How Effective is an Ambient Subsidy in Addressing Non-point Source Pollution? A Case of the Florida Everglades

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ECON 260B

January 2022

Abstract

This paper studies the effectiveness of the Everglades Forever Act (EFA) in reducing phosphorus loads. Specifically, I investigate what happened under the EFA which then allows me to uncover what would an optimal standard ambient subsidy mechanism look like for this setting. I use the two-step difference GMM estimator (Arellano-Bond) to show that the tax credits did, on average, reduce farms' runoffs. Using the Arellano-Bond estimates, I am able uncover the average marginal profit curve with respect to pollution allowing me to calculate the optimal ambient subsidy rates for different levels of ambient pollution targets. Further, I am able to estimate the counterfactual outcome

of only implementing the mandatory BMPs to gauge the effectiveness of mandatory BMP policy. The findings suggest that an ambient subsidy rate of $21.01 could have achieved the regulators ambient pollution target instead of relying on the EFA. Lastly, previous studies' findings on BMP effectiveness in the Everglades Agricultural Area are significantly biased upwards due to ignoring the incentive tax credit program.

Introduction

The field of economics has largely succeeded in providing policy prescriptions for point-source pollution defined as sources of pollution that are easily identifiable and whose contributions are measurable. However, there is much weaker guidance from the field about how to manage non-point source pollution (NPSP). NPSP occurs when pollution sources are so diffuse and/or whose transport mechanism so complex that it is infeasible to monitor individual pollution contributions which renders typical tools like Pigouvian taxation inoperable. Many have pinned their hopes on water quality trading mechanisms where point-source polluters would pay for projects that would improve water quality coming off of non-point sources like farms and in return, increase their own pollution quotas. 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.

Ambient mechanisms present one set of promising tools to tackle the challenge of managing NPSP. These mechanisms either tax or subsidize (or both) all known polluters at the same rate based on the entire group's performance relative to an ambient standard where the tax base is the difference between observed ambient quality and the target. A great deal of attention has been given to ambient mechanisms beginning with Segerson (1988) which showed theoretically how a regulator could construct an ambient tax/subsidy that could result in a Nash Equilibrium where the standard is met optimally. This has led to a large literature focusing on the theoretically appropriate policy under various contexts (Cabe and Herriges, 1992; Hansen and Romstad, 2007; Herriges, Govindasamy and Shogren, 1994; Horan, Shortle and Abler, 1998; Xepapadeas, 1991, 1992) and a large literature that focuses on testing various mechanisms in an experimental/laboratory setting (Camacho and Requate, 2004; Cochard, Willinger and Xepapadeas, 2005; Poe et al., 2004; Spraggon, 2002; Suter, Vossler and Poe, 2009). The latter set of papers have focused mainly on which types of ambient mechanisms work best.

However, there are virtually no real world implementations of ambient mechanisms to manage NPSP or any other collective action problem such as the management of common pool resources. Reichhuber, Camacho and Requate (2009) implemented and analyzed an experiment using real farmers from Ethiopia as participants. The experiment simulated actual activities and decisions of the farmer participants' jobs. The experiment tested various ambient mechanisms on the conservation of a common pool resource and found that overall, the ambient mechanisms increased conservation considerably.

Wong et al. (2019) undertook an observational study on the effect of Brazil's Bolsa Verde program which is an environmental cash transfer program aimed at low income households in deforestation prone areas. These households are paid according to the degree of observed deforestation via satellites. The authors find that this program also achieved lower deforestation rates compared to control areas suggesting that this ambient mechanism was effective.

However, these policies did not perfectly target non-point source polluters which allowed the possibility for non-extractors to make gains by enforcing the actions of extractors. Consequently, these studies cannot disentangle the total effect between abatement motivated by peer-to-peer enforcement and abatement motivated 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. In this paper, I study one key component of the Everglades Forever Act (EFA) of 1994 to try to uncover insights about the efficacy of ambient subsidies without the peer enforcement mechanism using real observed data. In my setting, peer enforcement is not likely to occur since farms cannot monitor water quality coming off other farms and what can be monitored/enforced is already being done so by the regulator.

The goal of this paper is to ask, what role did the incentive credit program from the EFA play in farmer's phosphorus runoffs? What would an optimal ambient subsidy mechanism look like for this setting? I find that the financial incentives (which is not solely based on ambient quality) did change behavior on the margin even when the pecuniary incentives were small relative to profits. On average, farms reduced phosphorus loads by roughly .00901 lbs/acre for each tax credit offered. There are two main takeaways from my findings. First, the ambient pollution target stated in the EFA policy could have been achieved if instead, a standard ambient subsidy mechanism were implemented with a subsidy rate of \$21.01. Second, previous studies on the efficacy of the mandatory BMP component of the EFA is significantly biased upward due to the analysis ignoring the impacts from the incentive credit program of the EFA. Preliminary findings suggest that BMP effectiveness is closer to the range of 0%-24.31% reduction relative to baseline levels.

Policy Context

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). 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.[1] To obtain a permit, parcel owners need to develop a best management practice (BMP) plan and a water quality/quantity monitoring plan. The water monitoring plan requires a third party labratory to collect and analyze the farm-specific runoff samples. Although this data is not 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. 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.[2] 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

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

[2] 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.

Table 1: EAA Agricultural Privilege Tax Schedule

Calendar Year	Tax Per Acre	Per Acre Credit Rate	% Reduction Required for Minimum Tax Eligibility	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

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.[3]

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 an incentive to induce TP load reductions beyond the 25% reduction target for the BMPs. The privilege tax started off at $24.89 per acre and follows a set schedule each year. 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

[3]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.

achieve a percent TP load reduction of 25% relative to a baseline historic TP level.[4] Water quality monitoring stations are placed down stream 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 all EAA parcel owners are rewarded tax credits that can go towards reducing future privilege tax obligations. Credits are awarded on a per acre basis and the rate is the same for all parcels; each parcel owner gets the same number of credits per acre for each percentage point above the 25% target. 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 but 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 dictated by the regulatory agency.

Individual Incentive Program

In addition, farms can earn credits based on individual performance as well as through group performance (EAA wide credits). Farms can submit applications to further earn credits through their individual performance by proving that their TP load reductions exceeded

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

the target given by column 4 of Table 1.[5] 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.[6] 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 2 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, compliance always occurred except for one year (Milon, 2018).

Throughout the empirical analysis portion of this paper, I will simply assume that all credits are earned via group performance even when some portion is earned through the individual performance. 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.

[5]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.

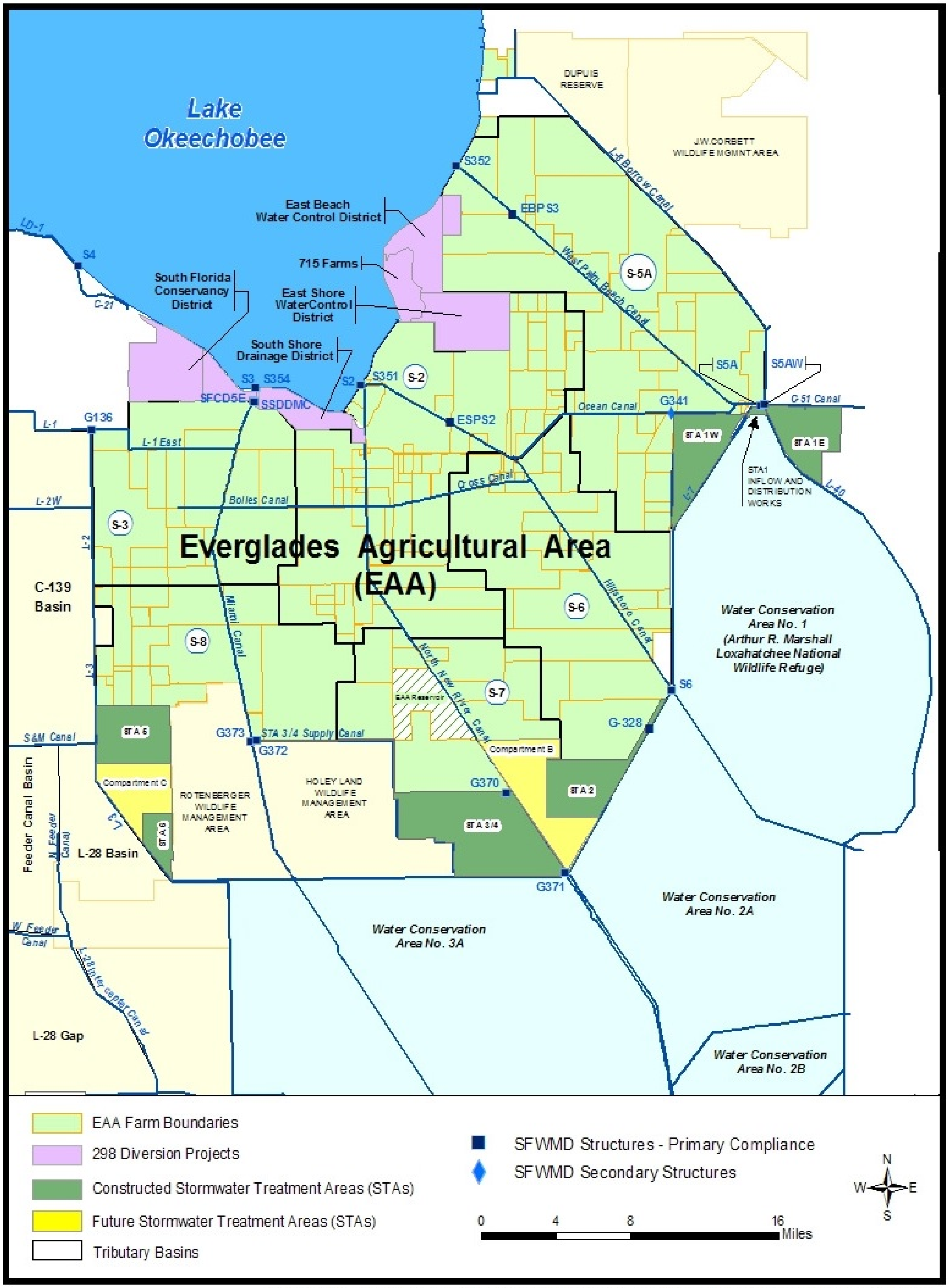
[6]Individual credits can also be earned if farms show that their TP loads were below 5 ppb. However, credits earned in this manner cannot be rolled over for future use.

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. This is done because 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 1, is largely publicly funded and allows farmers to drain their fields as well as providing irrigation from Lake Okeechobee without which 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 parcel 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.[7]

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

Figure 1: EAA Area with Canals/Drainages



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

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.[8] 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 and coincides with when the farm first achieved BMP compliance. The Early Baseline Option essentially allowed farms the option to achieve compliance earlier than required, agree to better water quality monitoring by SFWMD, 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.[9] 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[10]. Table 2 provides summary statistics for the variables that I currently have at the farm level. 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.[11]

[8] URL for the reports: https://www.sfwmd.gov/science-data/scientific-publications-sfer

[9] See F.A.C. 40E-63.145(4)(g)

[10] Data for years 1994 through 2000 was also obtained via public records request.

[11] 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.

Table 2: Individual Farm Data: Summary Statistics

	mean	sd	min	max	p25	p50	p75
Reported Load (lbs/acre)	1.00	1.47	0.00	24.14	0.33	0.61	1.18
% TP Reduction	12.94	410.01	-12379.00	100.00	32.00	67.00	83.00
First year water quality monitoring began	1,995.08	1.64	1,994.00	2,008.00	1,994.00	1,994.00	1,996.00
Basin Acreage	2,511.79	3,543.73	35.00	32,535.10	397.20	1,051.40	3,276.40
Baseline TP Load (lbs/acre)	3.11	4.18	0.02	35.32	0.86	1.81	3.68
Credits Still Needed (per acre)	24.48	52.52	0.00	180.13	0.00	0.00	0.00
Distance to Lake Okeechobee (meters)	19,680.26	9,041.32	1,375.98	43,948.64	12,461.71	19,221.51	25,953.87
Total Acres Dedicated to Vege	90.51	749.73	0.00	10,928.00	0.00	0.00	0.00

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.[12] 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.

