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

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Abstract

This paper 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. Few observational studies examine the cost effectiveness of NPSP policies because it is difficult to study how individual polluters respond to pecuniary incentives to abate. 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. The dataset allows the use of the two-step Arellano-Bond estimator to estimate a marginal abatement cost (MAC) curve for the average farm. Using 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%.

Keywords— Non-point Source, Pollution, Agricultural Runoff, Ambient Tax, Ambient Subsidy

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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.

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,

[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.

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.

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

[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).

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 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 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*

[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.

[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.

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 credits (shown in column 5 of Table 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 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",

[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.

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.

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.

[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.

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 4, 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]

[11] Political and institutional context for how this peculiar pollution management system came to be can be found in Milon (2018).

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 obtained 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]

[12]URL for the reports: https://www.sfwmd.gov/science-data/scientific-publications-sfer
[13]See F.A.C. 40E-63.145(4)(g)
[14]Data for years 1994 through 2000 was also obtained via public records request.
[15]URL: https://sfwmd.maps.arcgis.com

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.

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 succeeded 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

[16]It was originally aimed to achieve a concentration no greater than 50 ppb but was later amended in 2003 to 10 ppb.

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 Appendix A, 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 2 and 3 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.

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), 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 $Y = \sum_{i=1}^{n} y_i$.

$$S_i = \begin{cases} s(\overline{Y} - Y) & \text{if} \quad Y < \overline{Y} \\ \\ 0 & \text{if} \quad Y \geq \overline{Y} \end{cases} \tag{1}$$

If $\overline{Y} = \widetilde{Y}$, where $\widetilde{Y} = \sum_i \widetilde{y}_i$, then there is a unique Nash on a non-compliant outcome.

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

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 (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.

$$\pi'(\widetilde{Y}_i, \theta_i) = s \tag{2}$$

To achieve the first policy (henceforth referred to as the compliant Nash) it must be such that the incentive compatibility constraint, given by (3), holds for every agent. Note that the left hand side of (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 value $\overline{Y}$ must be chosen so that pivotal agents are incentivized to choose their minimum profitable pollution level (chosen so that (3) holds where Y^{NE} is the ambient pollution under compliant Nash).

[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 $\overline{Y}$.

$$s(\overline{Y} - Y^{NE}) \geq \pi_i(\theta_i) - \pi_i(\widetilde{y}_i) \tag{3}$$

Let the profit function be defined as in (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 $\overline{Y}$.

$$\pi_i(Y_{it}) = -\frac{\gamma_i}{2}(\theta_i - y_{it})^2 \tag{4}$$

Setting the right hand side of (2) equal to the subsidy rate s gives i's minimum profitable pollution (5), also known as their pollution demanded conditional on price s.

$$\widetilde{y}_i = \theta_i - \frac{s}{\gamma_i} \tag{5}$$

Then utilizing the pollution constraint (6) we get that the optimal subsidy rate, is given by (7)[20].

$$\overline{Y} = \sum_{i=1}^{n} \widetilde{y}_i \tag{6}$$

$$s^* = \frac{Y^{bau} - \overline{Y}}{\sum\limits_i \frac{1}{\gamma_i}} = \frac{Y^{bau}\left(1 - \frac{\overline{Y}}{Y^{bau}}\right)}{\sum\limits_i \frac{1}{\gamma_i}} \tag{7}$$

where $Y^{bau} = \sum\limits_{i=1}^{n} \theta_i$ 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

[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 (6) is the "true" target.

$(\gamma_i = \gamma_i^{bmp})$ 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 (2), it is instead governed by (8).

$$\pi'(y_{it}^*, \theta_i) = G_{it} \tag{8}$$

The term G_{it} is simply the partial derivative of the continuation value with respect to the pollution choice variable (see equation 26 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 (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 (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 (2).

$$\frac{\partial y^*_{it}}{\partial G_{it}} = \frac{1}{\frac{\partial g(y_{it}, \theta_i)}{\partial y_{it}}} = \frac{1}{\pi''\left(y^*_{it}, \theta_i\right)} = -\frac{1}{\gamma_i} \tag{9}$$

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.

[21] Abusing terminology a bit here because equation (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 (9) across farms.

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 (10), the number of credits still needed to be earned, as a proxy for G_{it}. The justification of D_{it} is detailed in Appendix C where I also show that $\left|\frac{\partial y_{it}^*}{\partial G_{it}}\right| > \left|\frac{\partial y_{it}^*}{\partial D_{it}}\right|$. Therefore, my estimates of slope γ_i using estimates of $\frac{\partial y_{it}^*}{\partial D_{it}}$ 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.

$$D_{it} = (T - t + 1)M - S_{it} \tag{10}$$

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}.

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

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 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 13 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 14 through 17 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 18), 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

[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.

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 (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 (11) where Y_{it} is the 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]

$$Y_{it} = \alpha_i + \alpha_t + \beta_1 D_{it} + \beta_2 X_{it} + \varepsilon_{it} \tag{11}$$

The problem with estimating (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 (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 (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

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

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 (10) together with the law of motion for credit stock (24). The exclusion restriction assumption is satisfied via the sequential exogeneity as seen by first differencing equation (10). First differenced values are denoted with a $\triangle$ symbol where $\triangle r_t = r_t - r_{t-1}$. The first differenced version of (11) is given by (12).

$$\triangle Y_{it} = \beta_1 \triangle D_{it} + \triangle \alpha_t + \beta_2 \triangle X_{it} + \triangle \varepsilon_{it} \tag{12}$$

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 previous discharges (Y_{it-k}) are uncorrelated with future error terms (ε_{it+k}). The first order condition (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 (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 2. 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 2 at face value would imply that the incentive credit program resulted in an average P load decrease of about 2.11 lbs/acre ($.0117 \times 180$) 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 13 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 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.

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

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

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 2 to produce the marginal abatement curve per acre (shown in Figure 20) 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 13).

Using the functional form assumptions under the static model for the compliant Nash subsidy rate (not per acre) from Equation (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 (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) of phosphorus during the baseline year,

[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).

the year before the EFA policy kicked in.

$$
\begin{aligned}
\widetilde{\pi}_i'(\widetilde{y}_i) &= \frac{1}{0.0117}(2.08 - \widetilde{y}_i) \\
\widetilde{y}_i &= 2.23 - 0.0117s
\end{aligned} \tag{13}
$$

Equation (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]

$$
s^* = \frac{402.04\left(1 - \dfrac{\overline{Y}^T}{402.04}\right)}{2.1177} \tag{14}
$$

Figure 21 plots Equation (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 21 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

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

have achieved, at a minimum, a 25% reduction relative to Y^{bau} with an ambient subsidy rate of \$47.46.

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 2 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 22. 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 (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.

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]

[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.

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 \$2 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 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]

[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).

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 Appendix C), 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 4. Each row of Table 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 (15).

$$\gamma^{estimated} = \lambda \gamma^{bau} \tag{15}$$

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).

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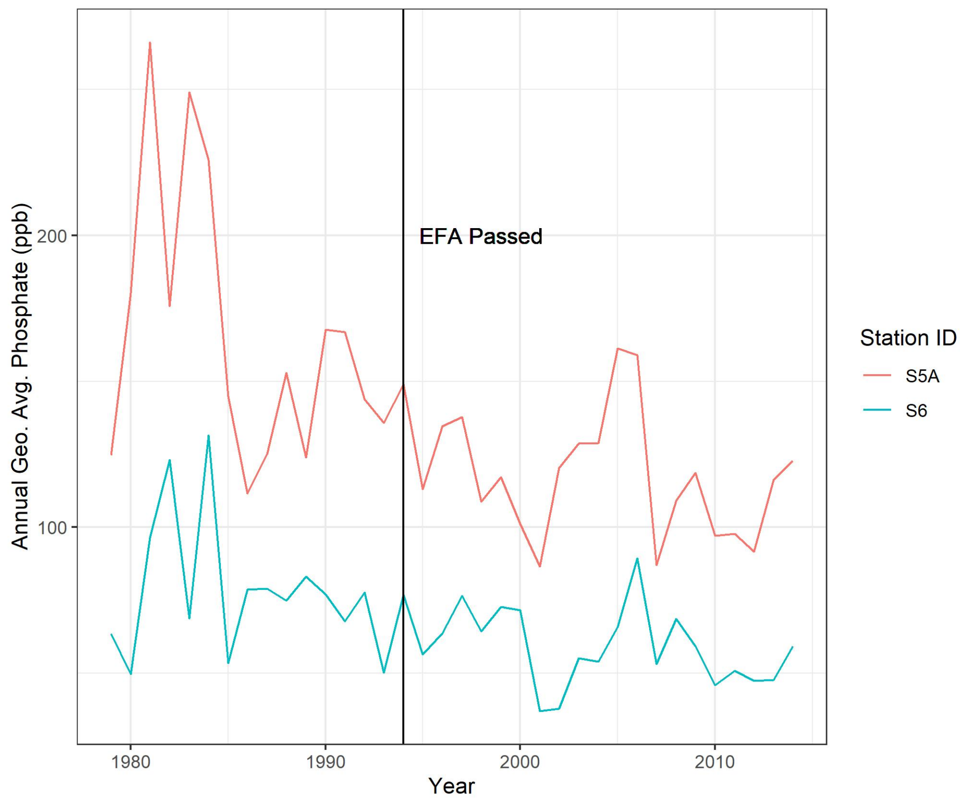
Appendix A

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 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.[33]

[33] 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.

Figure 1: Phosphate (ppb) Readings from Select EAA Water Quality Monitoring Stations



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 5 and 6 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.[34] Units in the treated group are only assigned the treated 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

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

is the annual geometric average of measured nitrate (ppb).

The optimal weights (w_i) are chosen so that equation (16) 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 (16) is done separately for both treated units.

