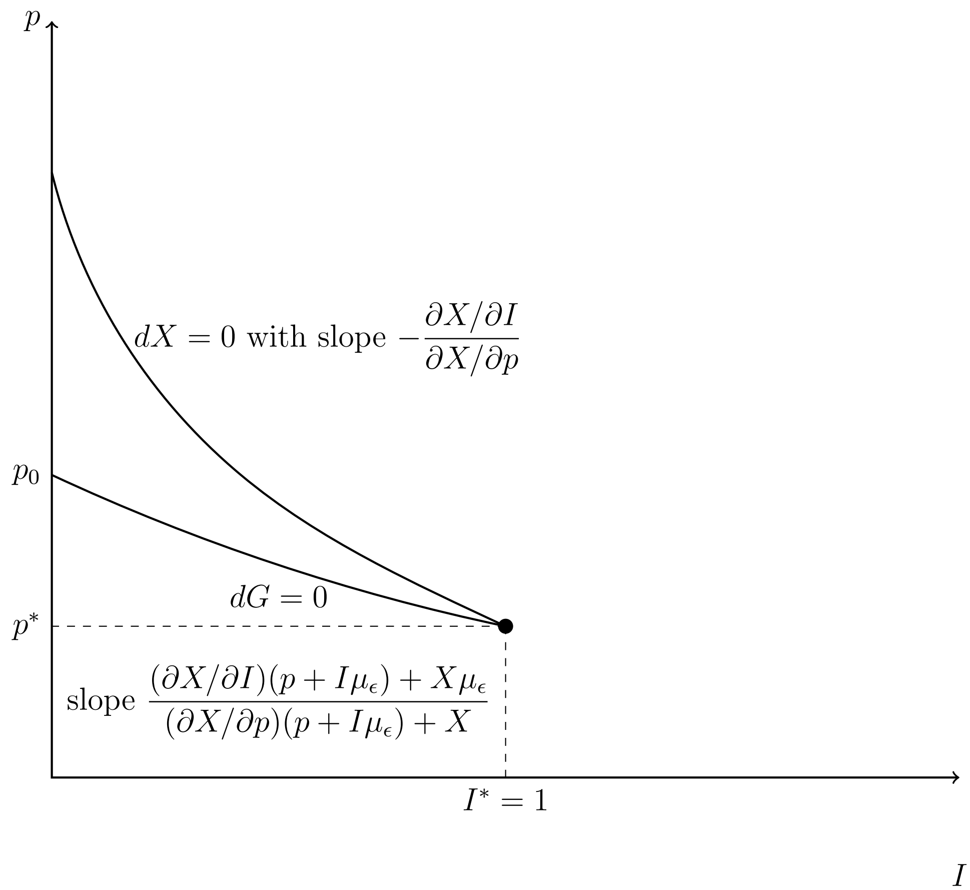


Figure C.2: Simple Example: Pivotal Agent's Indiffernce Curves

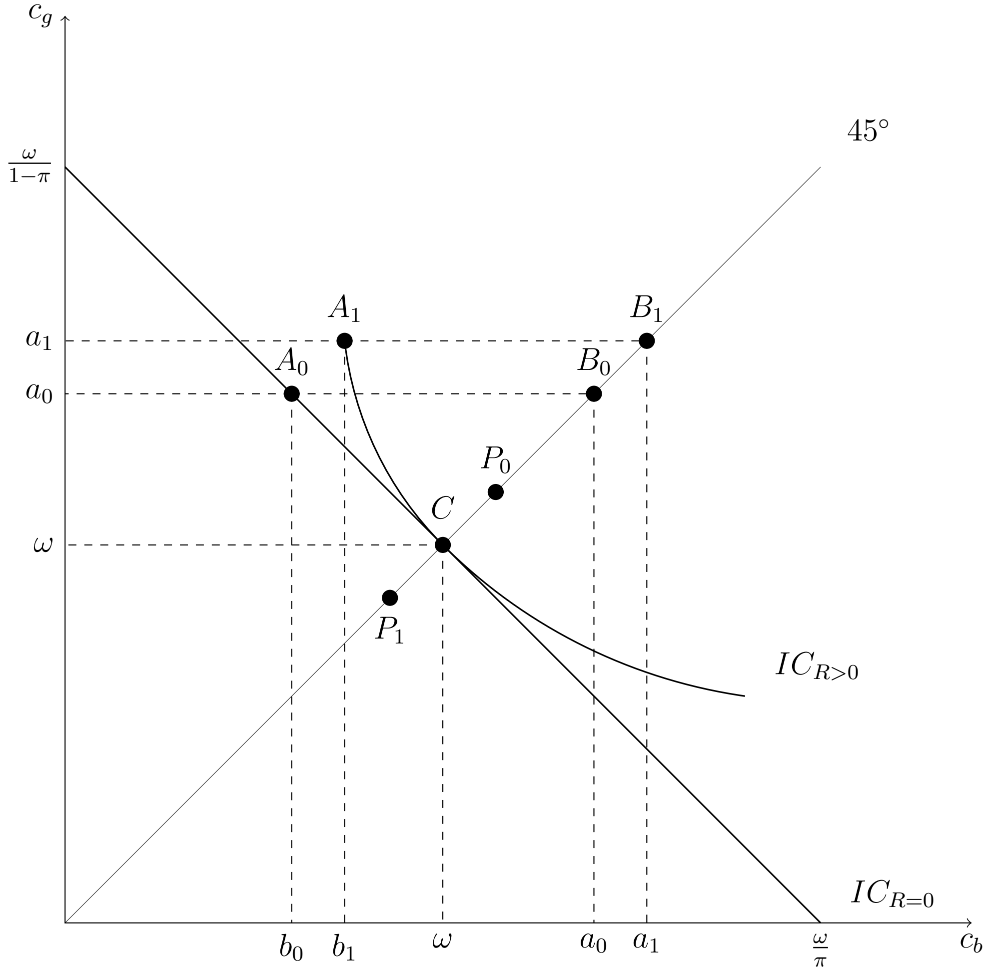


Table C.1: Risk Aversion and Value Added

	Estimated risk aversion	Value added (%)
Overall best practice	3.73	18.75
Economics literature	1.24	5.56
Finance literature	7.16	42.5
US	5.81	32.56
EU	1.57	5.56
Stockholder	1.49	5.56
GMM	3.79	18.75
Quarterly data	6.33	35.71

Estimated risk aversion values are taken from Table 6 of Elminejad, Havranek and Irsova (2022).

Table C.2: Simulation Parameters

Parameter	Value
Number of agents	100
Probability of shock	0.10
Cost shock (e)	25.35
Budget	1000