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

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 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 control 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 do 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.

Model

The purpose of this section is to build a model that can guide empirical design and provide a prediction about whether one should expect the incentive credit program to have affected discharge behavior. Let s denote the ambient subsidy rate, Y denotes observed ambient pollution, and $\overline{Y}$ denotes the ambient pollution standard. Under a standard ambient subsidy mechanism, 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 receive a subsidy equal to $s(\overline{Y} - Y)$. Profit per acre from farming operations is assumed to be a standard concave function with a satiation point and is given by $\pi(Y_i, \theta_i)$ where Y_i is chosen discharge (per acre) and θ_i is i's business-as-usual (BAU) level of discharge (per acre). Observed ambient pollution is assumed be a linear sum of each farm's total discharge $Y_i L_i$ where L_i is acreage.

In this static and deterministic model, farms take the discharge from others as given and chooses own discharge to maximize farm profit plus the subsidy payout. Farms would abate an additional unit of pollution if the marginal financial gain from doing so (s) exceeds the marginal loss ($\pi'(Y_i, \theta_i)$). Starting from the BAU levels of discharge, which by definition occurs at the point where marginal profit $\pi'(Y_i, \theta_i)$ is zero, any positive financial incentive will pressure farmers to move away from their BAU levels. Specifically, 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). 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).[13] Since s and $\widetilde{Y}_i$ are inversely related, too small of an s could result in $\widetilde{Y}_i$'s that are too large to reach compliance and the Nash equilibrium will always result in noncompliance.

$$\pi'(\widetilde{Y}_i, \theta_i) = s \tag{1}$$

Let the marginal profit function be defined as in (2).[14] Then one only needs to evaluate the values for θ_i^{bmp} (the BMP-BAU discharge level), γ_i (the slope of the marginal profit curve wrt to discharge), and s (the implied static marginal incentive from the incentive credit program) to answer the question of whether a standard ambient subsidy mechanism of similar incentive magnitude would have produced similar results.

$$\pi'(Y_{it}, \theta_i^{bmp}) = \gamma_i(\theta_i^{bmp} - Y_{it}) \tag{2}$$

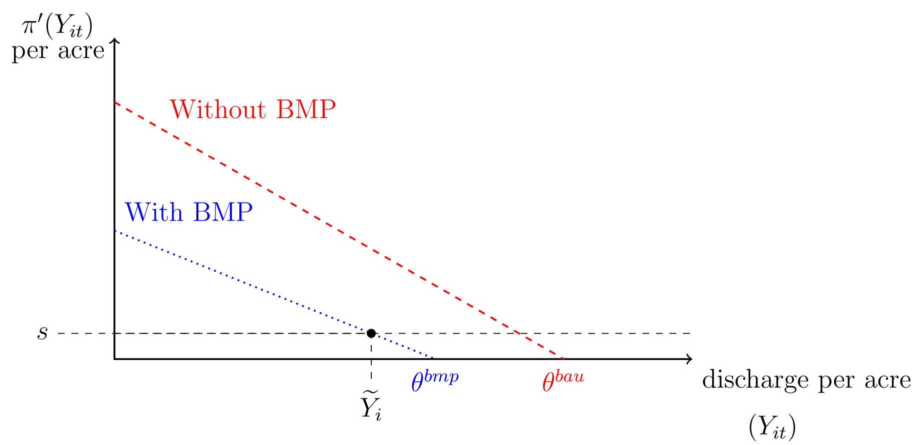
[13]It should be noted that there are two possible Nash Equilibria in general. Either noncompliance occurs where everyone pollutes at their BAU levels or compliance occurs where everyone pollutes at their $\widetilde{Y}_i$ levels so that Y is strictly less than $\overline{Y}$.

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

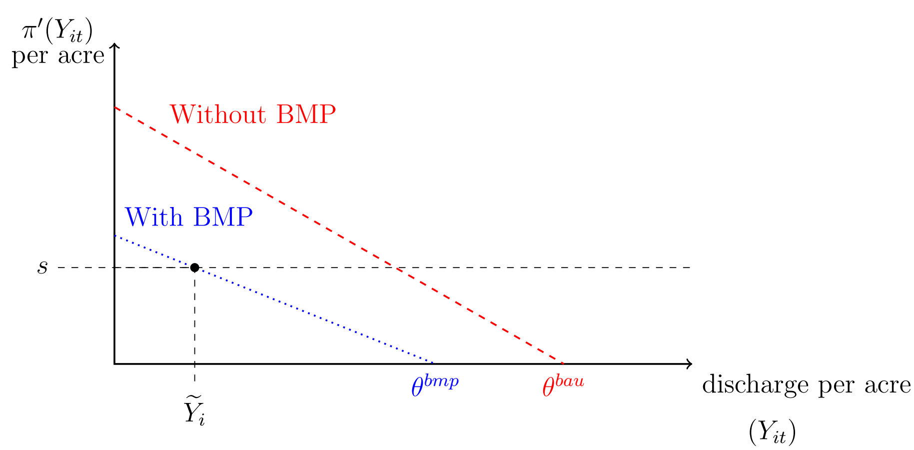
This idea is depicted in Figure 2 where panel 2a depicts a case where the marginal profit curve is sufficiently far from the origin so that a subsidy rate of s leads to minimum profitable pollution levels that are similar to the BAU levels after BMP adoption (θ_i^{bmp}). If the curve is much closer to the origin under BMPs, then it is possible that even a low s will lead to minimum pollution levels that are significantly below the BMP-BAU levels (shown in panel 2b).[15]

Figure 2

(a) Weak incentive



(b) Strong incentive



[15] There are two notions of BAU level of discharge here. One is the BAU without BMP implementation and the other is the BAU with BMP implementation. For this paper, the idea of business-as-usual refers the case where no ambient mechanism is in place.

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 further induce abatement. Importantly, the threshold for which the incentive credits are triggered is based on that same 25% reduction target. Therefore, it is as if the target in our model satisfies (3). Setting the pollution standard in such a way dissolves the strategic interactions between polluters. So long as polluters collectively reduce discharge below the BMP-BAU ambient pollution level, then everyone receives a subsidy equal to the subsidy rate times the difference between observed and BMP-BAU ambient quality. In such a scenario, each farmer can be confident that their abatement efforts will always translate into some financial 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.

$$\overline{Y} \geq \sum_{i=1}^{n} \theta_i^{bmp} L_i \tag{3}$$

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 section 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 model the farmer's decision problem as a dynamic optimization problem with no strategic interactions. I then show that the parameter γ_i can be backed out via a simple comparative static. 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).[16] 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. The farm's per acre

[16]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.

discharge decision *after optimally deciding* Q_{it} is given by the Bellman equation (4).[17]

$$
\begin{aligned}
V_t(S_{it}) = \max_{Y_{it}} \ & \pi(Y_{it}, \theta_i) - \left(\overline{T} - Q^*_{it}\right) + \delta \mathbb{E} V_{t+1}(S_{i,t+1}) \\
\text{s.t.} \qquad S_{i,t+1} &= S_{it} - Q^*_{it} + \left(\overline{Y} - Y_t\right) \\
Y_t &= \alpha_t + \sum_i Y_{it} L_i \\
\overline{Y} &\geq \alpha_t + \sum_i \theta_i L_i \\
\alpha_t &\overset{iid}{\sim} F(0, \sigma^2_\alpha) \\
Q^*_{it} &= \min\{M, S_{it}\}
\end{aligned}
\tag{4}
$$

The timing of events in this dynamic problem is as follows: farms first make decisions about discharge, then uncertainty parameter α_t is resolved and ambient quality Y_t is observed.[18] Then credits owed can be calculated and issued out for use in the next period. In Appendix F, I solve (4) backwards under finite time with T being the terminal date and normalizing the terminal value to zero. The FOC is given by (5).

$$
\pi'(Y^*_{it}, \theta_i) = G_{it} \tag{5}
$$

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

[17] The model presented in (4) intentionally ignores the rates presented in column 3 of Table 1 for notational simplicity.

[18] 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 (6).

$$G_{it} = -\sum_{k=t+1}^{T} \delta^{k-t} \mathbb{E}\left[\frac{\partial Q^*_{ik}}{\partial Y_{it}}\right] \tag{6}$$

Note that since Y_{it} denotes discharges, the partials in (6) are weakly negative. The G_{it} term captures the implied s for the static model since it represents the pecuniary incentive to abate an additional unit of Y_{it} as evidenced by (1) and (5). Further, because (i) G_{it} cannot be observed, (ii) it changes over time and (iii) it changes with S_{it} (shown later) I instead choose to focus on an upper bound for the implied s. The upper bound is reached by removing discounting and uncertainty from (6) and setting t equal to 1998, the first period in which credits were excercisable. Therefore, the upper bound for the implied subsidy is found by summing the values from column 3 in Table 1 for the years 1998 and onward. The sum is equal to 9.8 and its value will be denoted as $\hat{s}$.[19] The policy function can be written in general as

$$Y^*_{it} = g^{-1}(G_{it}, \theta_i) \tag{7}$$

where $g(\cdot) = \pi'(\cdot)$. 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 (8) which shows how a simple comparative static on the policy function can retrieve the parameter γ_i.[20]

$$\frac{\partial Y^*_{it}}{\partial G_{it}} = \frac{1}{\frac{\partial g(Y_{it},\theta_i)}{\partial Y_{it}}} = \frac{1}{\pi''\left(Y^*_{it}, \theta_i\right)} = -\frac{1}{\gamma_i} \tag{8}$$

[19] Note that there are no time or individual subscripts for $\hat{s}$, this is intentional.

[20] Abusing terminology a bit here because equation (8) is not truly my estimand due to it being individual specific.

A Proxy for G_{it}

I cannot use $\hat{s}$ (the upper bound for the implied s) directly in the estimation portion of this paper because it does not vary over i or t. Ideally, I would use G_{it} directly but the problem is that it represents the farmer's expectations about how future exercised credits will change with today's discharge levels. Additionally we have no way of knowing each farmer's discount factors. One way to proxy for G_{it} is to follow a similar approach to the creation of $\hat{s}$. That is, I find a suitable upper bound on the G_{it} term that varies depending on credit-stock levels by stripping the discounting and uncertainty components from G_{it}. This varying upper bound (D_{it}) is then used as a proxy for G_{it} in the estimation portion of the analysis. The derivation of D_{it} is detailed in Appendix C where I also show that $D_{it} \geq G_{it}$.

$$D_{it} = (T - t + 1)M - S_{it} \tag{9}$$

I propose using D_{it} as defined in (9) to proxy for G_{it} which is not observable. The variable D_{it} represents the amount of credits that a farmer needs at the start of period t in order to maximize Q^*_{it} each period, including period T, after which all credits become irrelevant. If $D_{it} \leq 0$ then S_{it} is enough to cover current and all future period's credit demands leaving $G_{it} = 0$ because earning more credits today via reducing Y_{it} will *not* increase the amount of exercised credits in the future. So as D_{it} increases, G_{it} increases (weakly) as well. Thus one motivation for using D_{it} as a proxy is that both D_{it} and G_{it} decrease with S_{it}. A second reason for using D_{it} is that both terms decrease with the distance between t and 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}.

Effect of the Incentive Credits

The effects from the ambient subsidy is confounded by two other effects. First, is the effects from the mandatory BMPs and the second is that the tax credits a firm earns can come from both group performance or the individual performance. The empirical strategy does not account for the second issue and instead the conclusion will be adjusted accordingly.