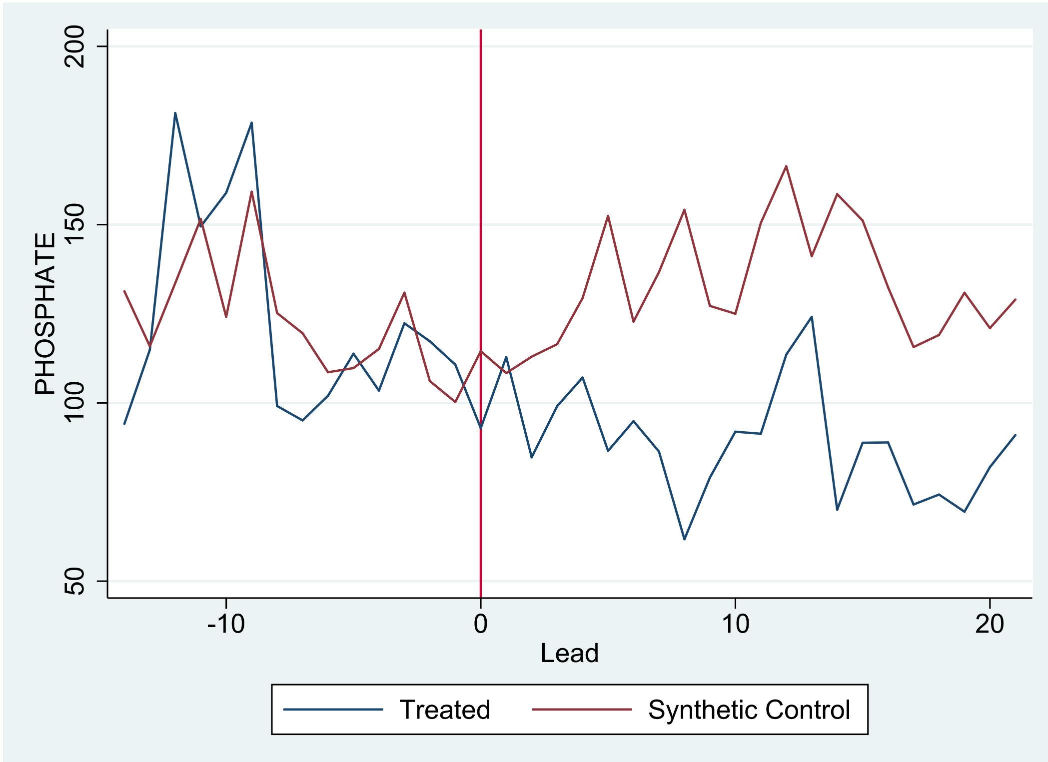
$$\frac{1}{15}\sum_{t=1979}^{1993}\left(X_{1t} - w_2 X_{2t} - \cdots w_{J+1} X_{J+1,t}\right)^2 \tag{16}$$

X_{it} denotes the annual geometric average phosphorus levels for station i and no other co-variates are used.[35] Once the optimal weights are computed, average treatment effect, α_t, is calculated via (17) and the results of which are implicitly shown in Figure 2.

$$\widehat{\alpha}_t = \frac{1}{2}\sum_{i=1}^{2}\left(X_{it} - \sum_{j=2}^{J+1} w_{ij}^* X_{jt}\right) \tag{17}$$

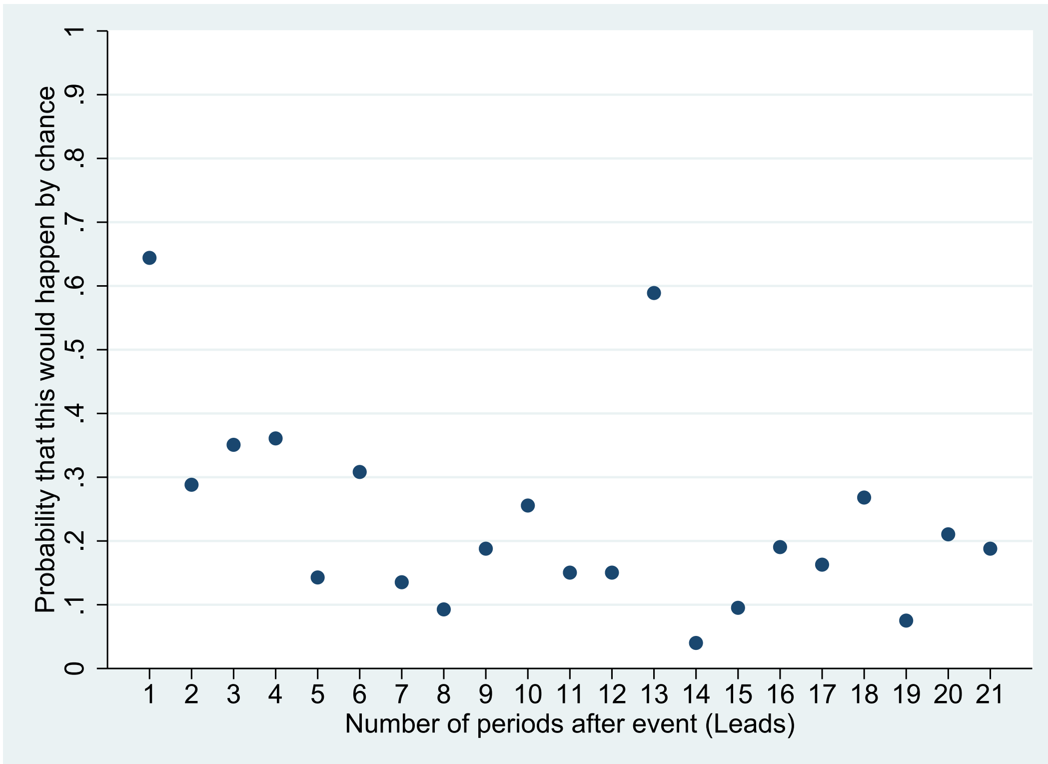
[35] Geometric average is used because measured phosphorus is a flow measure and in such instances, geometric averages provides a more accurate summary of the occurrences over time.

Figure 2: 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 3. 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 3: P-Values for Treatment Effects



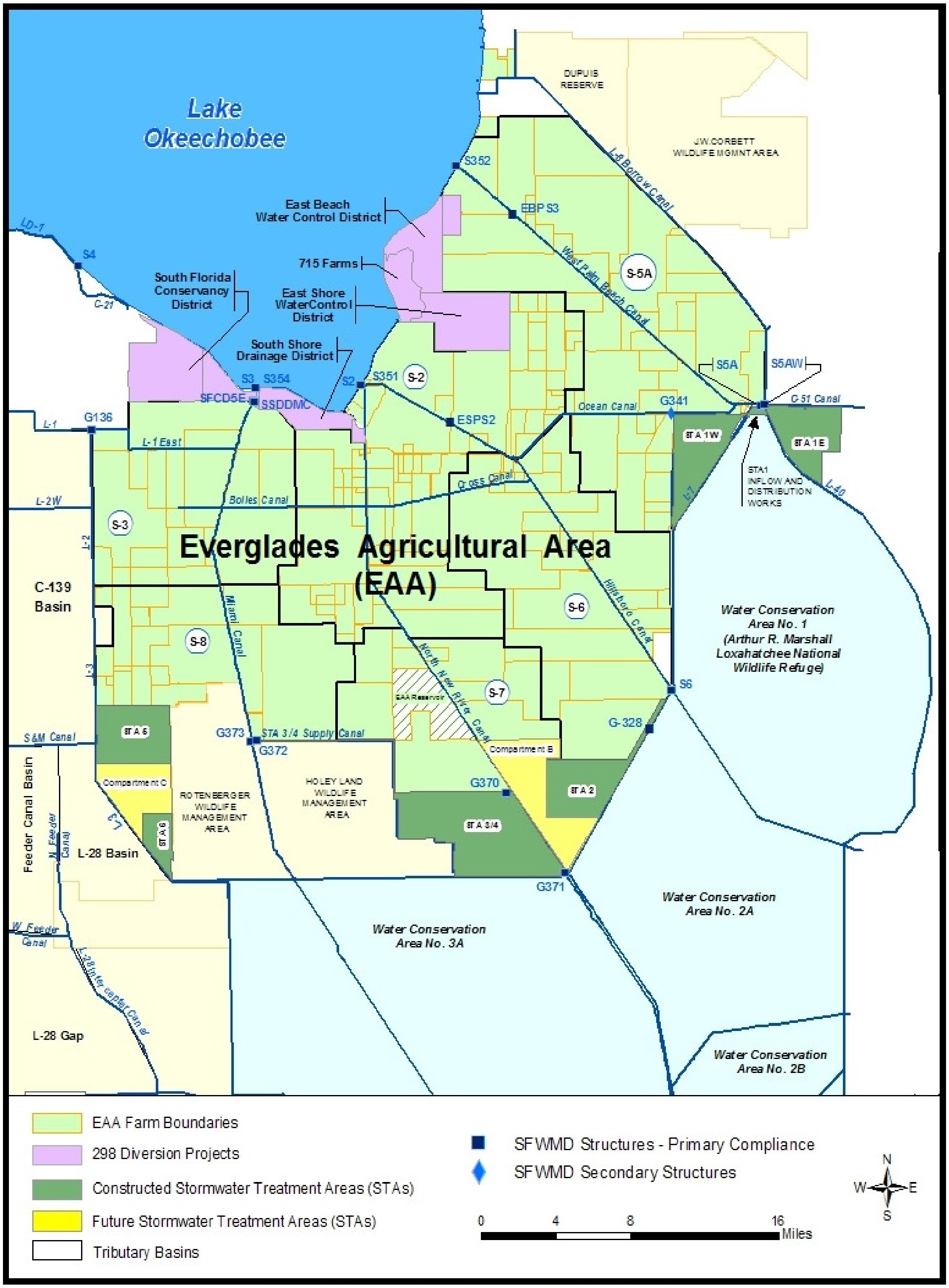
There are a number of robustness I have implemented and the results are shown in Appendix A. First, I try to incorporate anticipatory effects by treating the "effective" policy implementation date as *if* it were in 1992. The actual policy implementation date was 1994 but the policy is a culmination of legal proceedings that occurred with public attention starting in 1992. The results of changing the intervention date are shown in Figures 7 and 8. 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 9 through 12 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.