Figure C.3: Randomly Generated Distribution of g and ω

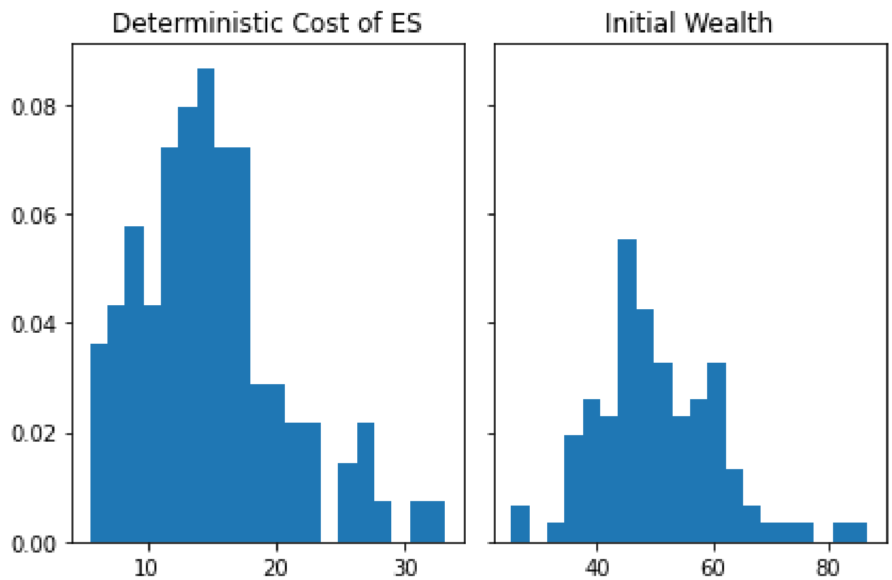