The mandatory BMPs were required to be in place by 1996 for all farms who were in operation in 1994. Thus, I restrict the estimation period to start on 1996 to avoid spurious correlation.[21] 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.

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 stock of credits from the maximum exercisable credit level for 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

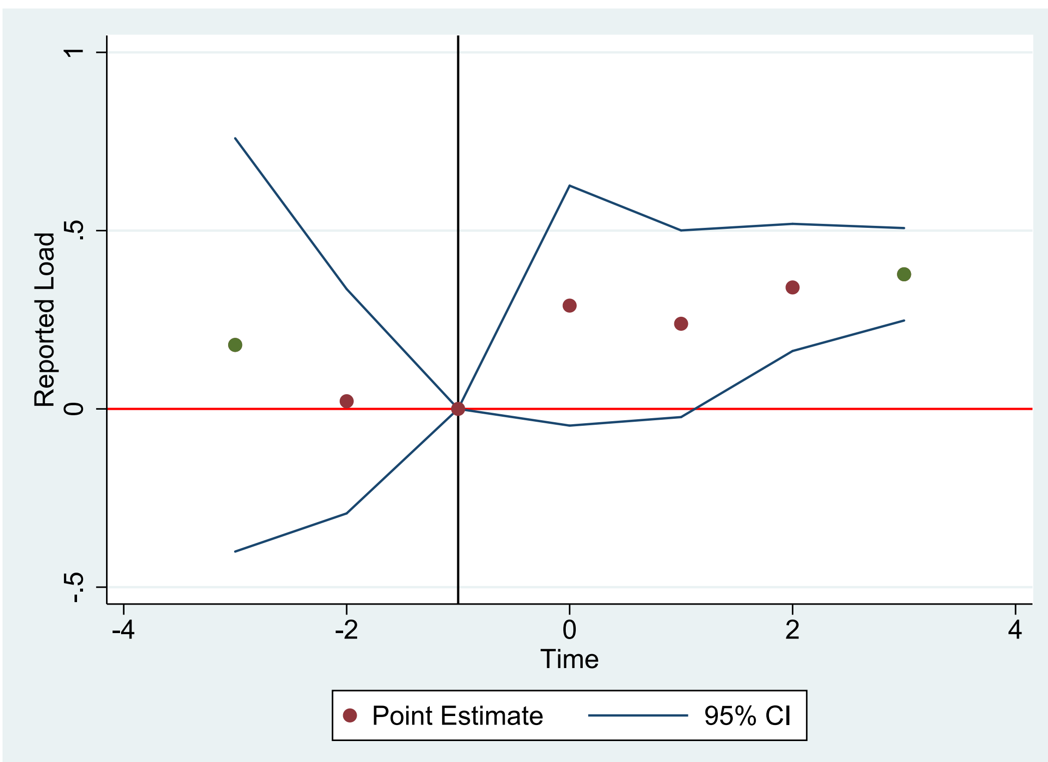
[21] Some farms came into operation after 1994; the timeline of when BMPs were required to be fully implemented is not known in those cases. I chose to drop the first 2 years of available data for such farms.

0 otherwise. The event study design in Equation (10)

$$Y_{it} = \alpha_i + \delta_t + \sum_{\substack{k=-3 \\ k\neq -1}}^{3} \gamma_k \mathbb{1}\{t - E_i = k\} + \varepsilon_{it} \tag{10}$$

is used to summarize the data and the results of which are shown in Figure 3. The term Y_{it} is the farm-year specific phosphorus outcome and is measured total phosphate (TP) load measured in lbs/acre. I use three leads and lags so that there will be some farms in the study horizon who have never reached their "treatment". In other words, it is best to have some farms who always had credits left to earn when estimating (10).

Figure 3: Event Study: Outcome is Measured TP Load (lbs/acre)



From the graph, we can see that there is a positive trend throughout the time horizon and after farms have exceeded their credits, the TP loads increase relative to farms who are a year from their event. This suggests that farms did increase discharge levels after the they have completely met their credit demands and thus no longer have incentives to increase abatement performance beyond the mandatory BMPs.

The event study design falls short of making any causal claims mainly because treatment status here depends on choices farmers made in the past which casts doubt that parallel trends and no treatment anticipation assumptions are met (Sun and Abraham, 2020). Furthermore, it is necessary to have units that are never treated which in this case means that we need a farm to continually demand credits thus never reaching their maximum needed. This obviously does not naturally occur in the data. Lastly, The event study, even if causal, does not really capture the does response estimate which is something needed to link to the parameter γ_i.

To achieve a causal estimate, 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 time 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.[22]

$$Y_{it} = \alpha_i + \alpha_t + \beta D_{it} + \gamma X_{it} + \varepsilon_{it} \tag{11}$$

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

The problem with estimating (11) is that D_{it} 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 S_{it} via (9). The stock value itself is a function of all past outcomes $(Y_{i1}, \ldots, Y_{i,t-1})$. A known workaround is to take first differences of (11) so that consistency only requires sequential exogeneity (Hansen, 2021; Anderson and Hsiao, 1981). 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 then pre-multiplied by the instrument matrix Z_{it}, and stacking over i and t gives (12).[23]

$$\boldsymbol{Z}'\triangle\boldsymbol{Y} = \triangle\alpha_t + \boldsymbol{Z}'\boldsymbol{D}\beta + \boldsymbol{Z}'\triangle\boldsymbol{X}\boldsymbol{\gamma} + \boldsymbol{Z}'\triangle\boldsymbol{\varepsilon} \tag{12}$$

where $\boldsymbol{Z}' = \left(\boldsymbol{Z}_1', \ldots, \boldsymbol{Z}_n'\right)'$ and $\boldsymbol{Z}_i$ is a $(T-1) \times \ell$ matrix given below

$$\boldsymbol{Z}_i = \begin{bmatrix} [D_{i1}, \triangle\alpha_2, \triangle X_{i2}] & [0] & [0] & \ldots & [0] \\ [0] & [D_{i1}, D_{i2}, \triangle\alpha_3, \triangle X_{i3}] & [0] & \ldots & [0] \\ \vdots & \vdots & \ddots & & \vdots \\ [0] & [0] & [0] & \ldots & [D_{i1}, \ldots, D_{i,T-1}, \triangle\alpha_T, \triangle X_{iT}] \end{bmatrix} \tag{13}$$

and is the instrument matrix used for $\boldsymbol{D}$. Each variable in X_{it} is treated as strictly exogenous as well as the time dummies.[24] The first element of the first row of (13) is the vector of instruments for $\triangle D_{i2}$, the second element of the second row is for $\triangle D_{i3}$, and so on. The relevance conditions are met by construction via (9) and the exclusion restriction is assumed via sequential exogeneity. If D_{it} satisfies the sequential exogeneity assumption then D_{it} is

[23] Bold indicates matrices.

[24] Control variables could also be treated as sequentially exogenous which I also run as a robustness check.

said to be predetermined.

The sequential exogeneity assumption essentially says that D_{it} can be correlated with past errors but not current or future ones. Said differently, the amount of credits left for farm i to earn at time t, cannot be correlated with current or future errors in the discharge levels. From (6) and (7), the optimal discharge level is a function of today's expectations about future credit stock levels. If errors are not autocorrelated, then there is little possibility for farm i to anticipate their values at time t. 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.

The result from estimating (12) using the collapsed version of (13) is reported in column 1 of Table 3. The estimation sample is restricted to years 1996 or later to avoid spurious correlation because most farms were in the middle of 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 my 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

Table 3: Two-step Difference GMM Results: Outcome is Measured TP Loads

	exogenous controls	predetermined controls	predetermined vege acres
rolling_incentives2	-0.00771*	-0.00945*	-0.00901*
	(0.041)	(0.010)	(0.015)
interact2	0.000000218*	0.000000242	0.000000199
	(0.045)	(0.091)	(0.132)
Total Acres Dedicated to Vege	0.000308	0.000109	0.0000569
	(0.450)	(0.379)	(0.579)
Basin Acreage	0.00000637	0.000169	0.0000215
	(0.868)	(0.209)	(0.630)
BMP Cycle (categorical)	0.0945	0.163	0.0672
	(0.108)	(0.169)	(0.310)
N	3425	3425	3425
F-stat			
p-val_Fstat			
Sargan_Test_Pval	2.10e-08	4.83e-09	1.16e-12
Hansen_Test_Pval	0.00109	0.0885	0.00815
AR1_pval	0.000218	0.000208	0.000216
AR2_pval	0.180	0.177	0.185
Instrument_count	74	140	94
Included_farms	174	174	174

p-values in parentheses

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

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

the only other predetermined covariate and is our preferred specification. The reason being 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.

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 3 at face value would imply that the incentive credit program resulted in an average P load decrease of about 1.62 lbs/acre (.00901 $\times$ 180) in 1994 (CY). By water year 2002, on average, firms had roughly 4 credits left to earn meaning that the incentive credits induced 0.035 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 18 of Appendix B 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 4 from Appendix B 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.[25] Importantly, the magnitudes of those coefficients are implausibly large since the maximum credits needed to earn in 1996 was about 180 credits. The results

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

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 P load percent decrease as the dependent variable comes with much more noise thus limiting the usefulness of those results considerably.

Conclusions

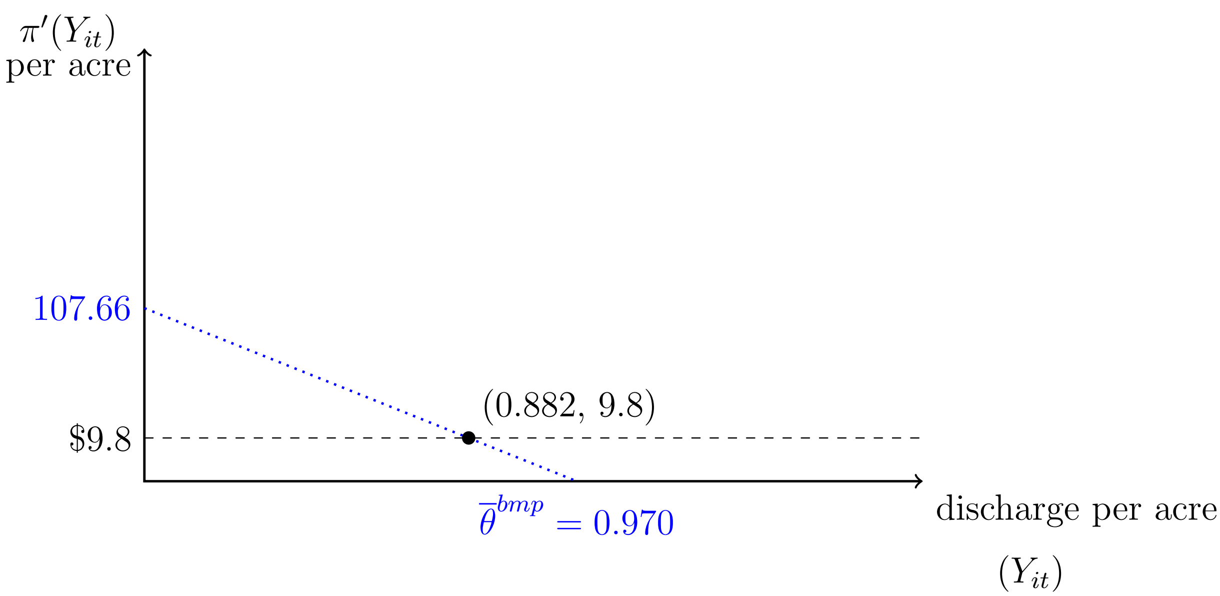
I conclude with two main contributions. First, for my specific empirical setting, I use some back of the envelope calculations to predict what an effective ambient subsidy schedule would look like for various ambient targets. These calculations are based on the assumption that BMPs did not change the slope of marginal profit curves (as depicted in Figure 2). However, it is reasonable to assume that BMPs reduced the slope of the marginal profit curves if one believes that the adoption of such BMPs leaves farmers with fewer options to adjust their P loads in response to incentives. In which case, the calculated subsidy schedules represent an upper bound for settings without BMP adoption.