Table 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			

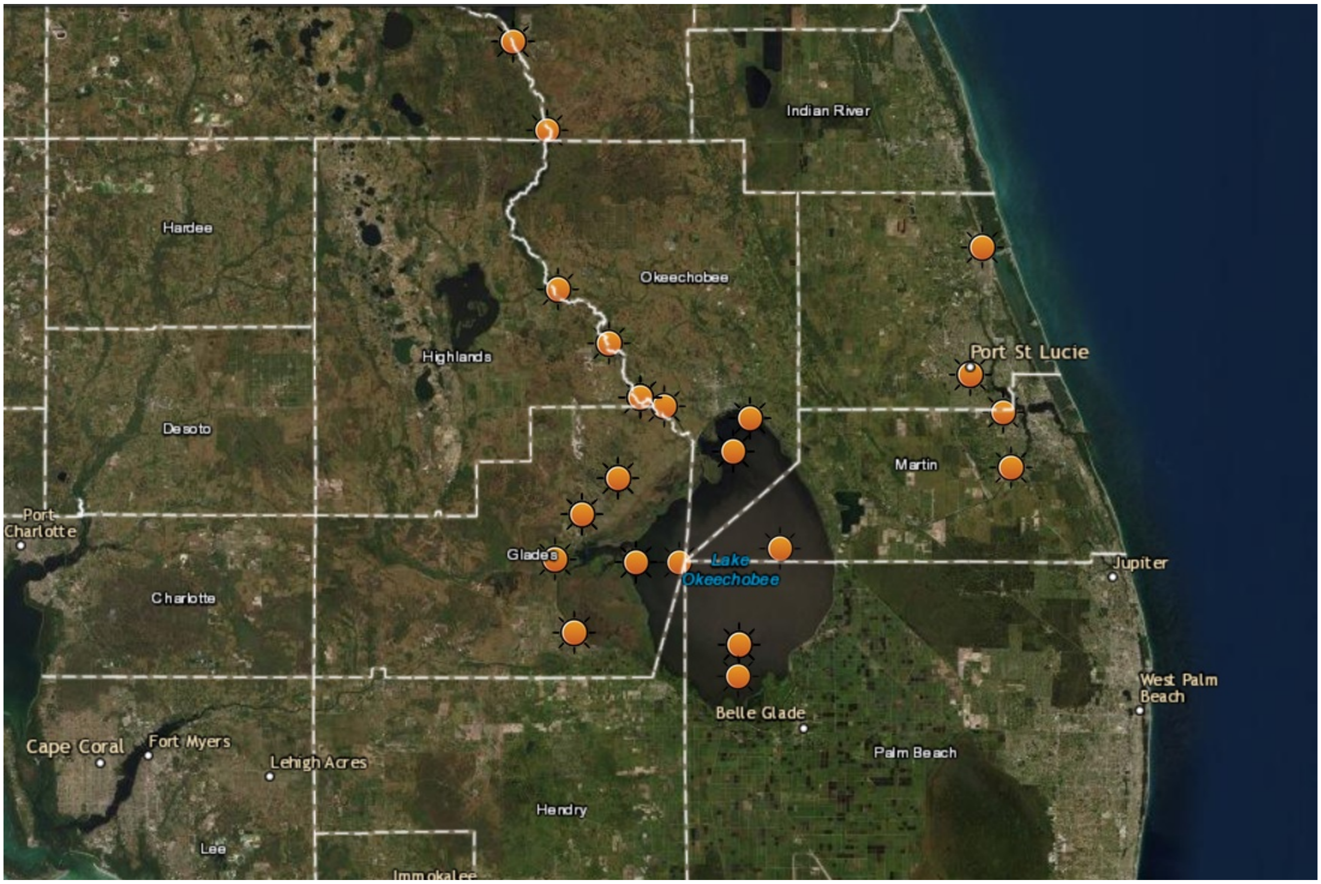
Source: Florida CS/HB 7065 and Fl. St. 373.4592

Figure 4: EAA Area with Canals/Drainages



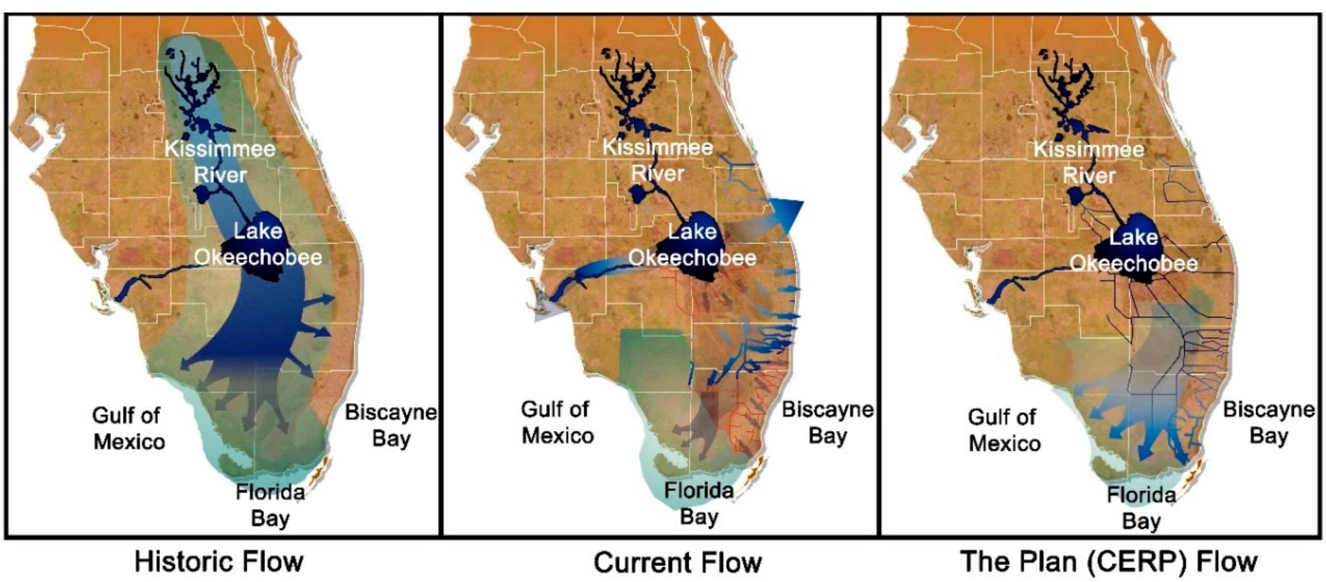
ERRD/EREG 19-Nov-2008 lursu\\dataserv\420\4260\gis\ever_gis\SFER2009\mxdfiles\eaaloc_sfer2009_lu.mxd

Figure 5: Map of Donors for Synthetic Ctrl



Source: DBHYDRO's Map Browser

Figure 6: Hydrological flow in Southern Florida



Source: Schade-Poole and Möller (2016)