Figure C.4: Additionality Increasing in Wealth

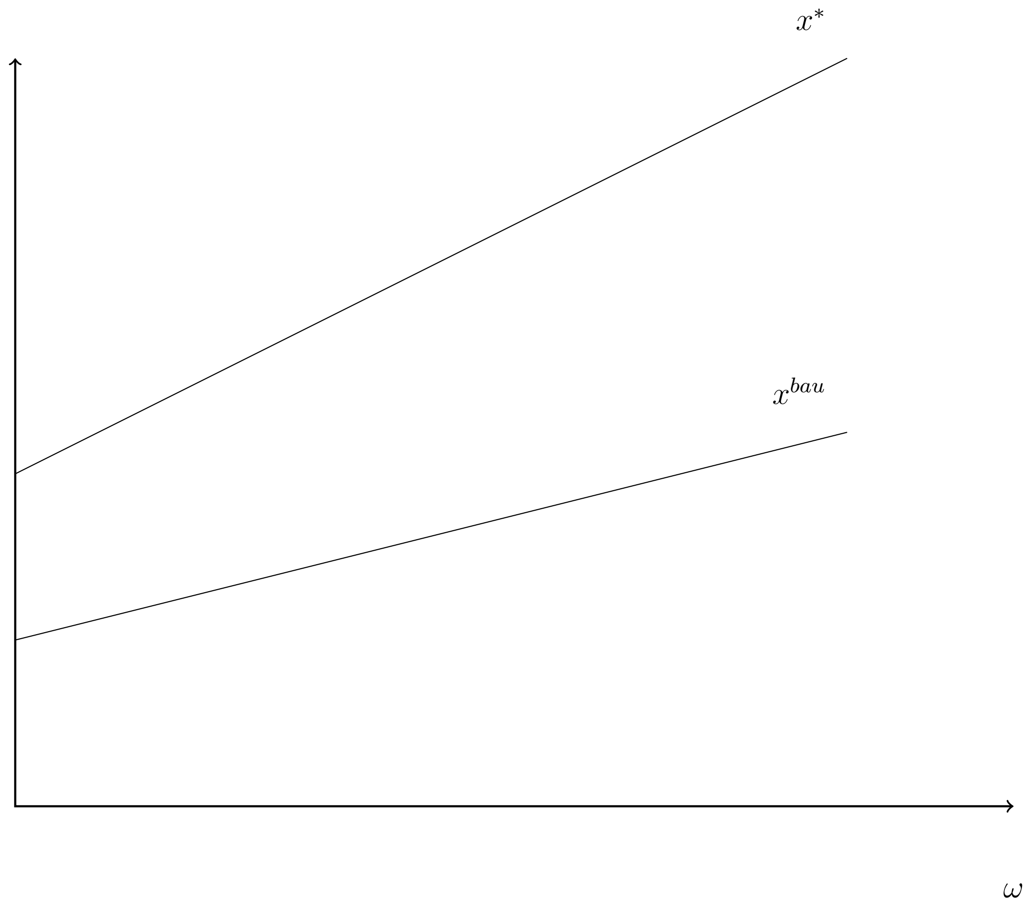
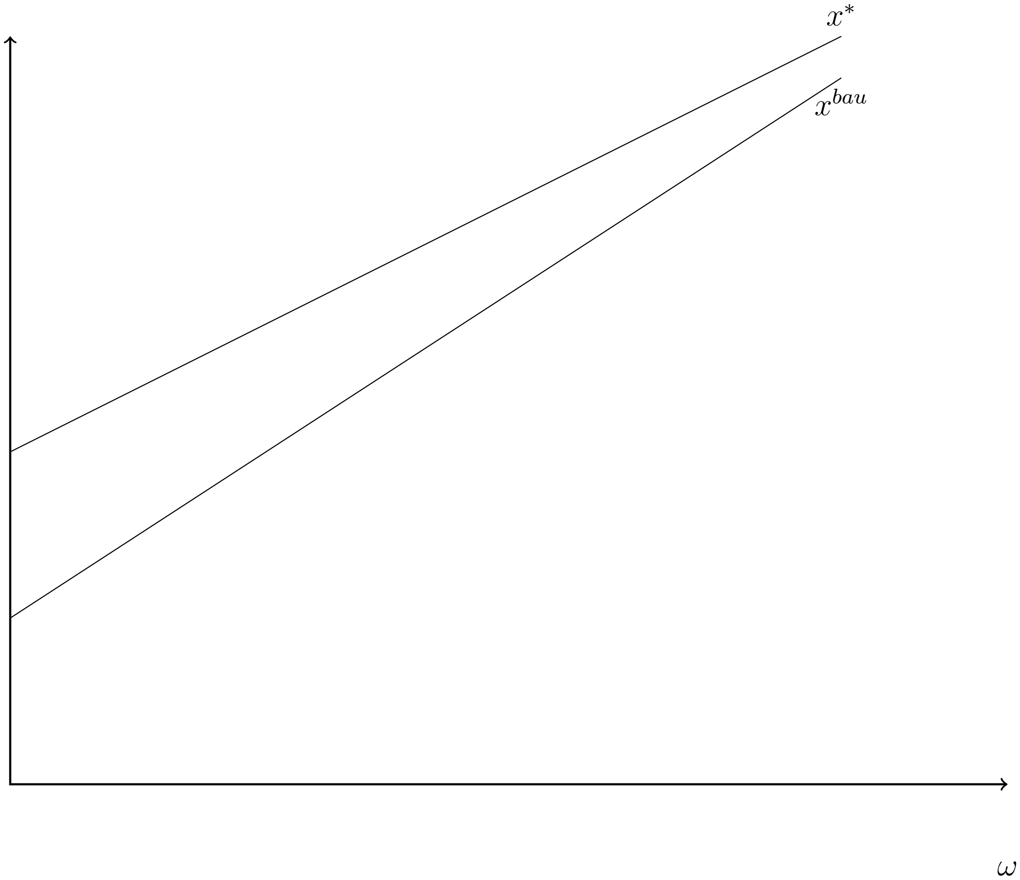