Lastly, I use the estimates from the previous section to predict the counterfactual response in average P loads per acre in the absence of the incentive credit program of the EFA. This will help give a more accurate picture of the effectiveness of mandatory BMP policies in addressing agricultural runoff. Previous studies (Rice, Izuno and Garcia, 2002; Daroub et al., 2011; Rice et al., 2013) have attempted to study the efficacy of BMPs in reducing runoff concentrations but have largely neglected the confounding effects of the incentive credit program which likely biased those studies' results upwards.

Optimal Ambient Subsidy for the EAA

The previous section presented evidence that the incentive credit program of the EFA had negative impact on farm level P loads. However, the incentive credit program is not your standard ambient subsidy mechanism and questions remain about the use of such mechanisms in my setting. Namely what would an effective pure ambient subsidy look like in our empirical setting? To address this question, I use estimates from the last column of Table 3 to produce the marginal profit curve for the average farmer in the EAA shown in Figure 4.[26]. To get an estimate of the average BMP-BAU discharge per acre (θ_i), I average the TP loads over farms and over each period after 2003 when all farms no longer needed any more credits (see Figure 18).

Figure 4: Estimated Marginal Profit Curve for the Avg. Farm



Using the functional form assumptions made earlier and a simple model for the optimal

[26]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).

subsidy rate (not per acre) from Equation (25) from Appendix D, I can map out what optimal subsidy should be for different targets. Without individual level estimates for γ, I approximate (24) for the average farmer using estimates from earlier so that I have

$$Y_i^* = 0.882 - .00901\lambda$$

which then implies that the equation for the optimal subsidy as a function of the ambient pollution target is given by (14). To estimate $Y^{bmp-bau}$, I estimate average P loads across years after 2003 for each farm and multiply that by the respective farm's acreage. I then sum that value across farms to get 35,0147.8 lbs of phosphorus under a BMP-BAU scenario for the average year. To convert values from pounds to metric tons, I simply divide 35,0147.8 by 2205 to get 158.80 metric tons.[27][28]

$$\lambda^* = \frac{Y^{bmp-bau}\left(1 - \dfrac{\overline{Y}}{Y^{bmp-bau}}\right)}{\sum\limits_i L_i/\gamma_i} = \frac{158.80\left(1 - \dfrac{\overline{Y}}{158.8}\right)}{1.89} \tag{14}$$

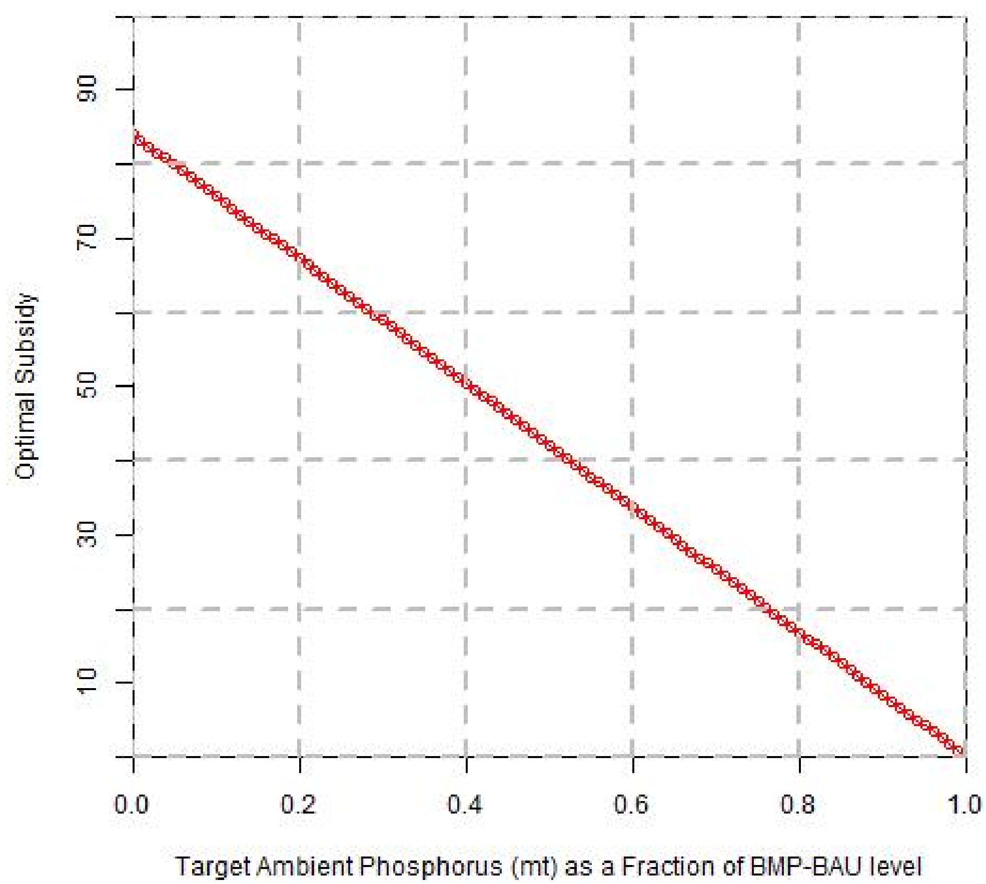
Since the EFA effectively sets the target of their incentive credit program ($\overline{Y}$) equal to the ambient pollution under BMP-BAU ($Y^{bmp-bau}$), then the optimal subsidy is of course zero since no subsidy is needed to maintain the status-quo. It appears then that the incentive credit program was not needed to achieve the original target of a 25% reduction in TP loads. Figure 5 applies the deterministic static model to the empirical results to back out what the ambient subsidy (not per acre) ought to be to achieve various ambient targets. For reference, the target loads for the EAA between 2013 to 2017 ranged from 139 to 213.8 metric tons.

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

[28]Note that the denominator in (25) is also divided by 2205.

The horizontal intercept in Figure 5 is the targeted ambient pollution level as a fraction of the BMP-BAU level. Thus the prediction is that if the regulator wanted to decrease ambient pollution by 25% from BMP-BAU levels, then the ambient subsidy needs to be roughly \$21.01. In other words, without the EFA in place, the regulator could have achieved its ambient pollution target with an ambient subsidy rate of \$21.01. If BMPs reduced the slope of the marginal profit curve, this subsidy rate is an upperbound for the true optimal rate.

Figure 5: Optimal Subsidy as a Function of Ambient P Target



For external validity, one must consider 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 under some ambient mechanisms, subsidies in particular (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.

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 a partially-cooperative story.[29] More importantly, Yoder (2019) notes that the collective rather than the individual liability design of the EFA was a concession made to the EAA farmers who had a voice in the drafting of legislation. The authors 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.[30] 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.

[29] Figure 6, Yoder, Chowdhury and Hauck (2020).
[30] Table 1, Yoder (2019).

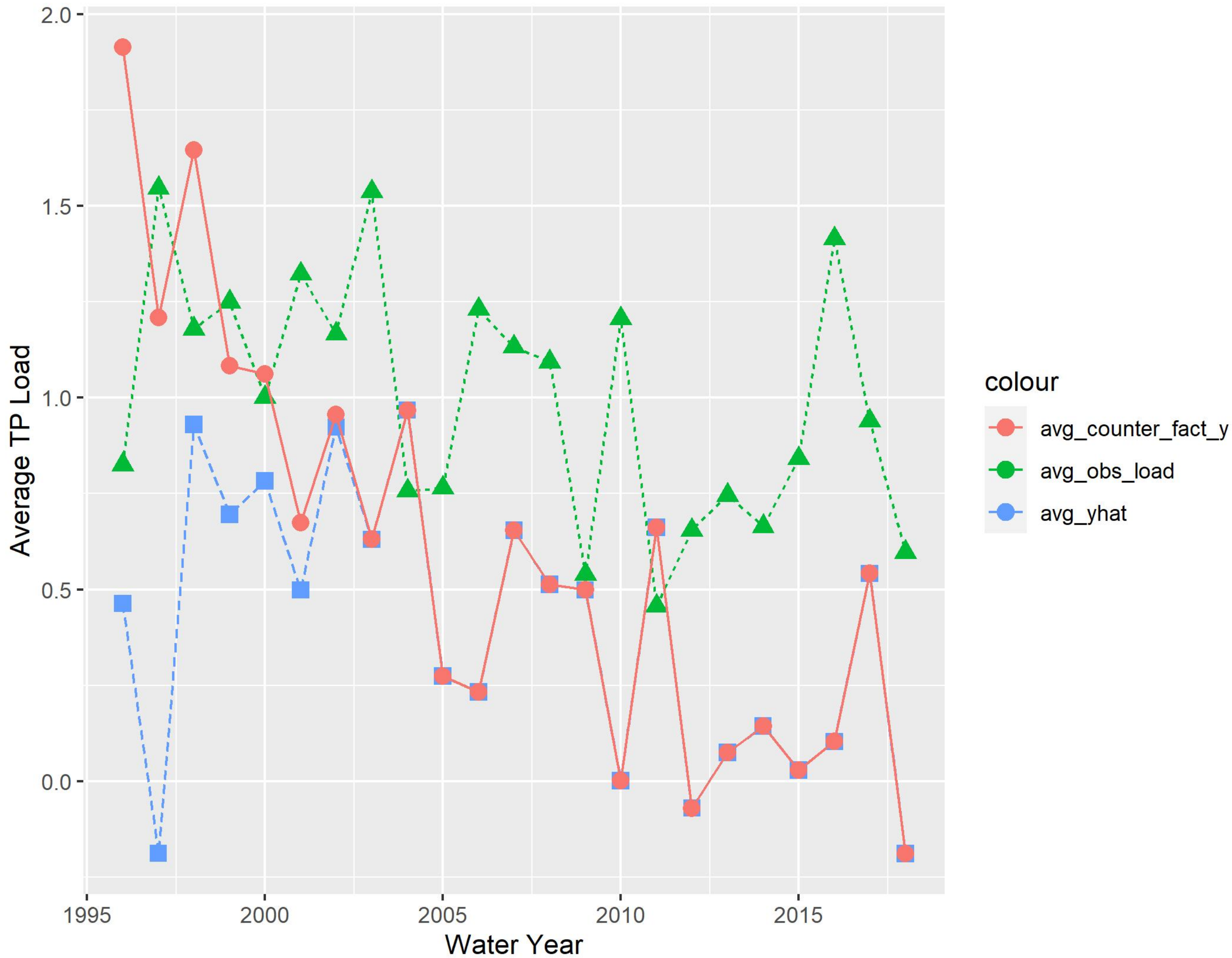
Counterfactual Scenario with no Incentive Program

A lot of attention and faith is focused on BMPs and their ability to reduce agricultural runoff and NPSP in general. Because of this significant reliance on this one policy prescription, there is a need to understand its efficacy. Our understanding of the physical mechanisms for many BMPs and how it might affect runoff outcomes is well understood. However, from a policy standpoint, it is much less clear how reliable these approaches are when farmers try to implement them in the real world. Furthermore, the use of a combination of BMPs is also less well understood. For instance, estimates from Rice, Izuno and Garcia (2002) found that BMPs reduced unit-area load of phosphorus anywhere from 20.4%-59.7% depending on their method used.

However, those previous studies ignored the incentive program effects on farm loads. To estimate the potential bias arising from the incentive program, I use the estimated model from the last column of Table 3 to produce estimated P loads for each farm for each year. I then use the same model to produce estimates of P loads for the counterfactual setting in which no incentive program exists by setting the incentive variable D_{it} equal to zero for all years and farms. The results are plotted in Figure 6 where the green-dotted-triangle line is the observed load, red-solid-circle line is the counterfactual load, and the blue-dashed-square line is the estimated load.[31]

[31] All are averaged across farms.