Figure 7: Synthetic Control Result: Robustness to Anticipatory Effect

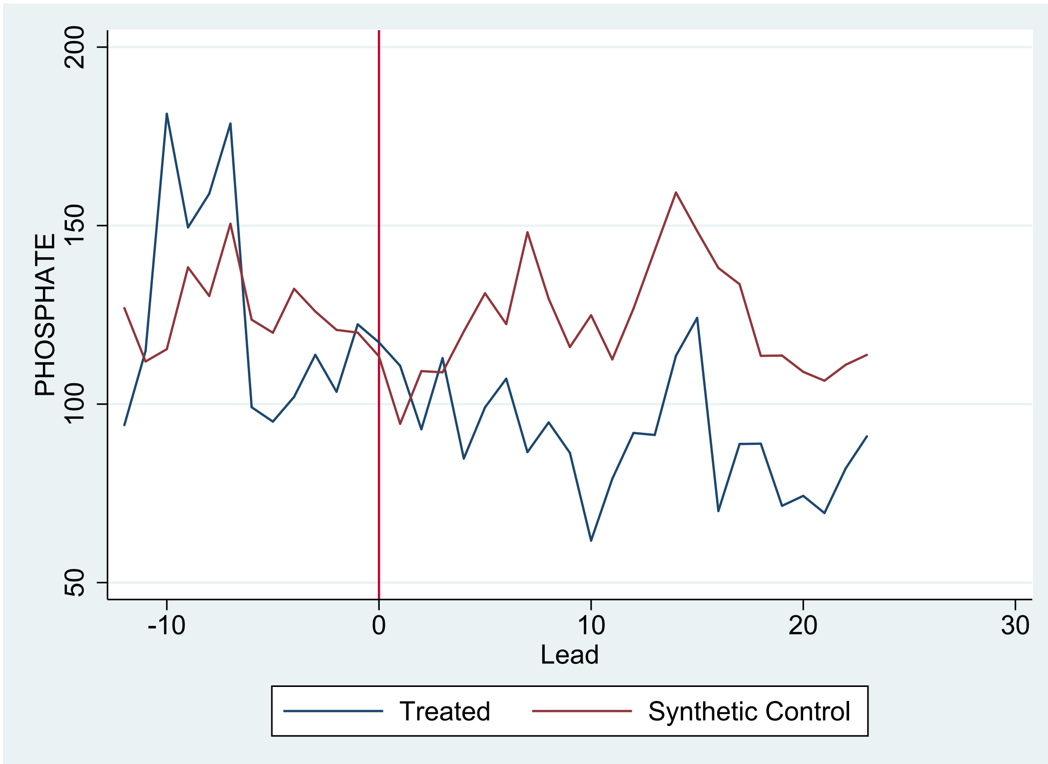


Figure 8: P-Values for Treatment Effects: Robustness to Anticipatory Effect

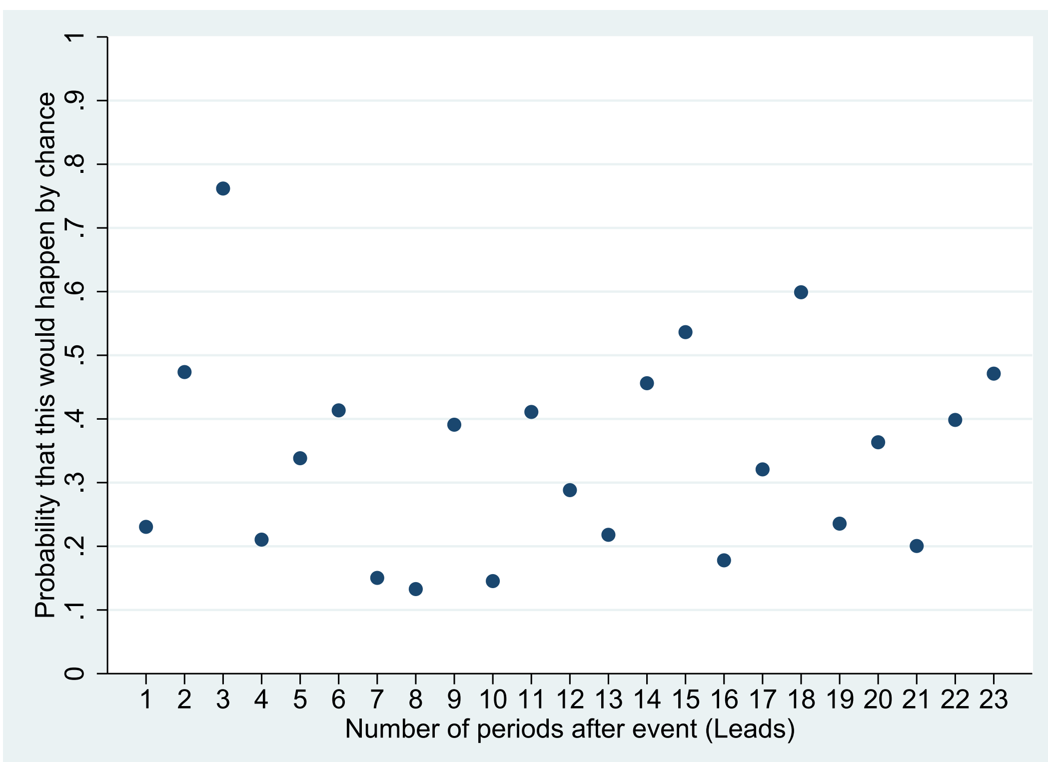


Figure 9: Synthetic Control Result: Robustness to Demeaning

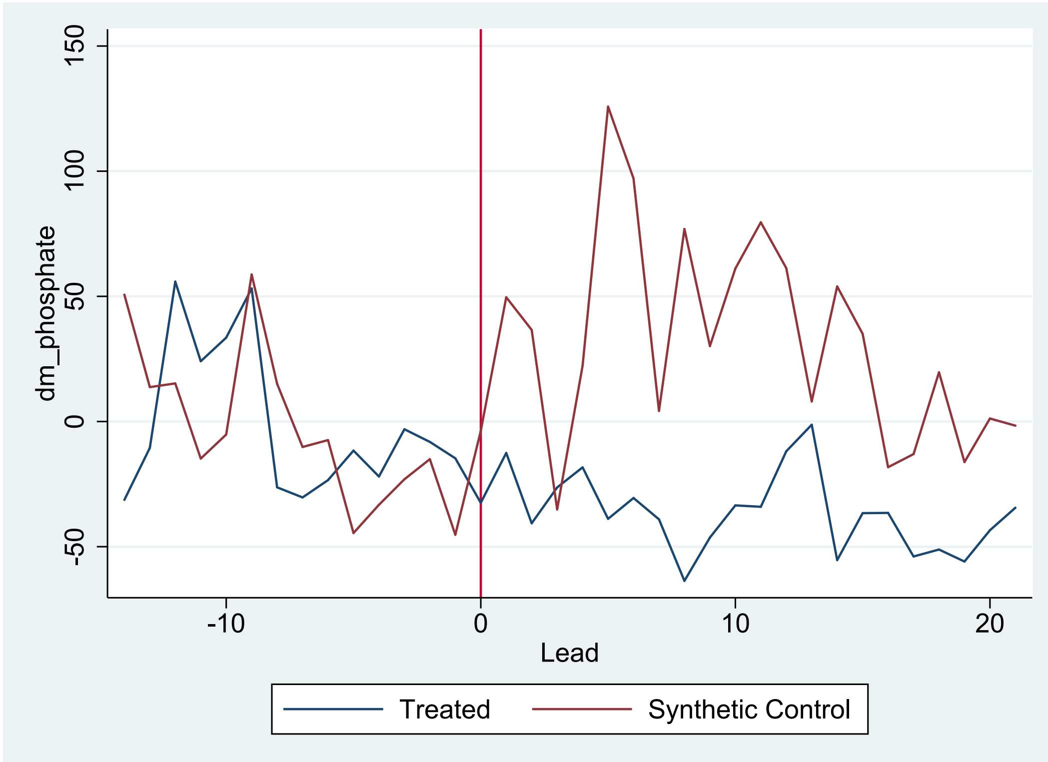


Figure 10: P-Values for Treatment Effects: Robustness to Demeaning

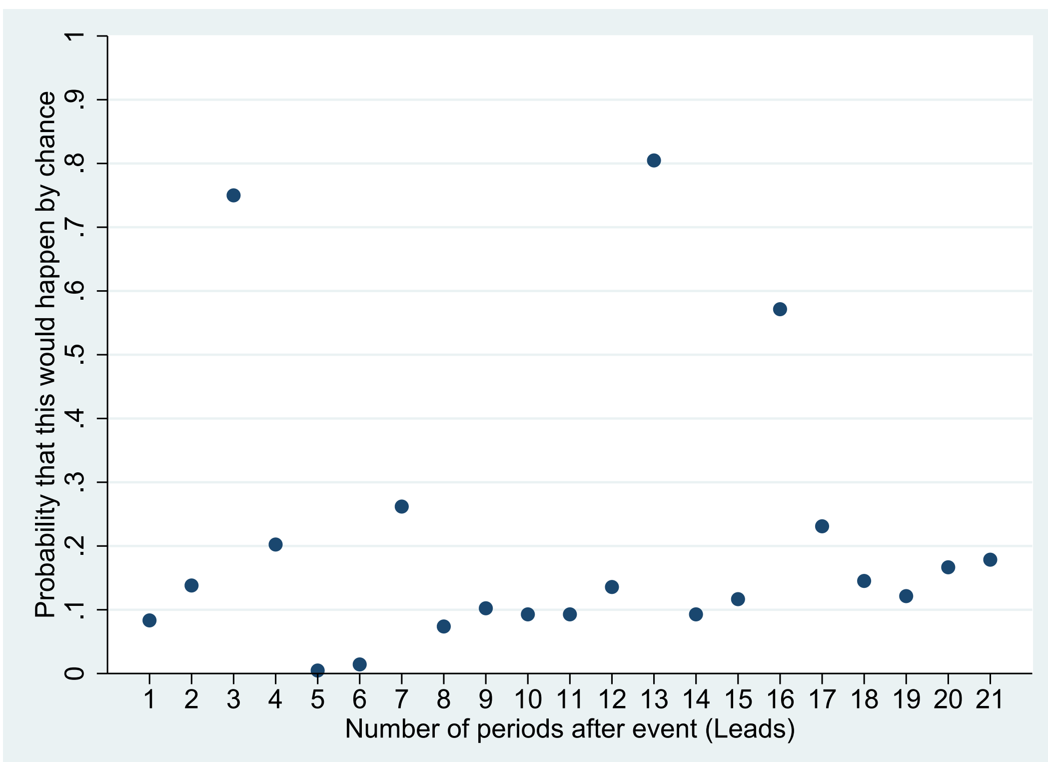


Figure 11: Synthetic Control Result: Robustness to Anticipatory Effect & Demeaning

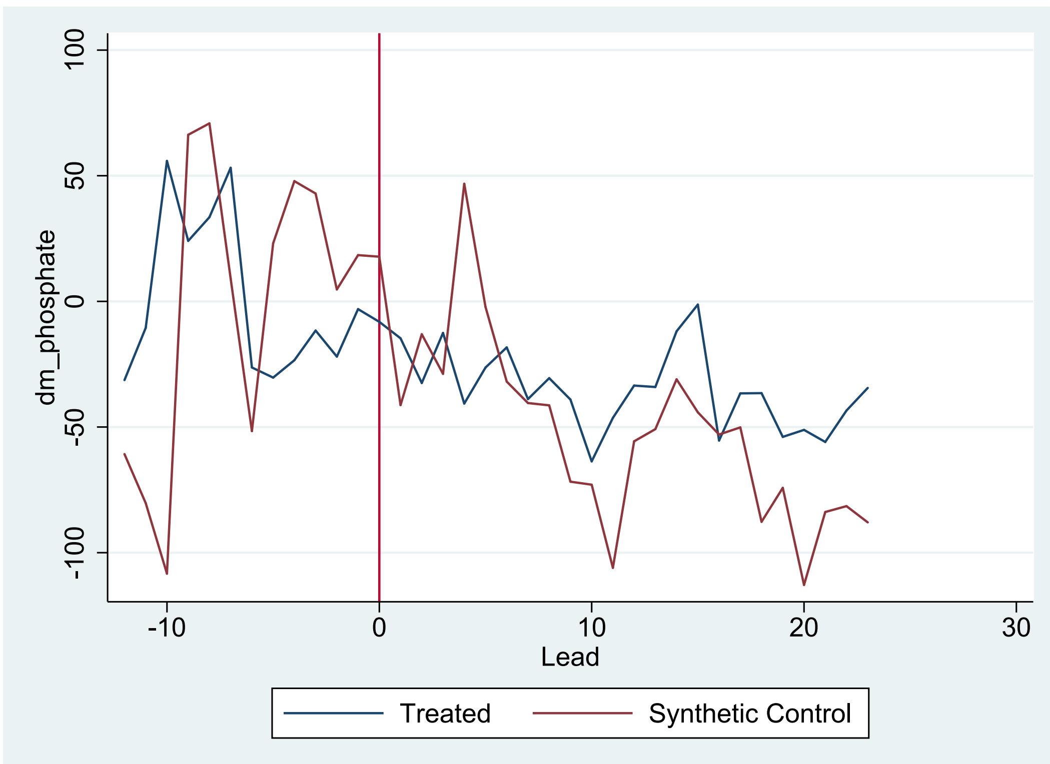


Figure 12: P-Values for Treatment Effects: Robustness to Anticipatory Effect & Demeaning