Figure C.5: Additionality Decreasing in Wealth



C.2 Slopes of dG and dX Curves

For tractability but without loss of generality, we assume agents are homogeneous so that $\dfrac{\partial X}{\partial I} = n\dfrac{\partial x}{\partial I}$.

<u>dG **Curve**</u>:

Total differentiation of budget from (3.4) and setting equal to zero gives

$$0 = \left(\frac{\partial x}{\partial I}dI + \frac{\partial x}{\partial p}dp\right)(p + \mu_\epsilon I) + x(dp + \mu_\epsilon dI)$$

rearranging and solving for dp/dI gives

$$\frac{dp}{dI} = -\frac{\frac{\partial x}{\partial I}(p + \mu_\epsilon I) + x\mu_\epsilon}{\frac{\partial x}{\partial p}(p + \mu_\epsilon I) + x}$$

Then rearranging (3.10) and plugging in gives

$$\frac{dp}{dI} = -\left[\mu_\epsilon + \frac{\frac{\widetilde{\sigma}}{\mathbb{E}[u'(c)(1-R\delta)]}\frac{\partial x}{\partial p}(p + \mu_\epsilon I)}{\frac{\partial x}{\partial p}(p + \mu_\epsilon I) + x}\right] \tag{C.1}$$

<u>dX **Curve**</u>:

Total differentiating X and setting equal to zero and rearranging gives

$$\frac{dp}{dI} = \frac{\partial x/\partial I}{\partial x/\partial p}$$

then plugging in (3.10) gives

$$\frac{dp}{dI} = -\left[\frac{\widetilde{\sigma}}{\mathbb{E}[u'(c)(1 - R\delta)]} + \mu_\epsilon\right] \tag{C.2}$$

Since, $\dfrac{\frac{\partial x}{\partial p}(p + \mu_\epsilon I)}{\frac{\partial x}{\partial p}(p + \mu_\epsilon I) + x} \in (0, 1)$, then the slope of the dX curve is always steeper than the slope of the dG curve.

C.3 Lower Bound for R

Start with the definition of $\overline{A}_\Gamma$

$$\overline{A}_\Gamma = -\frac{\mu_{u''\Gamma}}{\mu_{u'}} = -\frac{Cov(u'', \Gamma) + \mu_{u''}\mu_\Gamma}{\mu_{u'}}$$

Using definition of covariance gives

$$\overline{A}_\Gamma = \frac{-\sigma_{u''}\sigma_\Gamma}{\mu_{u'}} + \overline{A}\mu_\Gamma$$
$$\overline{A}_\Gamma < \overline{A}\mu_\Gamma$$
$$\frac{\overline{A}_\Gamma}{\mu_\Gamma} < \overline{A}$$

where $\overline{A} = -\frac{\mu_{u''}}{\mu_{u'}}$. Further we have

$$\overline{A} = R\frac{\mathbb{E}[c^{-1-R}]}{\mathbb{E}[c^{-R}]}$$

Therefore, $\frac{\overline{A}_\Gamma}{\mu_\Gamma} < \overline{A} < R$

C.4 Application of Slutsky

Let $e(I, p, u)$ denote the expenditure function defined in (C.3)

$$\begin{aligned} e = \min_x \;\; & g(x,\omega) - xp + x\epsilon(1-I) \\ \text{s.t.} \quad & u(c) \geq u \end{aligned} \tag{C.3}$$

The solution to (C.3) is known as the compensated (Hicksian) ES input supply function h. Applying the Envelope Theorem gives Sheppard's Lemma.

$$\frac{\partial e}{\partial p} = -x_c$$

Making use of the duality at the optimum produces the equality

$$h(I,p,u) = x(I,p,e)$$

Hence

$$\frac{\partial h}{\partial p} = \frac{\partial x}{\partial p} - \frac{\partial x}{\partial \omega}x$$

Q.E.D.