Figure 6: Estimated and Counterfactual TP Loads



For water-years 2003 and latter, we see that the counterfactual and estimated loads are identical which is consistent with the theory. On average, between water-years 1996 to 2002, the counterfactual level is about 88% greater than the estimated level. This suggests that the estimates for BMP effectiveness from Rice, Izuno and Garcia (2002) is closer to the range of 0%-24.34%. Factoring in the incentive credit program effects reduces the estimated effectiveness of the mandatory BMP policy by more than half.

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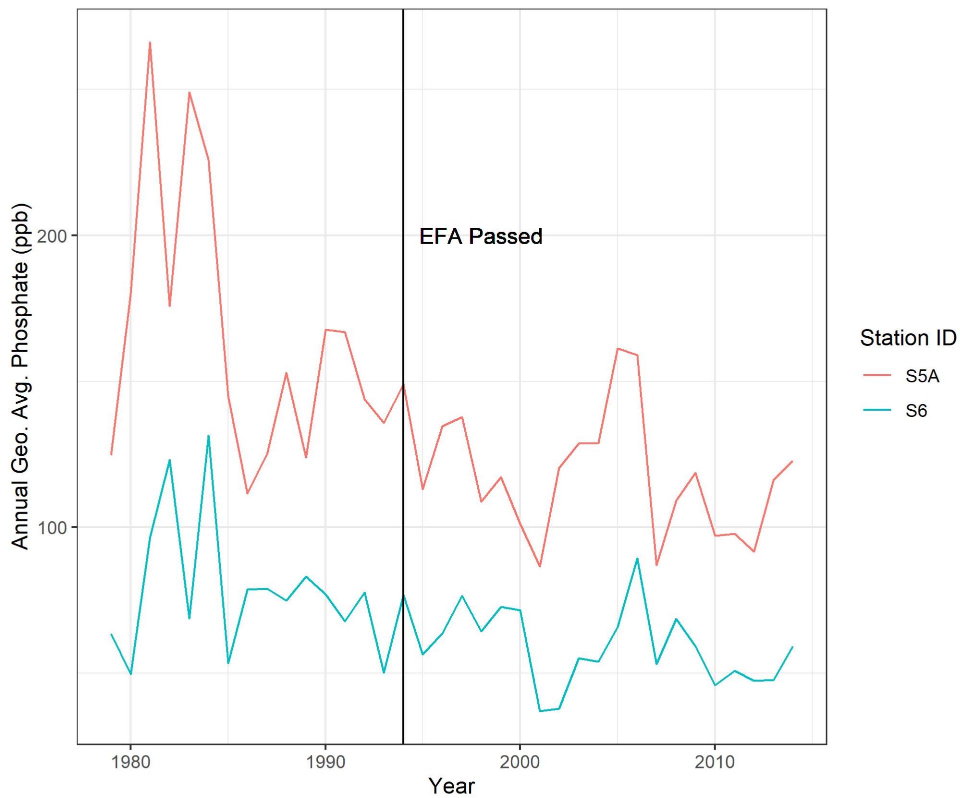
Appendix A

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 7. 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.[32]

[32] 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 7: 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 10 and 11 found in Appendix B). 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.[33] 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

[33]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.

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

The optimal weights (w_i) are chosen so that equation (15) 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 (15) is done separately for both treated units.

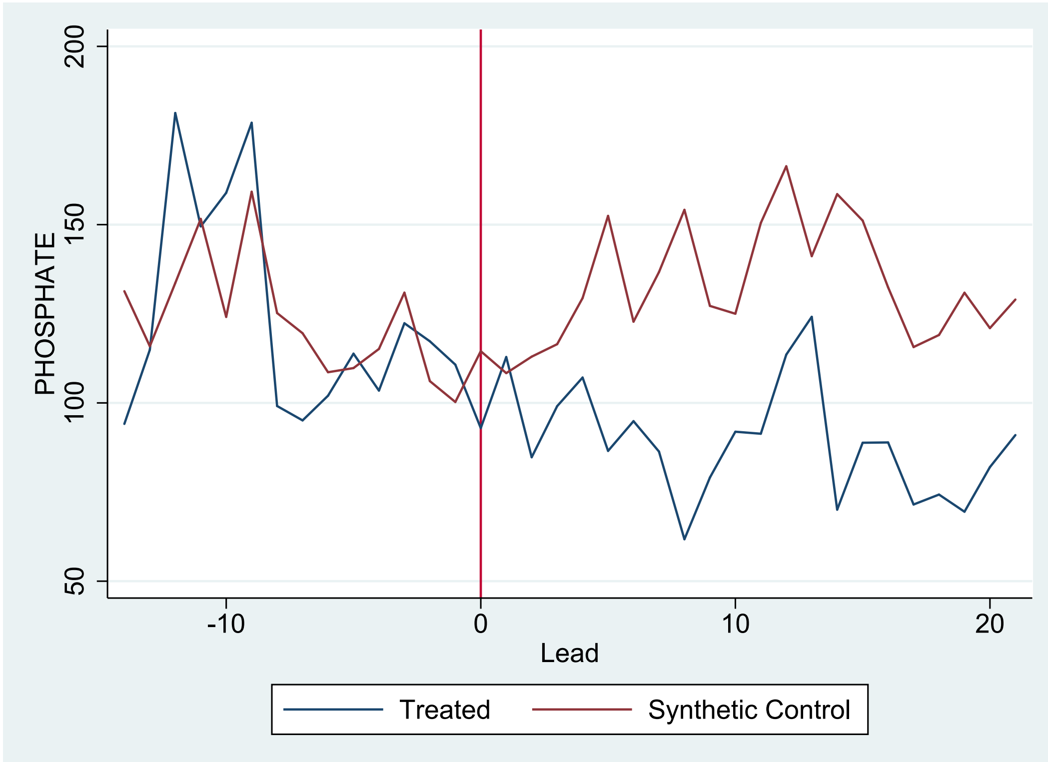
$$\frac{1}{15} \sum_{t=1979}^{1993} \left(X_{1t} - w_2 X_{2t} - \cdots w_{J+1} X_{J+1,t}\right)^2 \tag{15}$$

X_{it} denotes the annual geometric average phosphorus levels for station i and no other covariates are used.[34] Once the optimal weights are computed, average treatment effect, α_t, is calculated via (16) and the results of which are implicitly shown in Figure 8.

$$\widehat{\alpha}_t = \frac{1}{2} \sum_{i=1}^{2} \left(X_{it} - \sum_{j=2}^{J+1} w_{ij}^* X_{jt} \right) \tag{16}$$

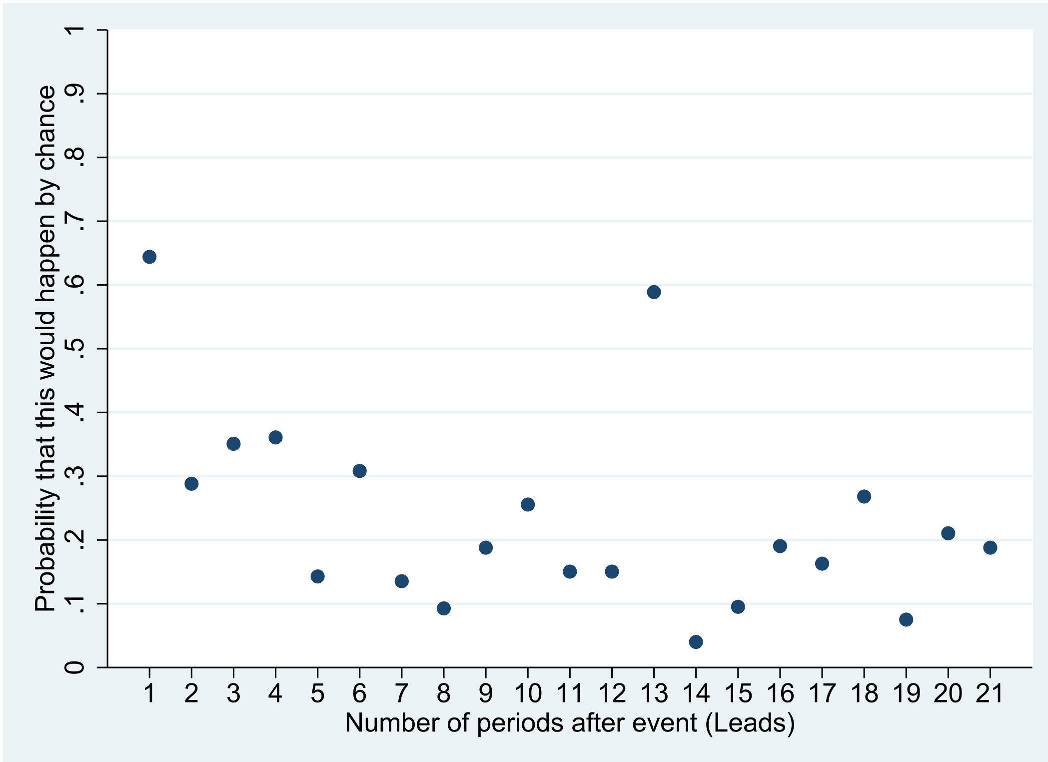
[34] Geometric average is used because measured phosphorus is a flow measure and in such instances, geometric averages provides a more accurate summary of the occurrences over time.

Figure 8: 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 9. 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.

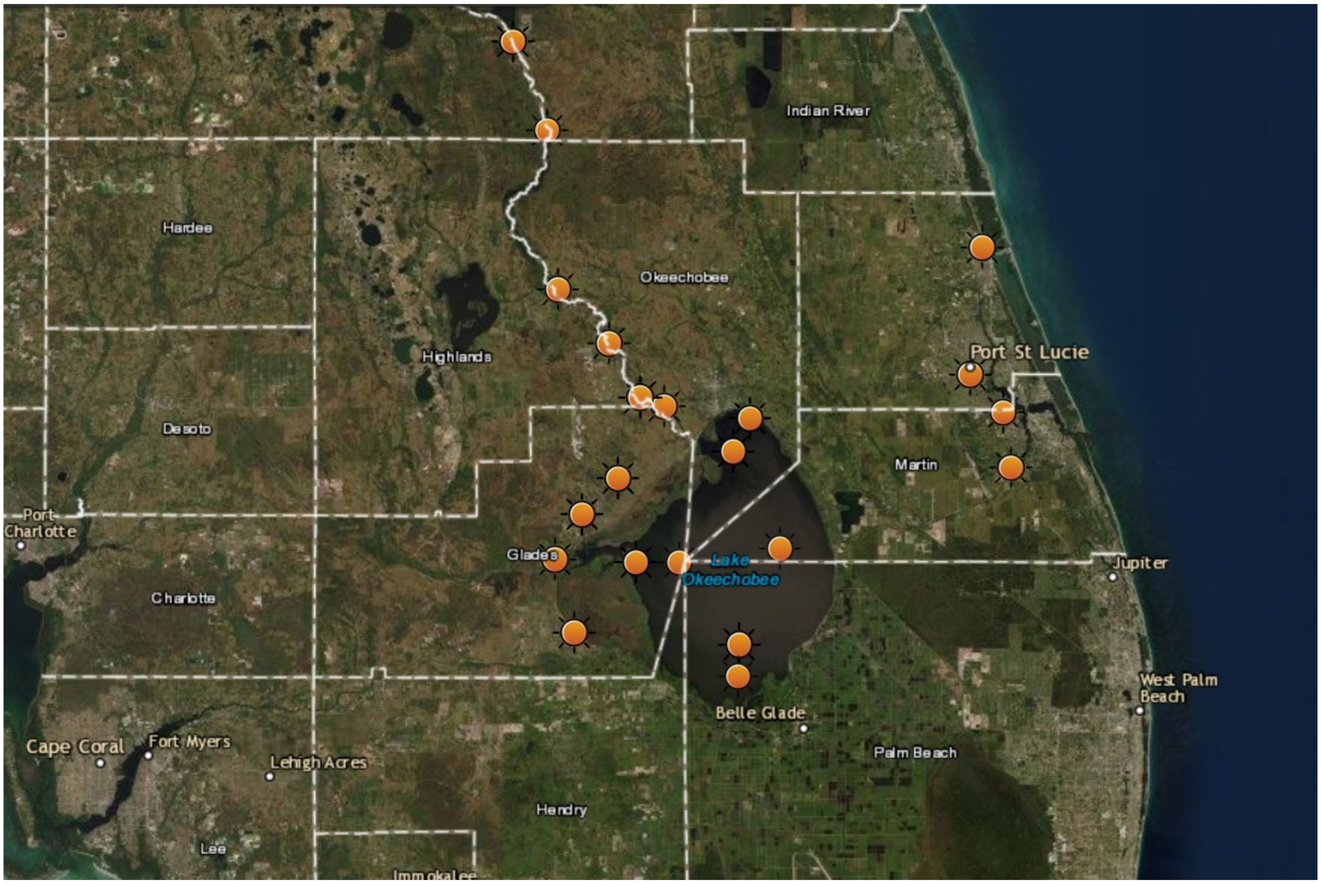
Figure 9: P-Values for Treatment Effects



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 12 and 13. 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 14 through 17 in Appendix B). 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.