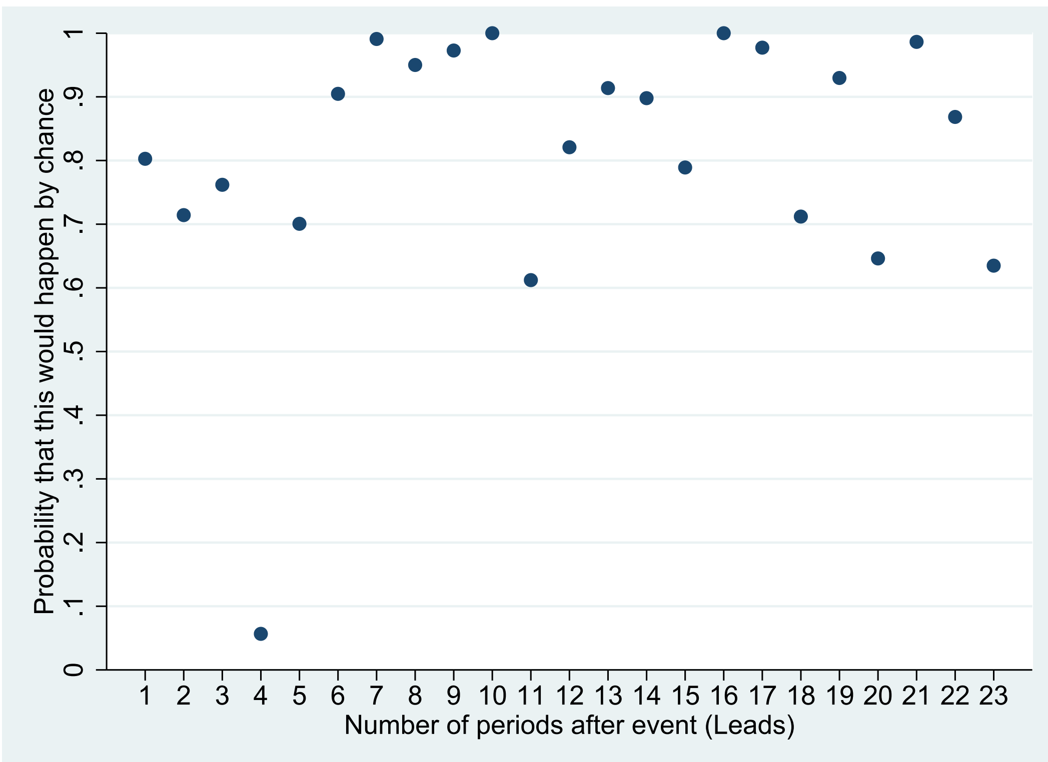


Figure 13: Heatmap Distribution of D_{it}'s

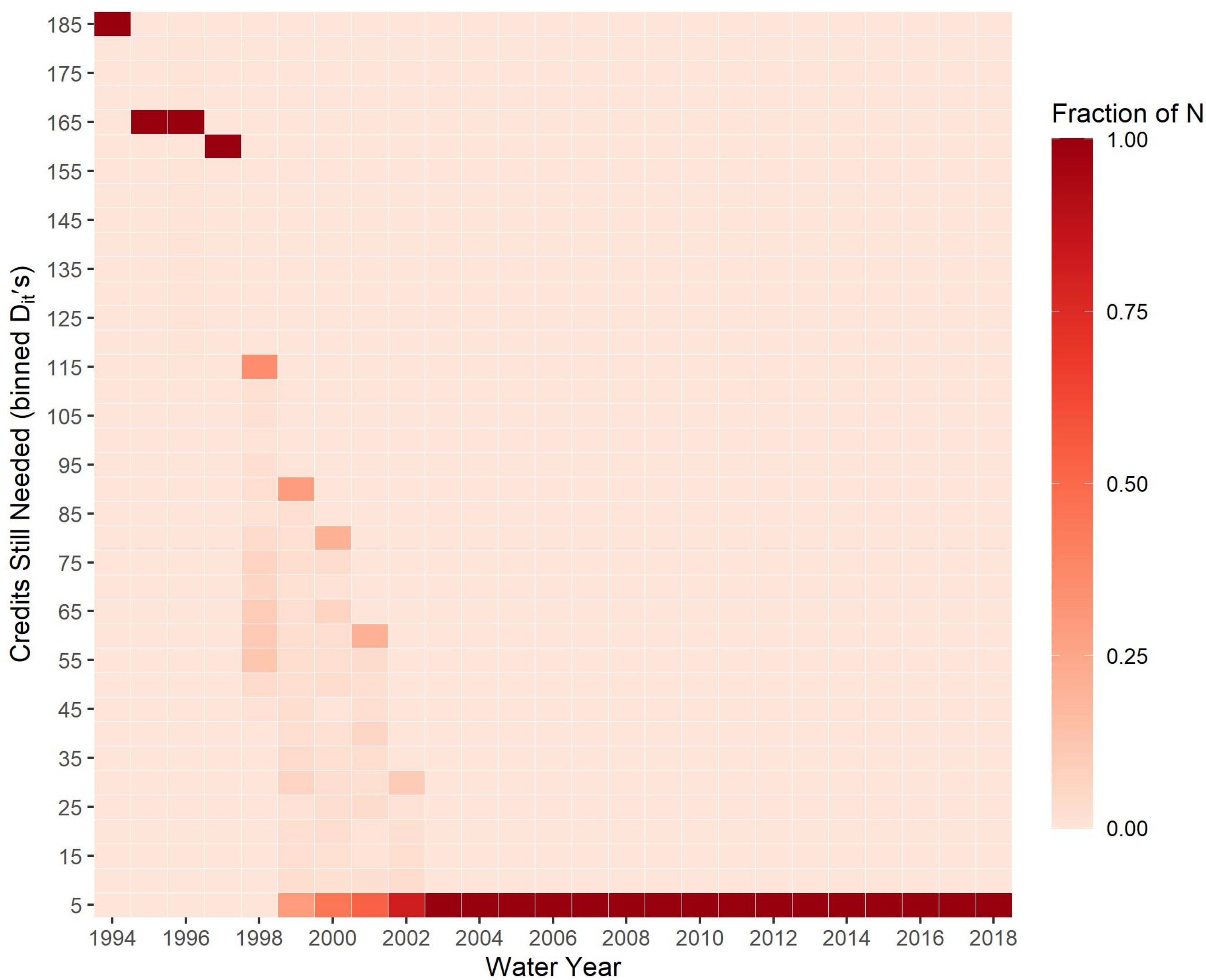


Table 2: Two-step Difference GMM Results: Outcome is Measured TP Loads

	(1)	(2)	(3)
	exogenous controls	predetermined controls	predetermined vege acres
Credits Still Needed (per acre)	-0.0129***	-0.0113**	-0.0117**
	(0.001)	(0.004)	(0.002)
Credits needed X Distance to Lake Okee	0.000000294	0.000000265	0.000000288
	(0.058)	(0.077)	(0.056)
Total Acres Dedicated to Vege	0.000460	0.000193	0.000228
	(0.405)	(0.159)	(0.102)
Basin Acreage	0.0000332	0.000164	0.0000366
	(0.395)	(0.055)	(0.362)
BMP Cycle (categorical)	0.0523	0.0700	0.0753
	(0.577)	(0.498)	(0.471)
Hansen_Test_Pval	0.512	1.000	0.839
Included_farms	172	172	172