Bibliography

Abadie, Alberto. n.d.. "Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspects." *Journal of Economic Literature*, Forthcoming.

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. 2010. "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program." *Journal of American Statistical Association*, 105(490): 493–505.

Anderson, T. W., and Cheng Hsiao. 1981. "Estimation of Dynamic Models with Error Components." *Journal of American Statistical Association*, 76(375): 598–606.

Arrow, Kenneth J., and Robert C. Lind. 1970. "Uncertainty and the Evaluation of Public Investment Decisions." *The American Economic Review*, 60(3): 364–378.

Bao, Ken. 2021. "Regulating Non-point Pollution with Ambient Tax: Are more monitors better?"

Bautista, Carlos, Eloy Revilla, Javier Naves, Jörg Albrecht, Néstor Fernández, Agnieszka Olszańskaa, Michal Adamec, Teresa Berezowska-Cnota, Paolo Ciucci, Claudio Groff, Sauli Härkönenh, Djuro Huber, Klemen Jerina, Marko Jonozovič, Alexandros A. Karamanlidis, Santiago Palazón, Pierre-Yves Quenette, Robin Rigg, Juan Seijas, Jon E. Swenson, Tõnu Talvi, and Nuria Selva. 2019. "Large carnivore damage in Europe: Analysis of compensation and prevention programs." *Biological Conservation*, 235: 308–316.

Bell, Andrew Reid, M. Azeem A. Shah, Arif Anwar, and Claudia Ringler. 2015. "What role can information play in improved equity in Pakistan's irrigation system? Evidence from an experimental game in Punjab." *Ecology and Society*, 20(1): 51.

Benítez, Pablo C., Timo Kuosmanen, Roland Olschewski, and G. Cornelis Van Kooten. 2006. "Conservation Payments under Risk: A Stochastic Dominance Approach." *American Journal of Agricultural Economics*, 88(1): 1–15.

Burton, Rob J.F., and G. Schwarz. 2013. "Result-oriented agri-environmental schemes in Europe and their potential for promoting behavioural change." *Land Use Policy*, 30(1): 628–641.

Cabe, Richard, and Joseph Herriges. 1992. "The Regulation of Non-Point-Source Pollution Under Imperfect and Asymmetric Information." *Journal of Environmental Economics and Management*, 22(2): 134–146.

Camacho, Eva, and Till Requate. 2004. "Collective and Random Fining Versus Tax Subsidy Schemes to Regulate Non-Point Source Pollution: An Experimental Study." *Economics Working Paper No 2004-10.*

Cavallo, Eduardo, Sebastian Galiani, Ilan Noy, and Juan Pantano. 2013. "Catastrophic Natural Disasters and Economic Growth." *The Review of Economics and Statistics*, 95(5): 1549–1561.

Chatterjee, Rhitu. 2009. "Economic damages from nutrient pollution create a "toxic debt"." *Environmental Science & Technology*, 43(1): 6–7.

Chetty, Raj. 2006. "A New Method of Estimating Risk Aversion." *American Economic Review*, 96(5): 1821–1834.

Cochard, Francois, Marc Willinger, and Anastasios Xepapadeas. 2005. "Efficiency of Nonpoint Source Pollution Instruments: An Experimental Study." *Environmental and Resource Economics*, 30(4): 393–422.

Daroub, Samira H., Stuart Van Horn, Timothy A. Lang, and Orlando A. Diaz. 2011. "Best Management Practices and Long-Term Water Quality Trends in the Everglades Agricultural Area." *Critical Reviews in Environmental Science and Technology*, 41(1): 608–632.

Daroub, Samira H., Timothy A. Lang, Orlando A. Diaz, and Sabine Grunwald. 2009. "Long-term Water Quality Trends after Implementing Best Management Practices in South Florida." *Journal of Environment Quality*, 38(4): 1683.

Davison, Thomas, Jodie Hansing, Carmela Bedregal, and Pamela Wade. 2017. "Chapter 4: Nutrient Source Control Programs." South Florida Water Management District.