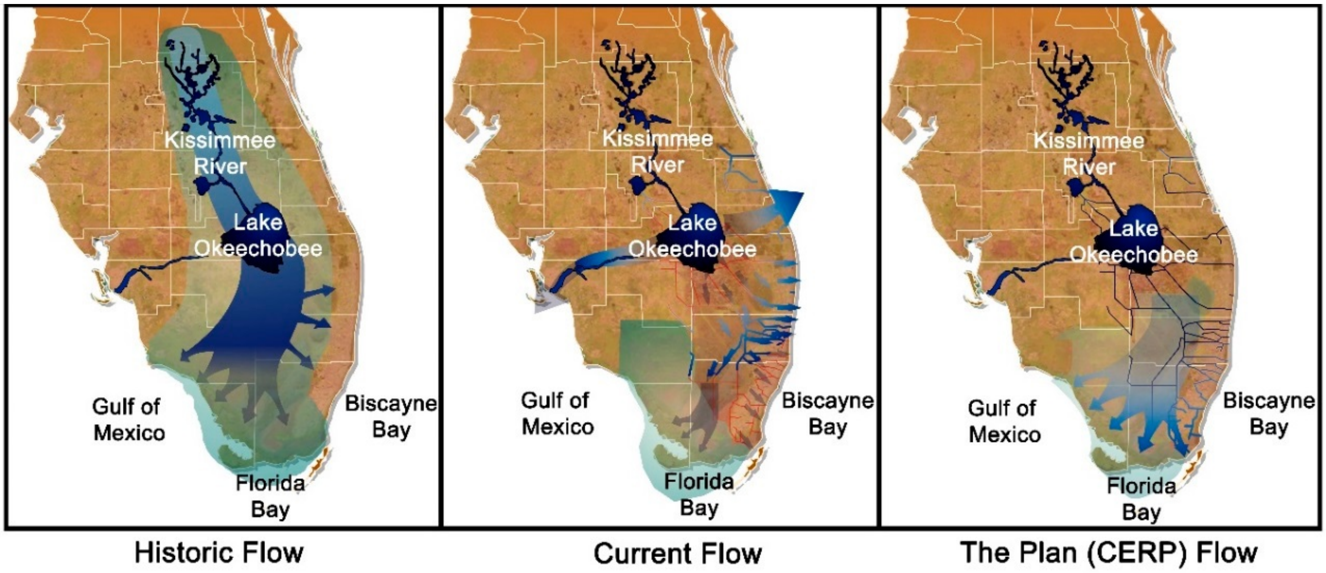
Appendix B

Figure 10: Map of Donors for Synthetic Ctrl



Source: DBHYDRO's Map Browser

Figure 11: Hydrological flow in Southern Florida



Source: Schade-Poole and Möller (2016)