p-values in parentheses

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

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

Table 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

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

Table 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

Figure 14: Annual Average Phosphorus Loads by Cohort

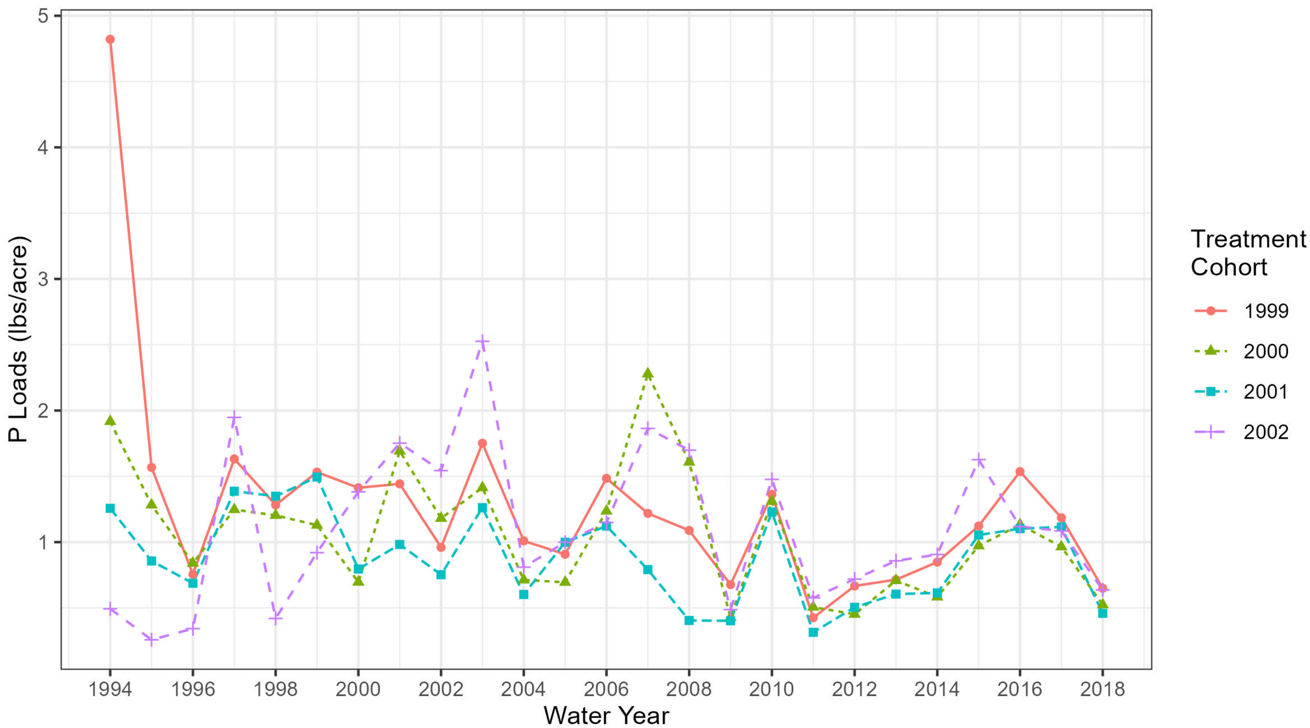


Figure 15: Annual Average Land Size by Cohort

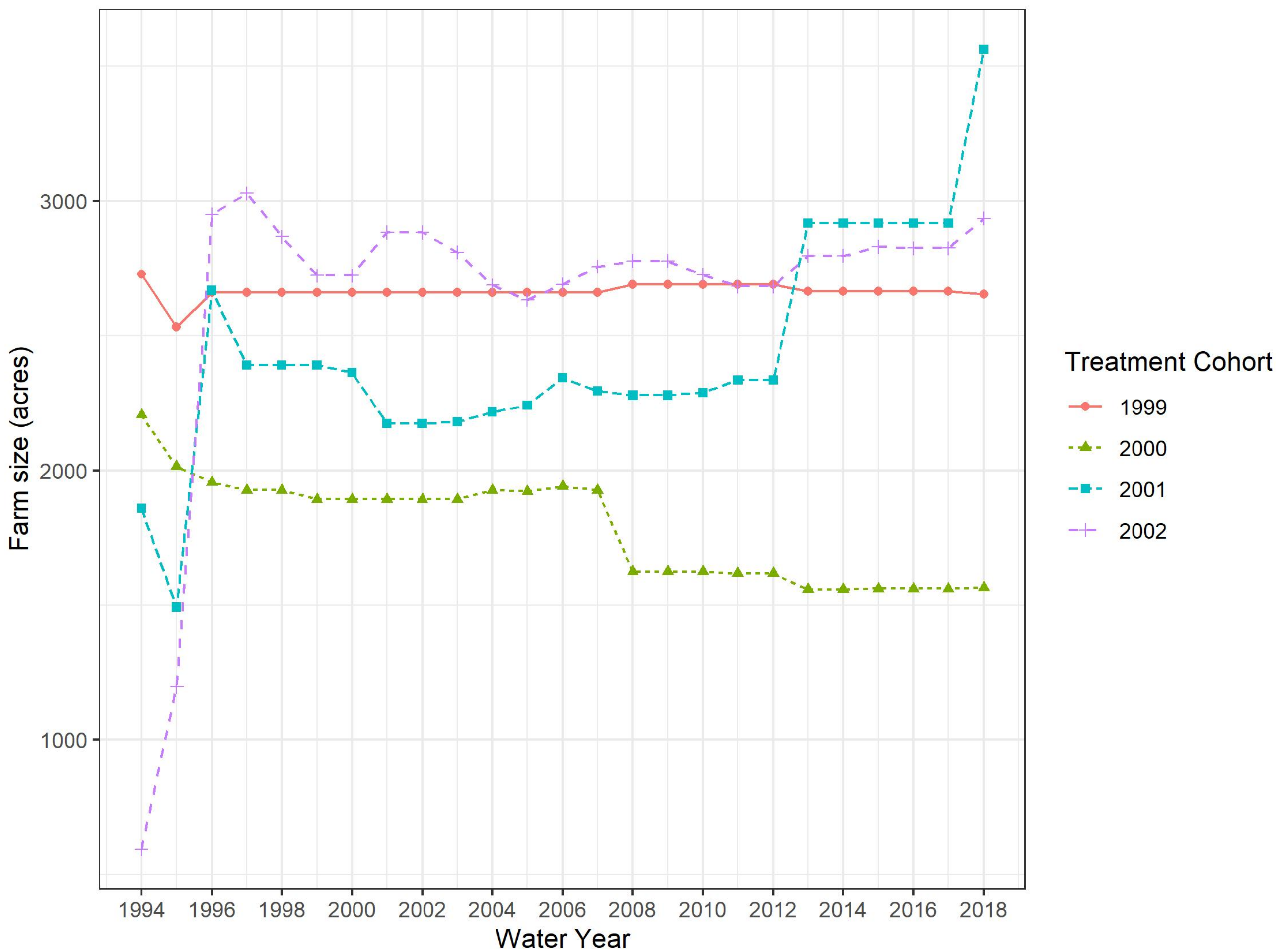


Figure 16: Annual Average Acres Dedicated for Vegetable Production by Cohort

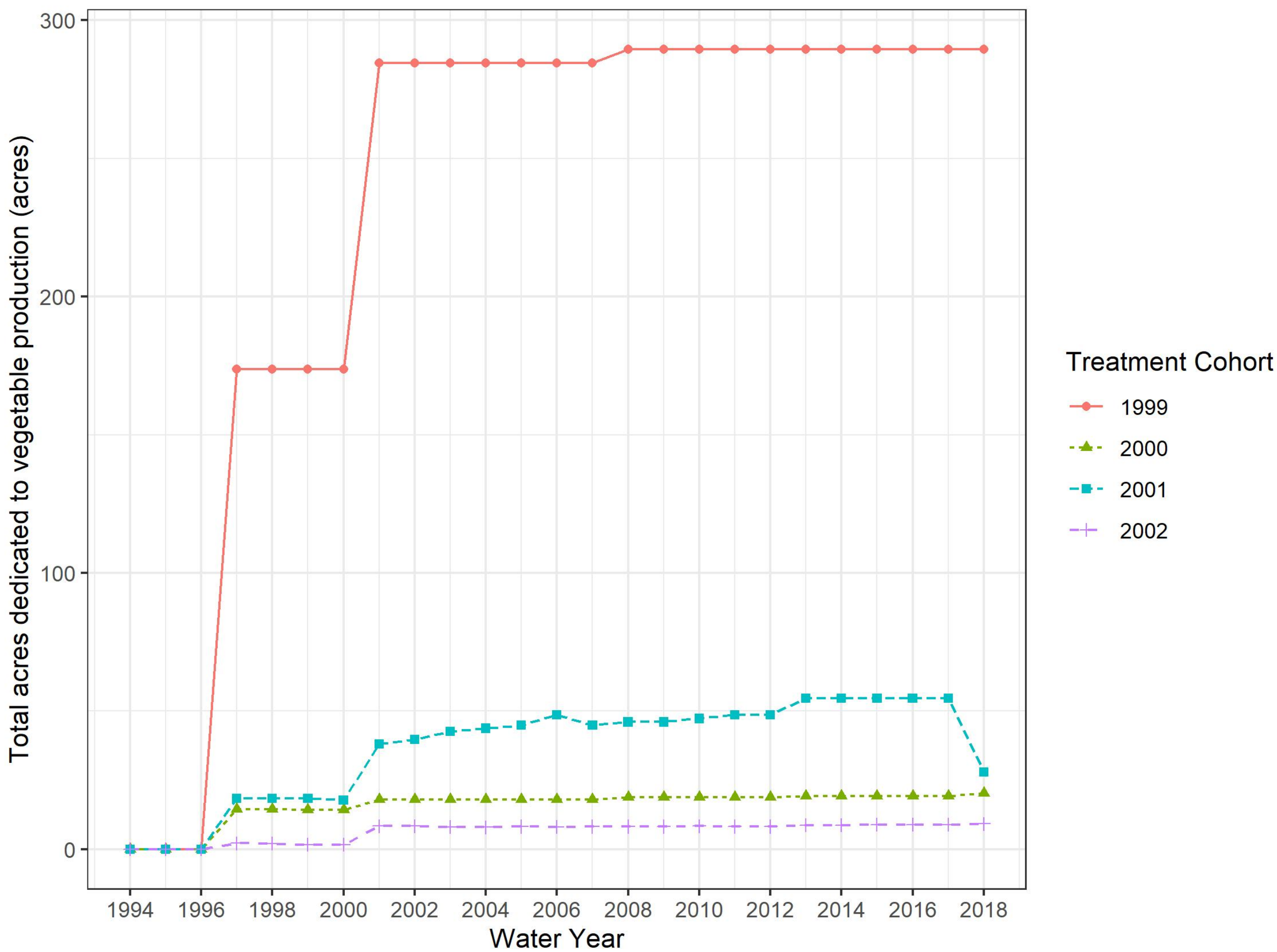


Figure 17: Annual Average Distance from Lake Okeechobee by Cohort

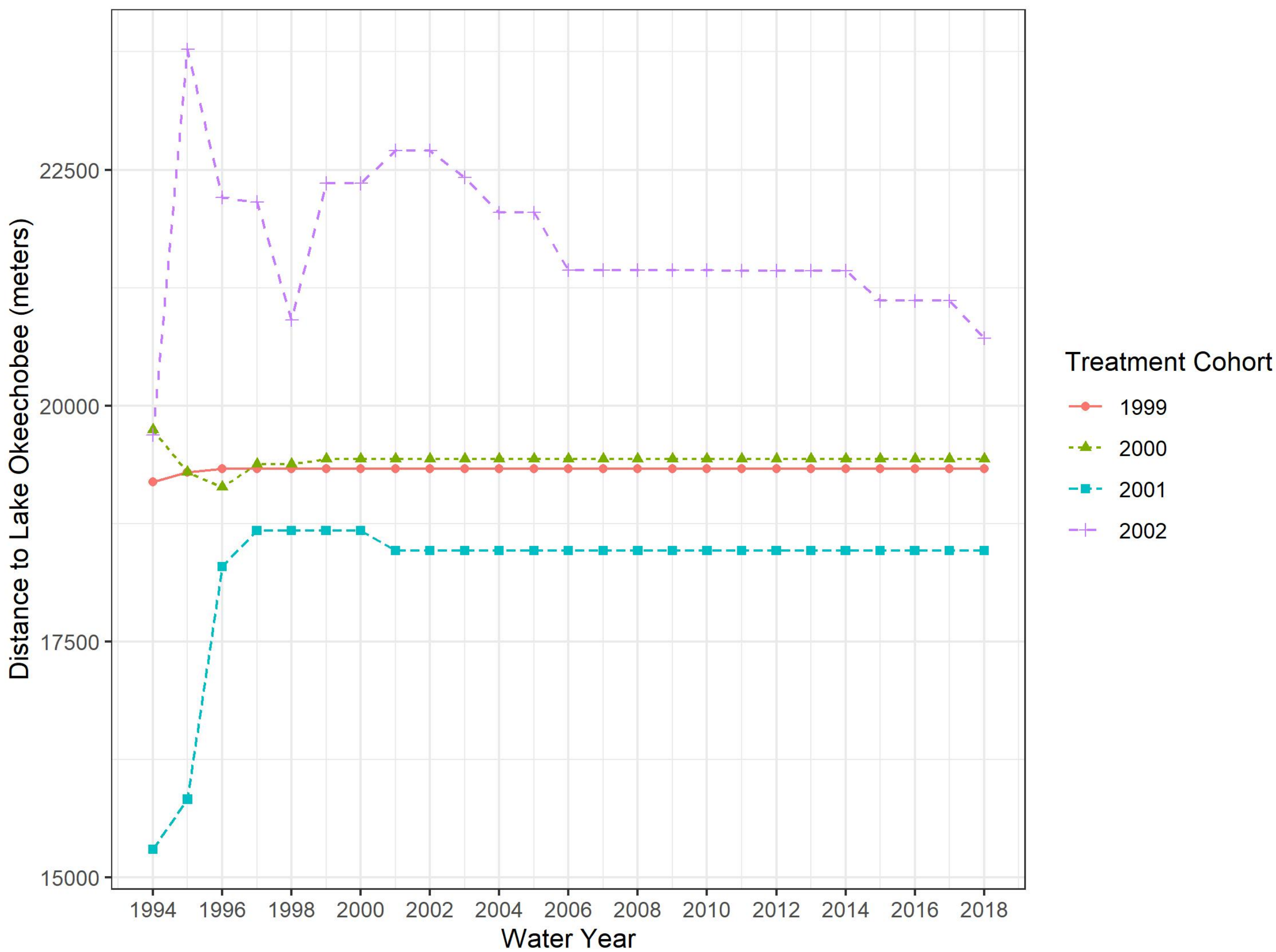


Figure 18: Distribution of Baseline Year by Cohort

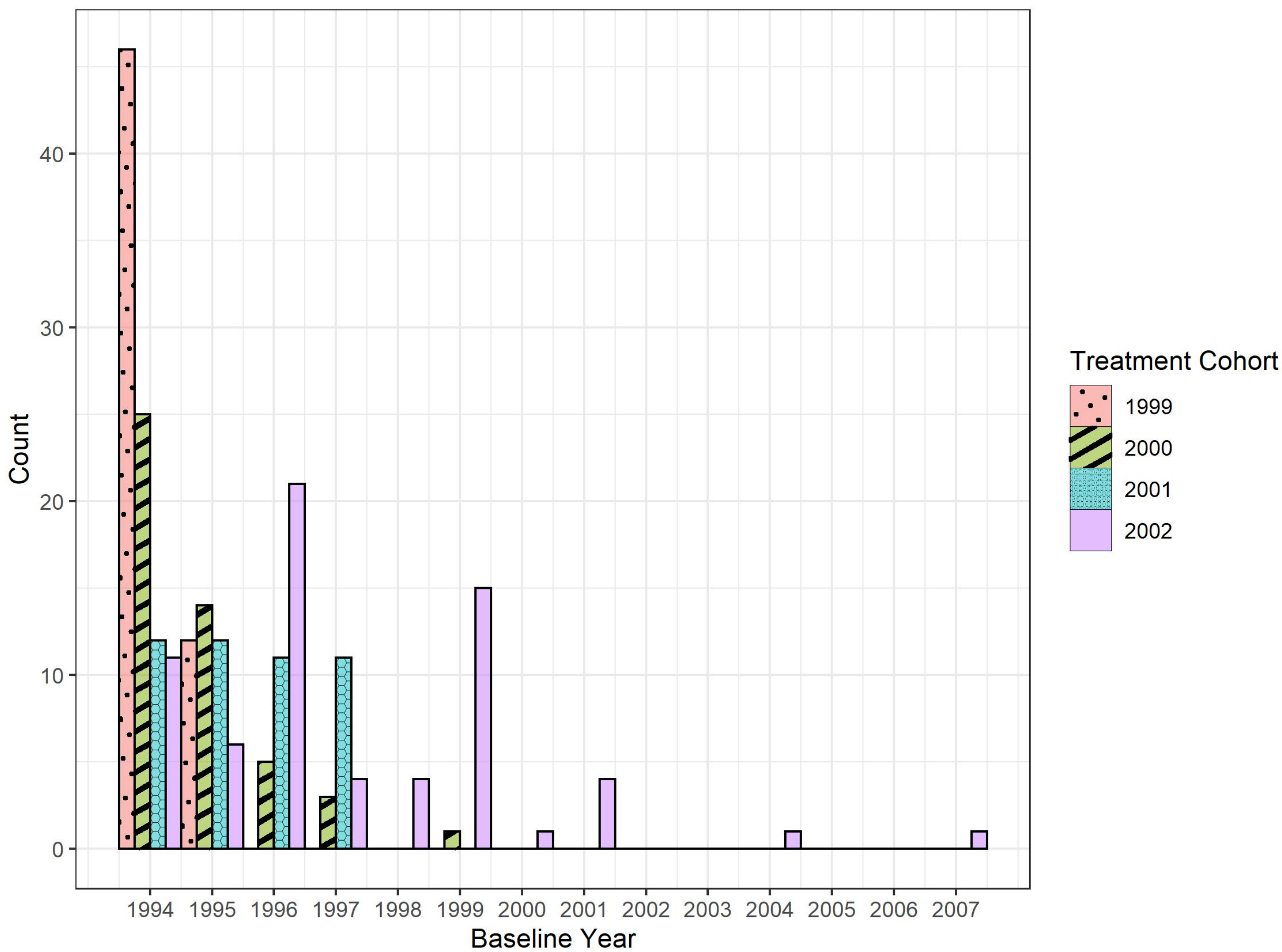


Figure 19: Histogram of Permuted $\widehat{\beta}$'s

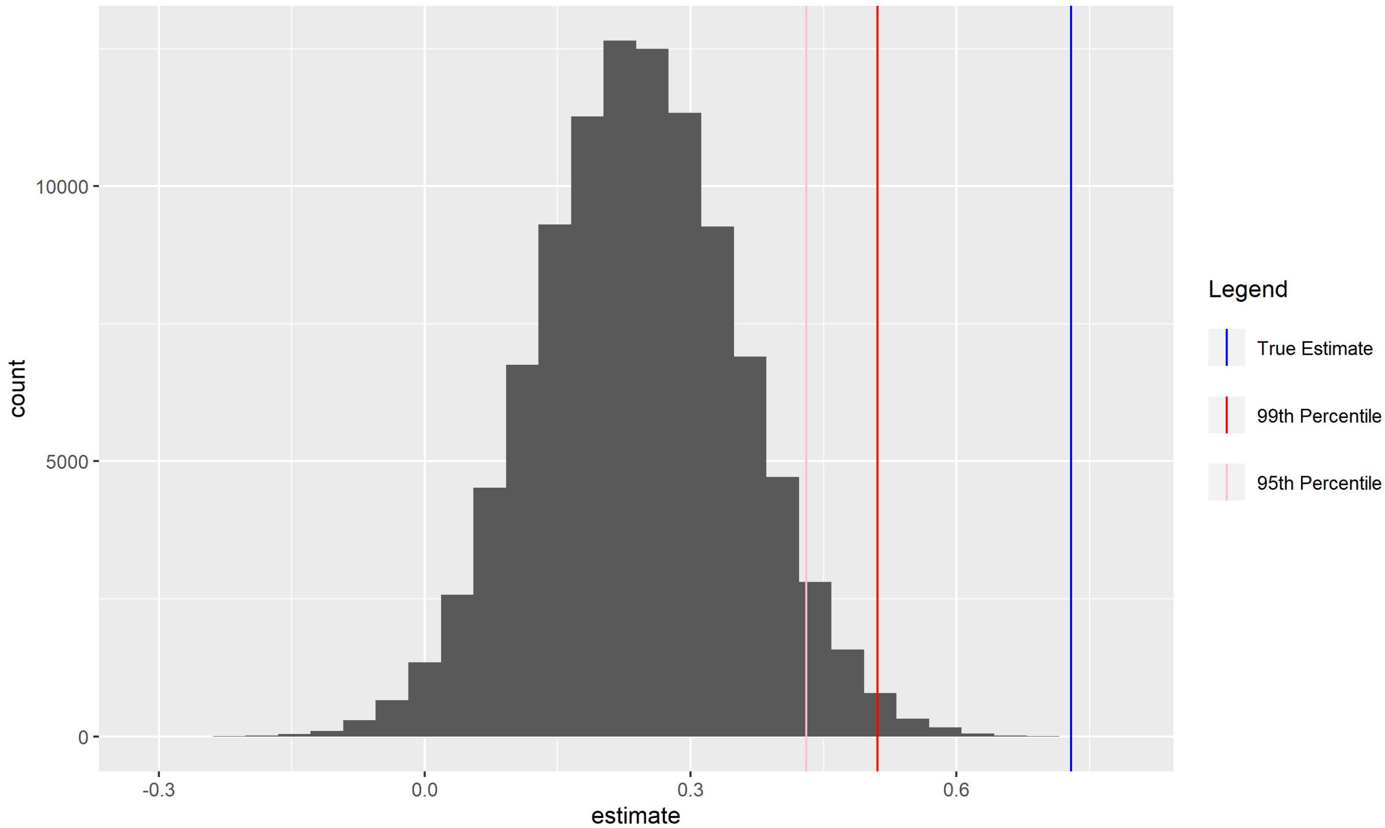


Figure 20: Estimated Marginal Profit Curve for the Avg. Farm

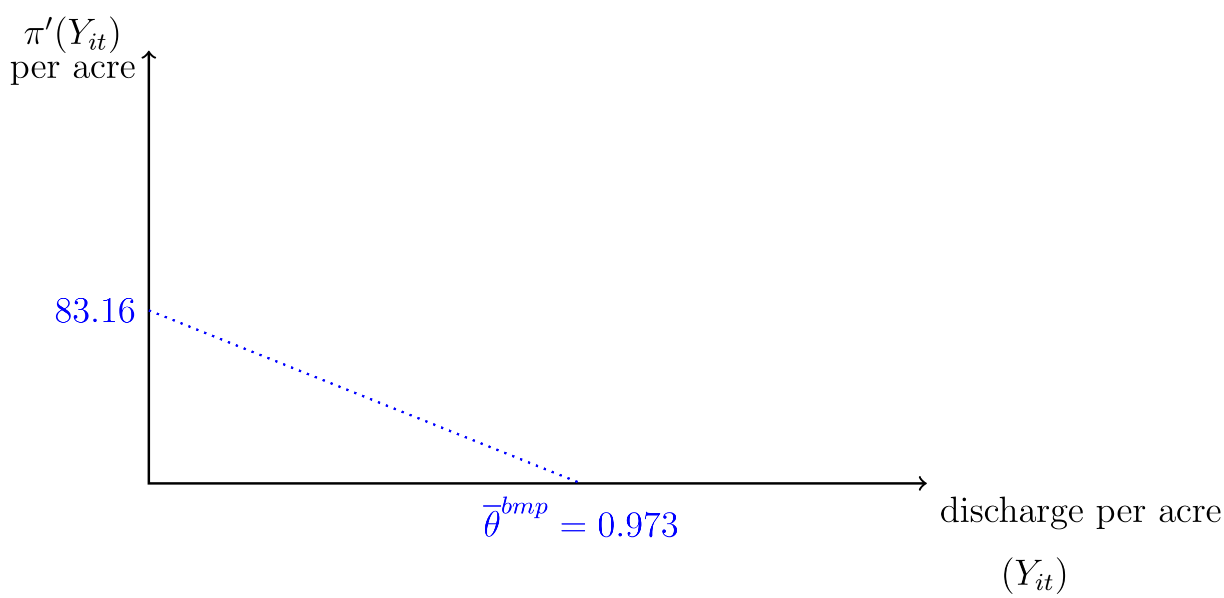


Figure 21: Compliant Nash Subsidy as a Function of Ambient P Target

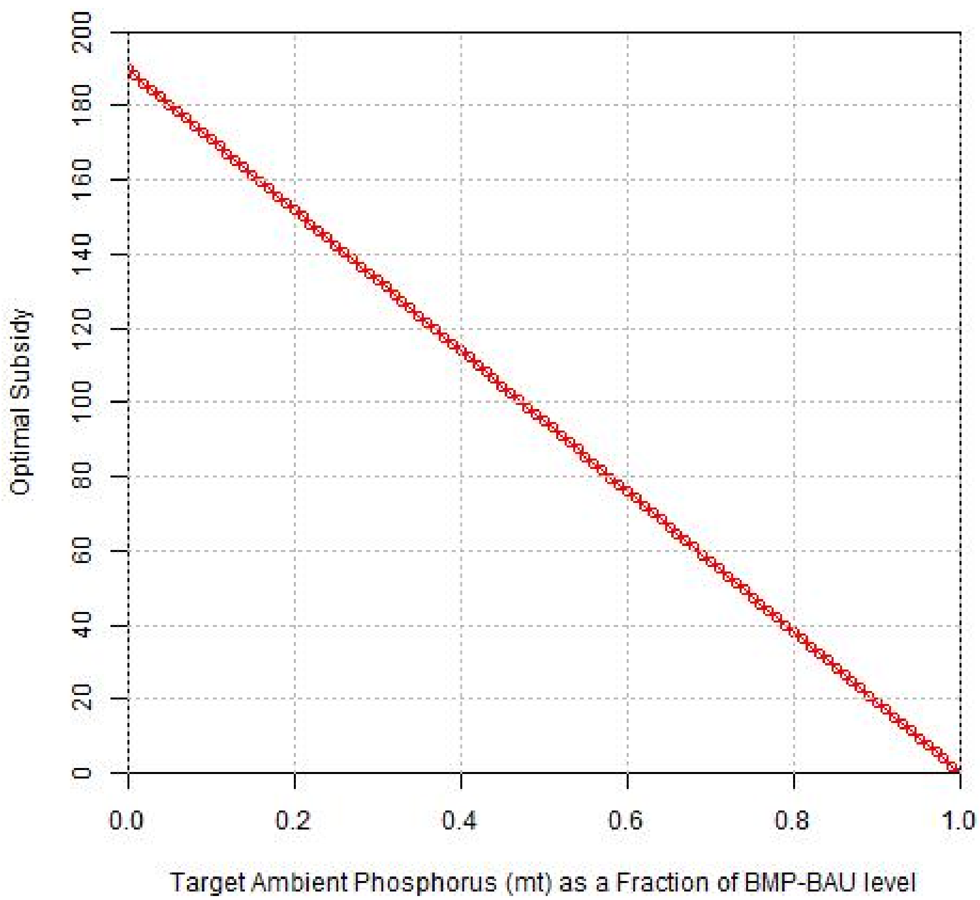
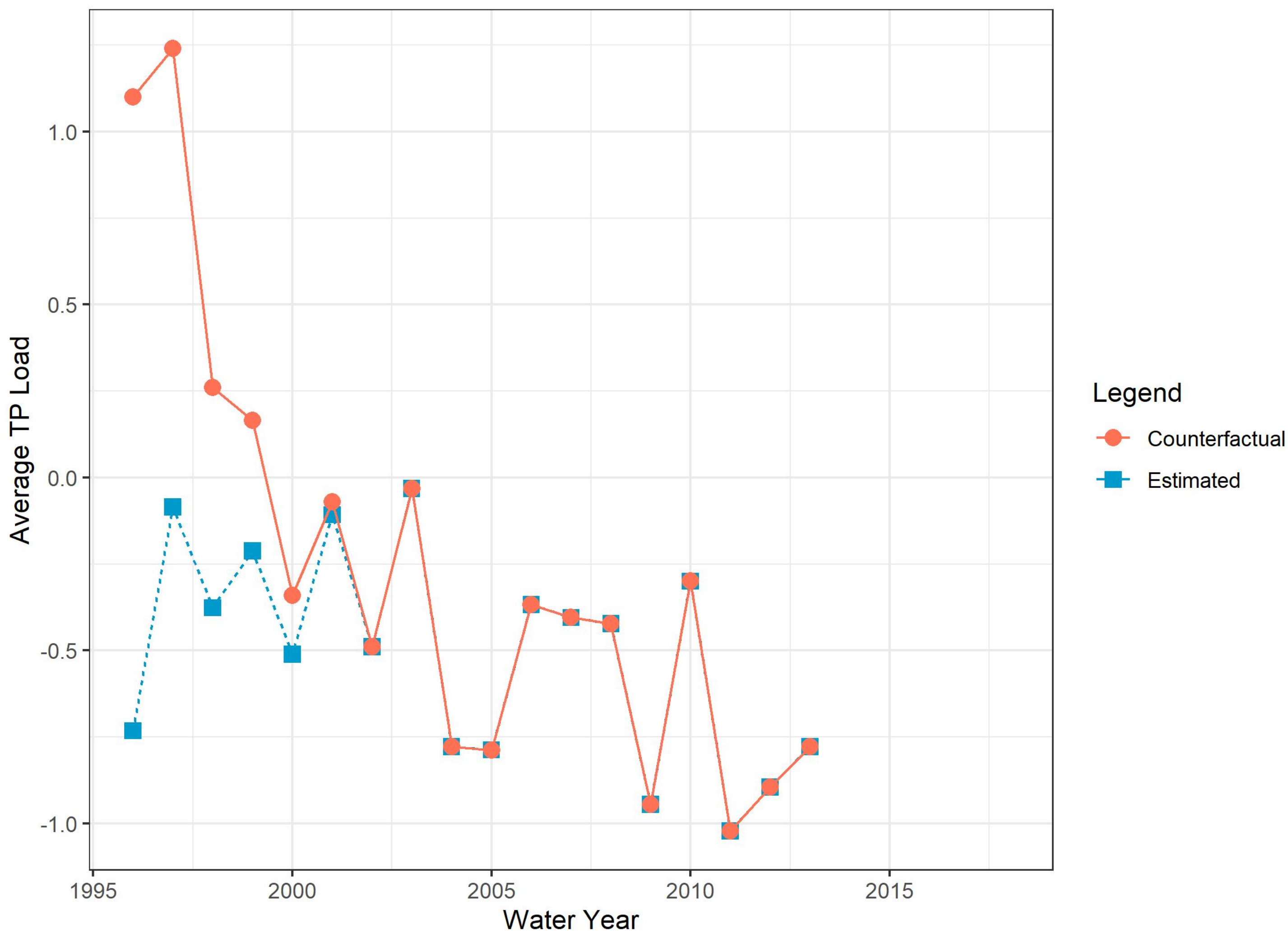


Figure 22: Estimated and Counterfactual TP Loads



Appendix C

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 $\left|\dfrac{\partial Y^*_{it}}{\partial G_{it}}\right| > \left|\dfrac{\partial Y^*_{it}}{\partial D_{it}}\right|$ and that the two partials have the same sign. First, via chain rule, we have (18).

$$\frac{\partial Y^*_{it}}{\partial D_{it}} = \left(\frac{\partial Y^*_{it}}{\partial G_{it}}\right)\left(\frac{\partial G_{it}}{\partial S_{it}}\right)\left(\frac{\partial S_{it}}{\partial D_{it}}\right) \tag{18}$$

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 (19) instead of (26).

$$G_{it} = -\frac{d}{dY_{it}}\delta\mathbb{E}\big[V_{t+1}(S_{it+1})\big] \tag{19}$$

Then we can apply Young's Theorem and standard regularity conditions to get (20).

$$\frac{\partial G_{it}}{\partial S_{it}} = -\frac{d}{dY_{it}}\delta\mathbb{E}\left[\frac{\partial V_{t+1}(S_{it+1})}{\partial S_{it}}\right] \tag{20}$$

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 $\frac{\partial S_{it}}{\partial S_{it-1}} = 1$.