De Pinto, Alessandro, Richard D. Robertson, and Beatrice Darko Obiri. 2013. "Adoption of climate change mitigation practices by risk-averse farmers in the Ashanti Region, Ghana." *Ecological Economics*, 86: 47–54.

Derissen, Sandra, and Martin F. Quaas. 2013. "Combining performance-based and action-based payments to provide environmental goods under uncertainty." *Ecological Economics*, 85: 77–84.

D'exelle, Ben, and Els Lecoutere. 2012. "Equity-Efficiency Trade-Offs in Irrigation Water Sharing: Evidence from a Field Lab in Rural Tanzania." *World Development*, 40(12): 2537–2551.

Dickman, Amy J., Ewan A. Macdonald, and David W. Macdonald. 2010. "A review of financial instruments to pay for predator conservation and encourage human-carnivore coexistence." *PNAS*, 108(34): 13937–13944.

Dowd, Brian M., Daniel Press, and Marc Los Huertos. 2008. "Agricultural non-point source water pollution policy: The case of California's Central Coast." *Agriculture, Ecosystems and Environment*, 128(3): 151–161.

Drevno, Ann. 2016. "Policy tools for agricultural nonpoint source water pollution control in the U.S. and E.U." *Management of Environmental Quality*, 27(2): 106–123.

Elminejad, Ali, Tomas Havranek, and Zuzana Irsova. 2022. "Relative Risk Aversion: A Meta-Analysis."

Ferman, Bruno, and Cristine Pinto. 2021. "Synthetic Controls with Imperfect Pre-Treatment Fit*."

Fisher, Brendan, R. Kerry Turner, and Paul Morling. 2009. "Defining and classifying ecosystem services for decision making." *Ecological Economics*, 68(1): 643–653.

Goulder, Lawrence H., and Ian W.H. Parry. 2008. "Instrument Choice in Environmental Policy." *Review of Environmental Economics and Policy*, 2(2): 152–174.

Goulder, Lawrence H., Ian W.H. Parry, Roberton C. Williams III, and Dallas Burtraw. 1999. "The cost-effectiveness of alternative instruments for environmental protection in a second-best setting." *Journal of Public Economics*, 72(3): 329–360.

Graff-Zivin, Joshua, and Leslie Lipper. 2008. "Poverty, risk, and the supply of soil carbon sequestration." *Environment and Development Economics*, 13(3): 353–373.

Hansen, Bruce E. 2021. *Econometrics.*

Hansen, Lars, and Eirik Romstad. 2007. "Non-point source regulation - A self-reporting mechanism." *Ecological Economics*, 62(3-4): 529–537.

Hansen, Lars Garn. 1998. "A Damage Based Tax Mechanism for Regulation fo Non-Point Emissions." *Environmental and Resource Economics*, 12(1): 99–112.

Herriges, Joseph, Ramu Govindasamy, and Jason Shogren. 1994. "Budget-Balancing Incentive Mechanisms." *Journal of Environmental Economics and Management*, 27(3): 275–285.

Holmstrom, Bengt. 1982. "Moral Hazard in Teams." *The Bell Journal of Economoics*, 13(2): 324–340.

Horan, Richard D., James S. Shortle, and David G. Abler. 1998. "Ambient Taxes When Polluters Have Multiple Choices." *Journal of Environmental Economics and Management*, 36(2): 186–199.

Horan, Richard D, James S. Shortle, and David G Abler. 2002. "Ambient Taxes Under m-Dimensional Choice Sets, Heterogeneous Expectations, and Risk-Aversion." *Environmental & Resource Economics*, 21(2): 189–202.

Jack, Kelsey B., Carolyn Kousky, and Katharine R.E. Sims. 2008. "Designing payments for ecosystem services: Lessons from previous experience with incentive-based mechanisms." *Proceedings of the National Academy of Sciences*, 105(28): 9465–9470.

Jack, Kelsey B., Seema Jayachandran, Namrata Kala, and Rohini Pande. 2022. "MONEY (NOT) TO BURN: PAYMENTS FOR ECOSYSTEM SERVICES TO REDUCE CROP RESIDUE BURNING." *NBER Working Paper Series*.

Johns, Grace M. 1993. "Section 9 - Economic Impacts of Implementing Best Management Practices." In *Twenty Year Evaluation: Economic Impacts from Implementing the Marjory Stoneman Douglas Everglades Restoration Act and United States versus SFWMD Settlement Agreement*. Hazen and Sawyer.