Figure 12: Synthetic Control Result: Robustness to Anticipatory Effect

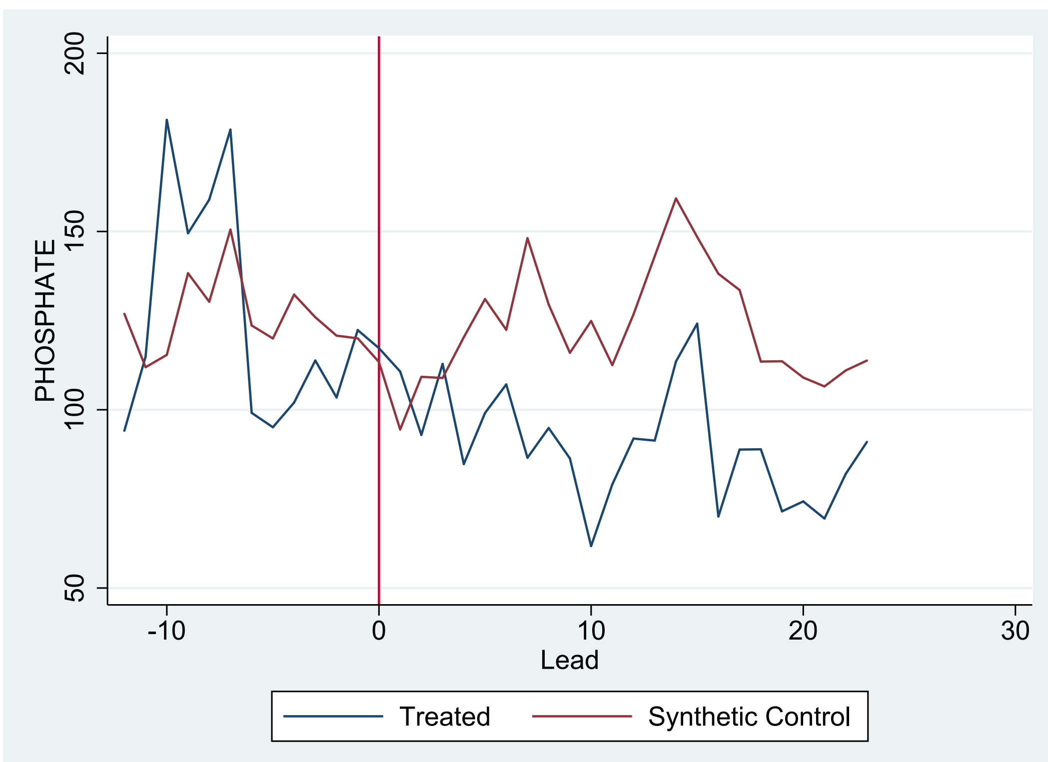


Figure 13: P-Values for Treatment Effects: Robustness to Anticipatory Effect

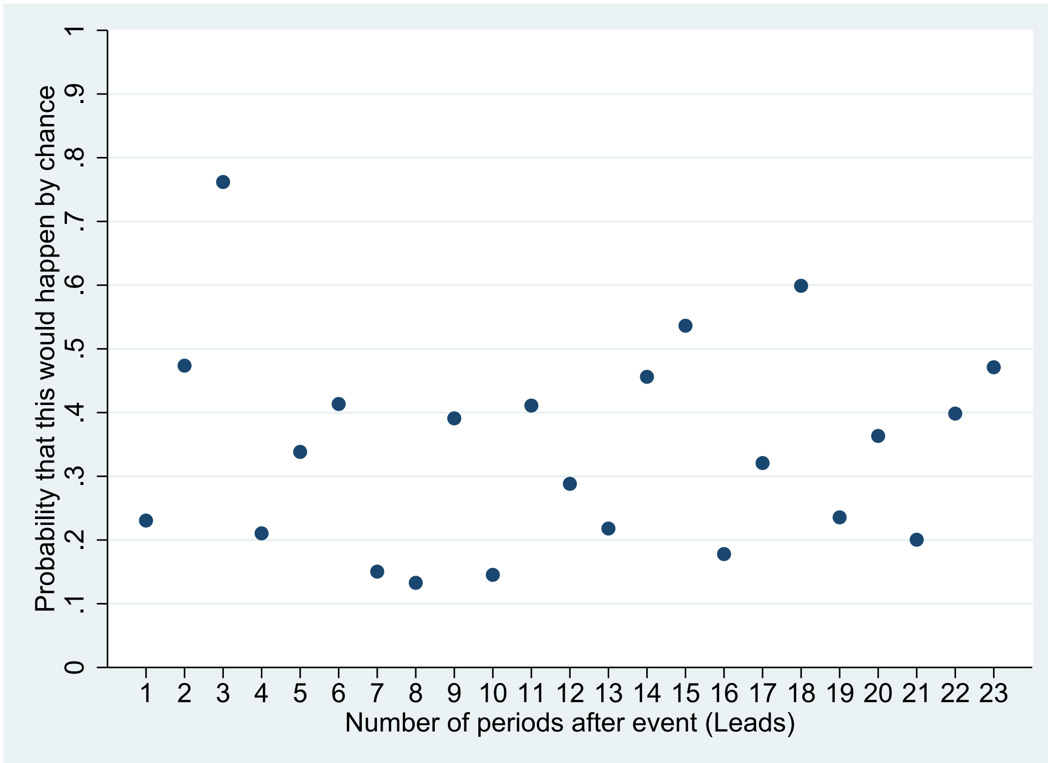


Figure 14: Synthetic Control Result: Robustness to Demeaning

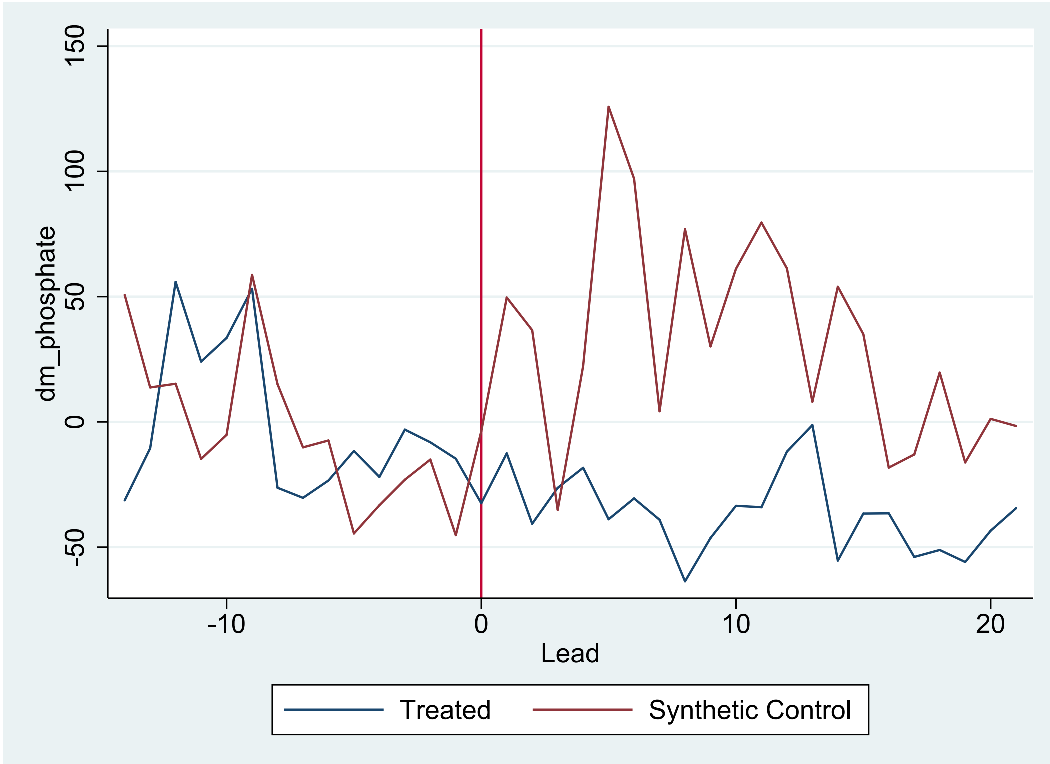


Figure 15: P-Values for Treatment Effects: Robustness to Demeaning

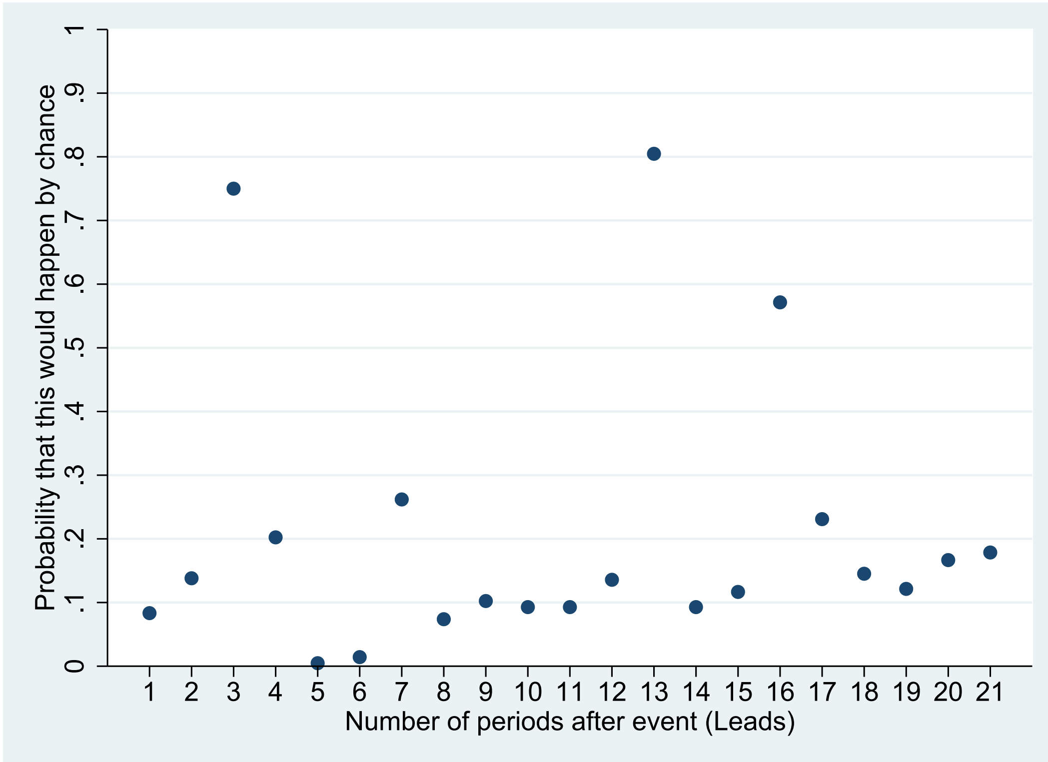


Figure 16: Synthetic Control Result: Robustness to Anticipatory Effect & Demeaning

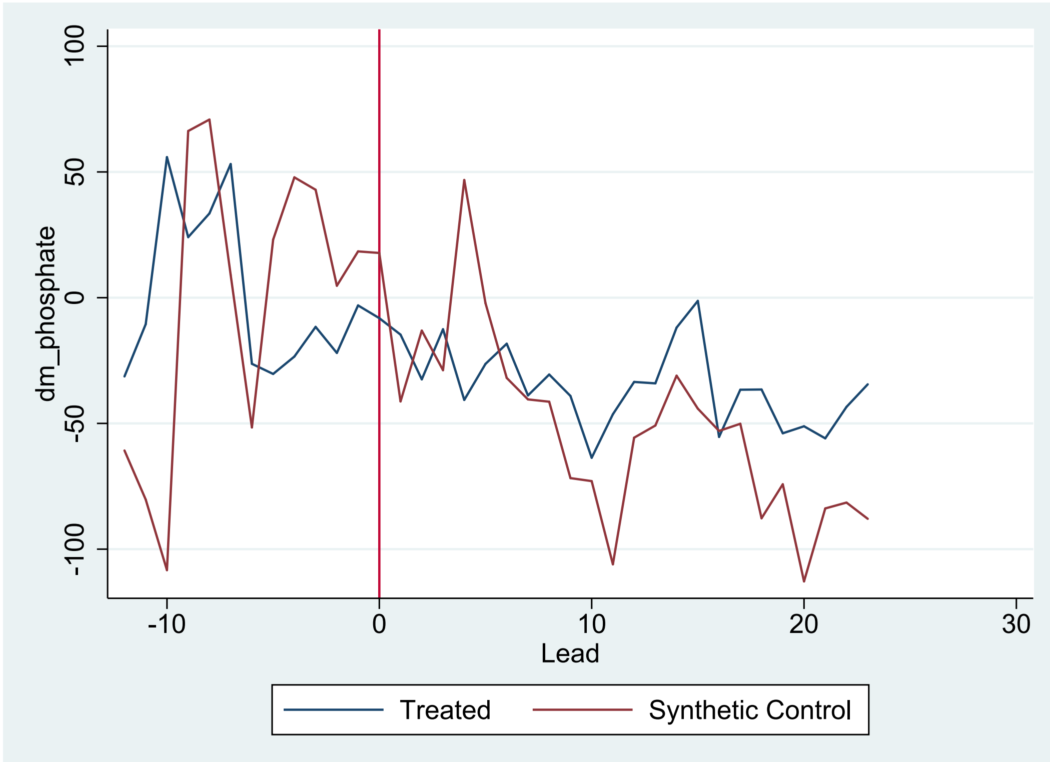


Figure 17: P-Values for Treatment Effects: Robustness to Anticipatory Effect & Demeaning

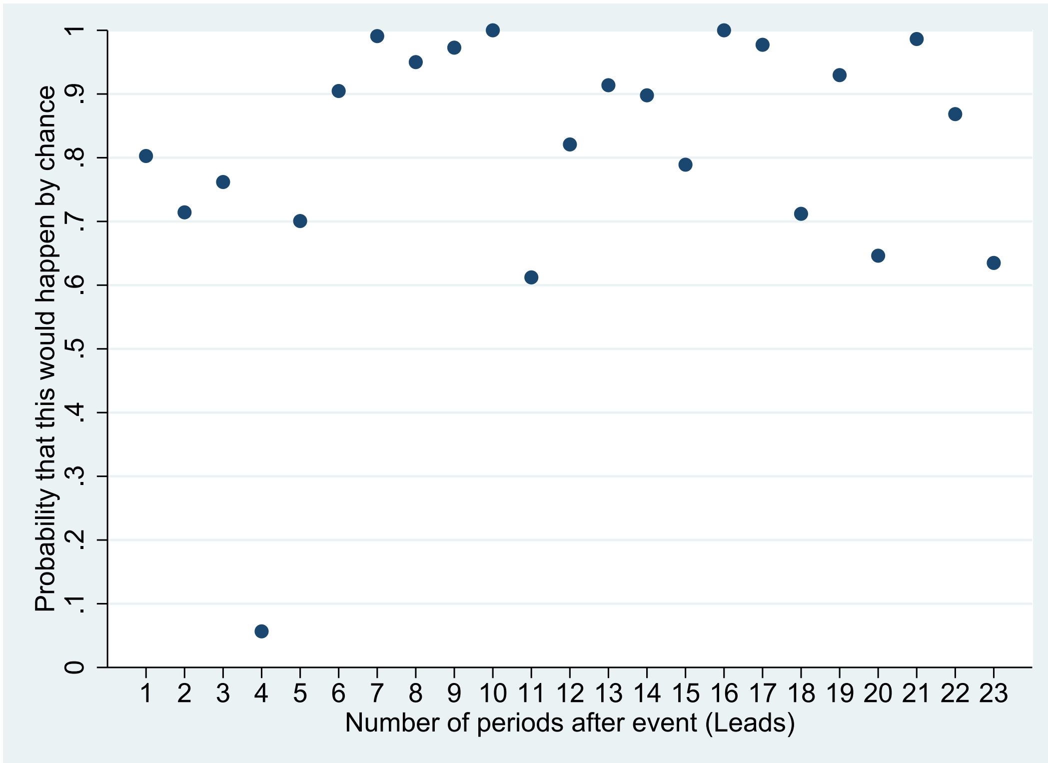


Figure 18: Heatmap Distribution of D_{it}'s

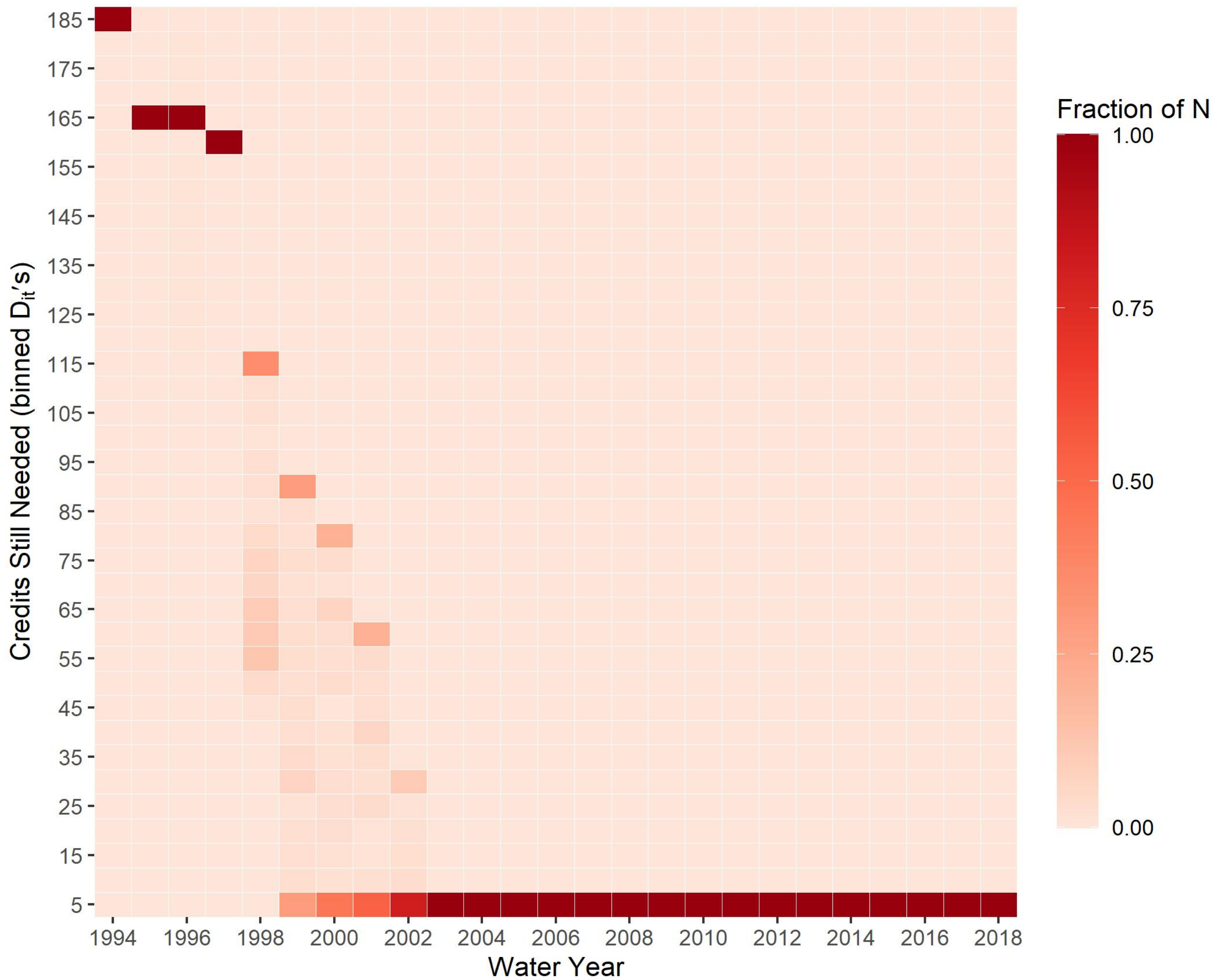


Table 4: Two-step Difference GMM Results: Outcome is Estimated TP Reduction (%)