$$\frac{\partial V_t(S_{it})}{\partial S_{it-1}} = \frac{\partial Q^*_{it}}{\partial S_{it}} = \mathbb{1}\{S_{it} < M\}. \tag{21}$$

Since $Q^*_{it} = \min\{M, S_{it}\}$. Thus (20) becomes (22)

$$\frac{\partial G_{it}}{\partial S_{it}} = -\frac{d}{dY_{it}}\delta\mathbb{P}(S_{it+1} < M) \tag{22}$$

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 (23).

$$\frac{\partial G_{it}}{\partial S_{it}} = -\frac{d}{dY_{it}}\delta\mathbb{P}(\alpha_t > \Gamma_t) = \frac{\partial\mathbb{P}(\alpha_t \leq \Gamma_t)}{\partial\Gamma_t} \tag{23}$$

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 (18), 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.

Appendix F

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).[36] The $\overline{T}$ term denotes the lump sum tax (values of this are shown in column 2 of Table 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 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 *after optimally deciding* Q_{it} is given by

[36] 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.

the Bellman equation (24).[37]

$$
\begin{aligned}
V_t(S_{it}) &= \max_{Y_{it}} \ \pi(Y_{it}, \theta_i^{bmp}) - \left(\overline{T} - Q_{it}^*\right) + \delta \mathbb{E} V_{t+1}(S_{i,t+1}) \\
\text{s.t.} \qquad S_{i,t+1} &= S_{it} - Q_{it}^* + \left(\overline{Y}^P - Y_t\right) \\
Y_t &= \alpha_t + \sum_i Y_{it} \\
\overline{Y}^P &\geq \alpha_t + \sum_i \theta_i^{bmp} \\
\alpha_t &\overset{iid}{\sim} F(0, \sigma_\alpha^2) \\
Q_{it}^* &= \min\{M, S_{it}\}
\end{aligned}
\tag{24}
$$

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.[38] Then credits owed can be calculated and issued out for use in the next period. In Appendix F, I solve (24) backwards under finite time with T being the terminal date and normalizing the terminal value to zero. The FOC is given by (25).

$$
\pi'(Y_{it}^*, \theta_i^{bmp}) = G_{it} \tag{25}
$$

The G_{it} term captures the expected present value of exercising credits in the future which

[37]The model presented in (24) intentionally ignores the rates presented in column 3 of Table 1 for notational simplicity.

[38]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.

are earned today by marginally reducing discharge Y_{it} and is defined by (26).