Keiser, David A., and Joeseph S. Shapiro. 2019. "US Water Pollution Regulation over the Past Half Century: Burning Waters to Crystal Springs?" *Journal of Economic Perspectives*, 33(4): 51–75.

Kotchen, Matthew, and Kathleen Segerson. 2020. "The Use of Group-Level Approaches to Environmental and Natural Resource Policy." *Review of Environmental Economics and Policy*, 14(2): 173.

Kreif, Noémi, Richard Grieve, Dominik Hangartner, Alex James Turner, Silviya Nikolova, and Matt Sutton. 2015. "Examination of the Synthetic Control Method for Evaluating Health Policies with Multiple Treated Units." *Health Economics*, 25(12): 1514–1528.

Mason, Charles F., and Andrew J. Plantinga. 2013. "The additionality problem with offsets: Optimal contracts for carbon sequestration in forests." *Journal of Environmental Economics and Management*, 66(1): 1–14.

Meran, Georg, and Ulrich Schwalbe. 1987. "Pollution Control and Collective Penalties." *Journal of Institutional and Theoretical Economics*, 143(4): 616–629.

Miao, Haoran, Jacob R. Fooks, Todd Guilfoos, Kent D. Messer, Soni M. Pradhanang, and Jordan F. Suter. 2016. "The impact of information on behavior under an ambient-based policy for regulating nonpoint source pollution." *Water Resources Research*, 52(5): 3294–3308.

Millennium Ecosystem Assessment. 2005. "Ecosystems and Human Well-Being." Island Press, Washington D.C.

Milon, Walter J. 2018. "The polluter pays principle and Everglades restoration." *Journal of Environmental Studies and Sciences*, 9(1): 67–81.

National Resource Defense Council. 2013. "Policy Basics - Clean Water."

Newell, Richard G., and Robert N. Stavins. 2003. "Cost Heterogeneity and the Potential Savings from Market-Based Policies." *Journal of Regulatory Economics*, 23(1): 43–59.

Poe, Gregory L., William D. Schulze, Kathleen Segerson, Jordan F. Suter, and Christian A. Vossler. 2004. "Exploring the Performance of Ambient-Based Policy Instruments When Nonpoint Source Polluters Can Cooperate." *American Journal of Agricultural Economics*, 86(5): 1203–1210.

Reichhuber, Anke, Eva Camacho, and Till Requate. 2009. "A framed field experiment on collective enforcement mechanisms with Ethiopian farmers." *Environment and Development Economics*, 14(5): 641–663.

Rendleman, C. Matthew, Kenneth A. Reinert, and James A. Tobey. 1995. "Market-based Systems for Reducing Chemcial Use in Agriculture in the United States." *Environmental and Resource Economics*, 5: 51–70.

Rhyan, Jack C., Pauline Nol, Christine Quance, Arnold Gertonson, John Belfrage, Lauren Harris, Kelly Straka, and Suelee Robbe-Austerman. 2013. "Transmission of Brucellosis from Elk to Cattle and Bison, Greater Yellowstone Area, USA, 2002-2012." *Emerging Infectious Diseases*, 19(12): 1992–1995.

Rice, Ronald W., Forrest T. Izuno, and Raymond M. Garcia. 2002. "Phosphorus load reductions under best management practices for sugarcane cropping systems in the Everglades Agricultural Area." *Agricultural Water Management*, 56(1): 17–39.

Rice, Ronald W., Jehangir Bhadha, Timothy Lang, Samira Daroub, and Leslie Baucum. 2013. "Farm-level Phosphorus-reduction Best Management Practices in the Everglades Agricultural Area." *Proceedings of the Florida State Horticultural Society*, 126: 300–304.

Roka, Fritz M., Leslie E. Baucum, Ronald W. Rice, and Jose Alvarez. 2010. "Comparing Costs and Benefits for Sugarcane Production on Sand and Muck Soils of Southern Florida, 2008-2009." *Journal of American Society of Sugar Cane Technologies*, 30.

Salzman, James, Genevieve Bennett, Nathaniel Carroll, Allie Goldstein, and Michael Jenkins. 2018. "Payments for Ecosystem Services: Past, Present and Future." *Texas A&M Law Review*, 6(1): 200–227.

Schade-Poole, Kristin, and Gregory Möller. 2016. "Impact and Mitigation of Nutrient Pollution and Overland Water Flow Change on the Florida Everglades, USA." *Sustainability*, 8(9): 940.