	exogenous controls	predetermined controls	Veg Acres Predetermined
rolling_incentives2	0.767	1.395	1.074
	(0.371)	(0.336)	(0.383)
interact2	-0.0000175	-0.0000247	-0.0000231
	(0.147)	(0.094)	(0.111)
Total Acres Dedicated to Vege	0.0157	0.0297	0.0147
	(0.549)	(0.381)	(0.372)
Basin Acreage	-0.00135	-0.0124	-0.00130
	(0.782)	(0.279)	(0.794)
BMP Cycle (categorical)	-9.105	-8.729	-12.68
	(0.326)	(0.754)	(0.343)
N	3189	3189	3189
F-stat			
p-val_Fstat			
Sargan_Test_Pval	0.348	1.000	0.920
Hansen_Test_Pval	0.0341	0.0447	0.000808
AR1_pval	0.265	0.263	0.264
AR2_pval	0.355	0.354	0.355
Instrument_count	74	140	94
Included_farms	172	172	172

p-values in parentheses

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

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

Appendix C

First, I use the law of motion for credit stock from (4) with the fact that $Q^*_{it} = \min\{M, S_{it}\}$ to get (17) where $k > t+1$ and $\mathbb{1}\{S_{ih} < M\} = 1$ when $S_{ih} < M$.[35]

$$\frac{\partial Q^*_{ik}}{\partial Y_{it}} = -\Big(1 - \mathbb{1}\{S_{i,t+1} < M\}\Big) \cdots \Big(1 - \mathbb{1}\{S_{i,k-1} < M\}\Big)\mathbb{1}\{S_{ik} < M\} \tag{17}$$

Thus, we can rewrite equation (17) as (18). The interpretation for (18) is that the change in exercised credits for future period k resulting from a marginal change in current period's discharge is zero whenever the stock of credits from a *less distant* future period, h, is not enough to cover the maximum exercisable credit level, M. This implies that any credits earned today through reductions in Y_{it} will go towards credits to be used in period $h < k$ instead of k. Alternatively, it can also be zero whenever the stock of credits for period k is more than what is needed to cover M.

$$\frac{\partial Q^*_{ik}}{\partial Y_{it}} = \begin{cases} -1 & \text{if} \quad S_{ih} > M \quad \forall h \in [t+1, k-1] \quad \text{and} \quad S_{ik} < M \\ \\ 0 & \text{if} \quad S_{ih} < M \quad \text{for some} \quad h \in [t+1, k-1] \quad \text{or} \quad S_{ik} > M \end{cases} \tag{18}$$

Because equation (18) depends on all future stock levels between and including periods $t+1$ and k, these values are unknown at time t so that direct use of G_{it} in the empirical strategy is not feasible. Instead, I exploit the fact that depending on the current stock level S_{it}, it may be possible to know that $\frac{\partial Q^*_{ik}}{\partial Y_{it}} = 0$. For example, if we observe that $S_{it} > (k - t + 1)M$, then we know that the current stock of credits is more than enough to cover all of farmer i's

[35] If $k = t+1$, then we have $\dfrac{\partial Q^*_{i,t+1}}{\partial Y_{it}} = -\mathbb{1}\{S_{i,t+1} < M\}$.

credit demands for all periods between t and k. In this case, we then know that $S_{ik} > M$ so that equation (18) equals zero. If we observe that S_{it} is between M and $(k-t+1)M$ then we know that the current stock level is enough to cover farm i's credit demands only up to a certain period $h \in (t,k)$. This then means that equation (18) is no longer known to be zero and so the uncertainty surrounding $\frac{\partial Q^*_{ik}}{\partial Y_{it}}$ is preserved.

Now I can drop the discount factor and expectation operator from (6) so that I can define $\widehat{G}_{it}$ as (19).

$$\widehat{G}_{it} = -\sum_{k=t+1}^{T} \frac{\partial Q^*_{ik}}{\partial Y_{it}} \tag{19}$$

Then I substitute each $\frac{\partial Q^*_{ik}}{\partial Y_{it}}$ term using (17) to get

$$\widehat{G}_{it} = \mathbb{1}\{S_{i,t+1} < M\} + \sum_{k=t+2}^{T} \left(\prod_{h=t+1}^{k-1} \mathbb{1}\{S_{ih} \geq M\} \right) \mathbb{1}\{S_{ik} < M\}$$

Next I define another term $\widetilde{G}_{it}$ in (20).

$$\widetilde{G}_{it} = \sum_{k=t+1}^{T} \mathbb{1}\{S_{ik} < M\} \tag{20}$$

It's straight forward to show that $G_{it} \leq \widehat{G}_{it} \leq \widetilde{G}_{it}$. If $S_{it} \geq 2M$ then $S_{i,t+1} \geq M$ for sure. Thus the first term in (20) equals zero. Define r_{it} as the number of periods where the existing S_{it} levels is enough to exercise the maximum level of credits. This is implicitly defined in (21) where $r_{it} \in \mathbb{Z}^+$ and $e_{it} \in [0,1)$ is just a remainder term.

$$\frac{S_{it}}{M} = r_{it} + e_{it} \tag{21}$$

Then for $2 \leq r_{it} < T - t + 1$, we have

$$\widetilde{G}_{it} = (T - t) - (r_{it} - 1)$$

$$= (T - t + 1) - r_{it}$$

$$= (T - t + 1) - \left\lfloor \frac{S_{it}}{M} \right\rfloor$$

Then $M\widetilde{G}_{it}$ is

$$M\widetilde{G}_{it} = (T - t + 1)M - M \left\lfloor \frac{S_{it}}{M} \right\rfloor$$

Define D_{it} as

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

So then we get that

$$M\widetilde{G}_{it} > D_{it}$$

Now I show that $\widetilde{G}_{it} \leq D_{it}$.

$$D_{it} - \widetilde{G}_{it} = (T - 1 + 1)(M - 1) - S_{it} + r_{it}$$

$$= (T - 1 + 1)(M - 1) - S_{it} + \frac{S_{it}}{M} - e_{it}$$

$$= (T - t + 1 - r_{it})(M - 1) - e_{it} \geq 0$$

Since r_{it} is restricted to be in the range $[2, T - t + 1)$, then the lowest $(T - t + 1 - r_{it})$ can go is 1. In my data, the lowest value that M can take is 3.91, then $D_{it} > \widetilde{G}_{it}$. When $r_{it} < 2$, then $D_{it} - \widetilde{G}_{it}$ gets more positive. When $r_{it} \geq (T - t + 1)$, then both D_{it} and $\widetilde{G}_{it}$ are forced to be zero since the original term G_{it} is also zero in that case. Q.E.D.

Appendix D

In a static model with ambient subsidy, a regulator who's objective is to implement a least cost solution to achieving the pollution target maximizes (22).

$$\mathcal{L} = \sum_i \pi(\theta_i, Y_i)L_i + \lambda\left(\overline{Y} - \sum_i Y_i L_i\right) \tag{22}$$

The first order condition WRT Y_i is (23).

$$\pi'(\theta_i, Y_i) = \lambda \tag{23}$$

Plugging in the functional form assumption for marginal profit I get that the policy function is (24).

$$Y_i^* = \theta_i - \frac{\lambda}{\gamma_i} \tag{24}$$

Then utilizing the pollution constraint we get that the shadow value, which also happens to be the optimal subsidy rate, is given by (25).

$$\lambda^* = \frac{Y^{bmp-bau} - \overline{Y}}{\sum\limits_i L_i/\gamma_i} \tag{25}$$

Appendix E

Full cooperation behavior solves

$$\max_{Y_i} \sum_j \pi(Y_j, \theta_j, \gamma_j) + sn(\overline{Y} - Y) \tag{26}$$

FOC WRT Y_i:

$$\pi_1'(Y_i, \theta_i, \gamma_i) = sn \tag{27}$$

Appendix F

Firms solve

$$
\begin{aligned}
V_t(S_{it}) &= \max_{Y_{it}} \ \pi(Y_{it}, \theta_i) - \left(\overline{T} - Q^*_{it}\right) + \delta \mathbb{E} V_{t+1}(S_{i,t+1}) \\
\text{s.t.} \qquad S_{i,t+1} &= S_{it} - Q^*_{it} + \left(\overline{Y} - Y_t\right) \\
Y_t &= \alpha_t + \sum_i Y_{it} L_i \\
\overline{Y} &\geq \alpha_t + \sum_i \theta_i L_i \\
\alpha_t &\overset{iid}{\sim} F(0, \sigma^2_\alpha) \\
Q^*_{it} &= \min\{M, S_{it}\}
\end{aligned}
\tag{28}
$$

Solve this in finite time via backward induction and normalizing terminal value so that

$$
V_{T+1}(S_{i,T+1}) = \sum_{k=0}^{\infty} \delta^k \pi(\theta_i^{bmp}, \theta_i^{bmp}) = 0 \tag{29}
$$

means that

$$
\begin{aligned}
V_T(S_{iT}) &= \max_{Y_{iT}} \ \pi(Y_{iT}, \theta_i^{bmp}) - (\overline{T} - Q^*_{iT}) \\
\text{FOC:} \quad \pi'(Y^*_{iT}) &= 0 \\
\implies Y^*_{iT} &= \theta_i^{bmp} \\
\implies V_T(S_T) &= -(\overline{T} - Q^*_{iT})
\end{aligned}
\tag{30}
$$

Then next iteration we have

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

Then the next iteration

$$V_{T-2}(S_{i,T-2}) = \max_{Y_{i,T-2}} \; \pi(Y_{i,T-2}, \theta_i^{bmp}) - (\overline{T} - Q^*_{i,T-2}) + \delta \mathbb{E}\left[\pi(Y^*_{i,T-1}, \theta_i^{bmp}) - (\overline{T} - Q^*_{i,T-1}) - \delta(\overline{T} - Q^*_{iT})\right]$$

$$\text{s.t.} \qquad S_{i,T-1} = S_{i,T-2} - Q^*_{i,T-2} + (\overline{Y} - Y_{T-2})$$

$$S_{i,T} = S_{i,T-1} - Q^*_{i,T-1} + (\overline{Y} - Y_{T-1})$$

$$\text{FOC:} \quad \pi'(Y^*_{i,T-2}, \theta_i^{bmp}) = \delta \mathbb{E}\left[\frac{\partial Q^*_{i,T-1}}{\partial S_{i,T-1}}\right] L_i + \delta^2 \mathbb{E}\left[\frac{\partial Q^*_{iT}}{\partial S_{iT}}\right] L_i \tag{32}$$

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

$$\pi'(Y^*_{it}, \theta_i^{bmp}) = \sum_{k=t+1}^{T} \delta^{k-t} L_i \mathbb{E}\left[\frac{\partial Q^*_{ik}}{\partial S_{ik}}\right] \tag{33}$$

Equation (33) is the same as (5) except $\frac{\partial Q^*_{ik}}{\partial Y_{it}}$ is replaced with the equivalent value of $\frac{\partial Q^*_{ik}}{\partial S_{ik}} L_i$.