$$G_{it} = -\sum_{k=t+1}^{T} \delta^{k-t} \mathbb{E}\left[\frac{\partial Q^*_{ik}}{\partial Y_{it}}\right] \tag{26}$$

Note that since Y_{it} denotes discharges, the partials in (26) are weakly negative. The G_{it} 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 (2) and (25). 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

$$Y^*_{it} = g^{-1}(G_{it}, \theta_i^{bmp}) \tag{27}$$

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

$$V_{T+1}(S_{i,T+1}) = \sum_{k=0}^{\infty} \delta^k \pi(\theta_i^{bmp}, \theta_i^{bmp}) = 0 \tag{28}$$

means that

$$\begin{aligned} V_T(S_{iT}) &= \max_{Y_{iT}} \; \pi(Y_{iT}, \theta_i^{bmp}) - (\overline{T} - Q^*_{iT}) \\ \text{FOC:} \quad & \pi'(Y^*_{iT}) = 0 \\ \implies & Y^*_{iT} = \theta_i^{bmp} \\ \implies & V_T(S_T) = -(\overline{T} - Q^*_{iT}) \end{aligned} \tag{29}$$

Then next iteration we have

$$
\begin{aligned}
V_{T-1}(S_{i,T-1}) &= \max_{Y_{i,T-1}} \ \pi(Y_{i,T-1}, \theta_i^{bmp}) - (\overline{T} - Q^*_{i,T-1}) - \delta \mathbb{E}(\overline{T} - Q^*_{iT}) \\
\text{s.t.} \qquad & S_{iT} = S_{i,T-1} - Q^*_{i,T-1} + (\overline{Y} - Y_{T-1}) \\
\text{FOC:} \quad & \pi'(Y^*_{i,T-1}, \theta_i^{bmp}) = -\delta \mathbb{E}\left[\frac{\partial Q^*_{iT}}{\partial Y_{iT-1}}\right]
\end{aligned} \tag{30}
$$

$$
\Longrightarrow \ V_{T-1}(S_{i,T-1}) = \pi(Y^*_{i,T-1}, \theta_i^{bmp}) - (\overline{T} - Q^*_{i,T-1}) - \delta \mathbb{E}(\overline{T} - Q^*_{iT})
$$

Then the next iteration

$$
\begin{aligned}
V_{T-2}(S_{i,T-2}) = \max_{Y_{i,T-2}} \ \pi(Y_{i,T-2}, \theta_i^{bmp}) - (\overline{T} - Q^*_{i,T-2}) + \delta \mathbb{E}\left[\pi(Y^*_{i,T-1}, \theta_i^{bmp}) - (\overline{T} - Q^*_{i,T-1}) - \delta(\overline{T} - Q^*_{iT})\right] \\
\text{s.t.} \qquad S_{i,T-1} = S_{i,T-2} - Q^*_{i,T-2} + (\overline{Y} - Y_{T-2}) \\
S_{i,T} = S_{i,T-1} - Q^*_{i,T-1} + (\overline{Y} - Y_{T-1}) \\
\text{FOC:} \quad \pi'(Y^*_{i,T-2}, \theta_i^{bmp}) = -\delta \mathbb{E}\left[\frac{\partial Q^*_{i,T-1}}{\partial Y_{i,T-2}}\right] - \delta^2 \mathbb{E}\left[\frac{\partial Q^*_{iT}}{\partial Y_{iT-2}}\right]
\end{aligned} \tag{31}
$$

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

$$
\pi'(Y^*_{it}, \theta_i^{bmp}) = -\sum_{k=t+1}^{T} \delta^{k-t} \mathbb{E}\left[\frac{\partial Q^*_{ik}}{\partial Y_{it}}\right] \tag{32}
$$

Thus we have (26).