Schomers, Sarah, and Bettina Matzdorf. 2013. "Payments for ecosystem services: A review and comparison of developing and industrialized countries." *Ecosystem Services*, 6: 16–30.

Segerson, Kathleen. 1988. "Uncertainty and incentives for nonpoint pollution control." *Journal of Environmental Economics and Management*, 15(1): 87–98.

Segerson, Kathleen, and JunJie Wu. 2006. "Nonpoint pollution control: Inducing first-best outcomes through the use of threats." *Journal of Environmental Economics and Management*, 51(2): 165–184.

Shortle, James, and Richard D. Horan. 2013. "Policy Instruments for Water Quality Protection." *Annual Review of Resource Economics*, 5(1): 111–138.

Shortle, James S., and Richard D. Horan. 2001. "The Economics of Nonpoint Pollution Control." *Journal of Economic Surveys*, 15(3): 255–289.

Shortle, James S., Marc Ribaudo, Richard D. Horan, and David Blandford. 2012. "Reforming Agricultural Nonpoint Pollution Policy in an Increasingly Budget-Constrained Environment." *Environmental Science & Technology*, 46(3): 1316–1325.

Spraggon, John. 2002. "Exogenous Targeting Instruments as a Solution to Group Moral Hazards." *Journal of Public Economics*, 84(3): 427–456.

Stephenson, Kurt, and Leonard Shabman. 2017. "Can Water Quality Trading Fix the Agricultural Nonpoint Source Problem?" *Annaul Review of Resource Economics*, 9: 95–116.

Sun, Liyang, and Sarah Abraham. 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." *Journal of Econometrics*, 225(2): 175–199.

Suter, Jordan F., Christian A. Vossler, and Gregory L. Poe. 2009. "Ambient-based pollution mechanisms: A comparison of homogeneous and heterogeneous groups of emitters." *Ecological Economics*, 68(6): 1883–1892.

Suter, Jordan F., Christian A. Vossler, Gregory L. Poe, and Kathleen Segerson. 2008. "Experiments on Damage-Based Ambient Taxes for Nonpoint Source Polluters." *American Journal of Agricultural Economics*, 90(1): 86–102.

U.S. Environmental Protection Agency. 2016. "National Nonpoint Source Program—a catalyst for water quality improvements."

Weitzman, Martin. 1974. "Prices vs. Quantities." *The Review of Economic Studies*, 41(4): 477–491.

White, Ben, and Nick Hanley. 2016. "Should We Pay for Ecosystem Service Outputs, Inputs or Both?" *Environmental and Resource Economics*, 63: 765–787.

Wong, Po Yin, Torfinn Harding, Karlygash Kuralbayeva, Liana O. Anderson, and Ana M. Pessoa. 2019. "Pay For Performance and Deforestation: Evidence from Brazil."

Wuepper, David, and Robert Huber. 2022. "Comparing effectiveness and return on investment of action- and results-based agri-environmental payments in Switzerland." *American Journal of Agricultural Economics*, 104(5): 1585–1604.

Xepapadeas, Anastasios. 1991. "Environmental Policy Under Imperfect Information: Incentives and Moral Hazard." *Journal of Environmental Economics and Management*, 20(2): 113–126.

Xepapadeas, Anastasios. 1992. "Environmental Policy Design and Dynamic Nonpoint-Source Pollution." *Journal of Environmental Economics and Management*, 23(1): 22–39.

Xepapadeas, Anastasios. 2011. "The Economics of Non-Point-Source Pollution." *Annual Review of Resource Economics*, 3(1): 355–373.

Yoder, Landon. 2019. "Compelling collective action: Does a shared pollution cap incentivize farmer cooperation to restore water quality?" *International Journal of the Commons*, 13(1): 378–399.

Yoder, Landon, Rinku Roy Chowdhury, and Carson Hauck. 2020. "Watershed restoration in the Florida Everglades: Agricultural water management and long-term trends in nutrient outcomes in the Everglades Agricultural Area." *Agriculure, Ecosystems and Environment*, 302: 107070.

Zia, Asim, Shanshan Ding, Kent D. Messer, Haoran Miao, Jordan F. Suter, Jacob R. Fooks, Todd Guilfoos, Simona Trandafir, Emi Uchida, Yushiou Tsai, Scott Merrill, Scott Turnbull, and Christopher Koliba. 2020. "Characterizing Heterogeneous Behavior of Non-Point_Source Polluters in a Spatial Game under Alternate Sensing and Incentive Designs." *Journal of Water Resources Planning and Management*, 146(8).