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. Non-point source pollution (NPSP) is notoriously difficult to regulate as it is extremely difficult to observe and estimate individual level discharge. There is a dearth of observational studies on the cost effectiveness of NPSP policies because the answer requires the study of 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. In this context, command-control comes in the form of mandatory best management practices (BMPs) which are a set of verifiable pollution reducing projects/procedures that do not offer firms flexibility in abatement choices. Market incentives can offer a much higher degree of flexibility and thus lower compliance costs and in this context, they come in the form of ambient mechanisms (AMMs). AMMs impose uniform tax (or subsidy) to all firms based on aggregate emissions and such approaches are theoretically appealing but have rarely been applied in practice and thus relatively little is known about them. I study a program called the Florida Everglades Forever Act intended to reduce phosphorus runoffs from entering the sensitive Everglades. The program consists of both a command-control component as well as a market incentive component. I develop a new dataset with farm level discharge and subsidies for pollution reduction to estimate a marginal abatement cost (MAC) curve

for the average farm. Using the estimated MAC curve, I simulate the costs under AMM and compare that with both data-estimated and engineer-estimated costs under BMPs. I find that to achieve the same benchmark pollution outcome, AMM could be about 1/6 the cost under BMPs.

Introduction

Non-point source pollution (NPSP) poses a unique challenge for regulators and economists. The challenge lies in how to best regulate pollution when you cannot observe or measure individual contributions? Such is the case for NPSP which is an increasingly important area for policy makers. Agricultural runoff is an important example of NPSP and is the main focus of this paper. Agricultural runoff, specifically excess nutrients such as nitrates and phosphates entering water systems, cause at least \$4 billion in economic damages per year (Chatterjee, 2009). This figure does not include all damages from nutrient runoff nor does it capture the effects from pesticide and herbicide runoff. The U.S. has spent almost \$5 trillion dollars (or 0.8 percent of GDP every year) trying to clean up the nation's waters (Keiser and Shapiro, 2019) but a significant portion remain too polluted to allow *any* economic activities.[1]

There are two main approaches in the realm of mandatory policies used to regulate agricultural runoff (and NPSP more broadly) 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 addressing agricultural runoff. 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.

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[1] 2004 National Water Quality Inventory: Report to Congress.

Market incentives on the other hand, come in many forms. The primary challenge is to find something that can be observed or estimated that correlates with pollution so that incentives can be tied to it. Economists have developed an eloquent theory of ambient-based market mechanisms (henceforth AMMs) 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/punishmen is based on the distance 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 socially optimal 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 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) which focused on testing underlying behavioral assumptions from the standard AMM theory and which instruments among the AMMs produced the best outcomes.

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.

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 the point-source context (Goulder et al., 1999; Newell and Stavins, 2003; Goulder and Parry, 2008). However, there has not, to the best of my knowledge, been as much progress in this area for the non-point source context. Rendleman, Reinert and Tobey (1995) is the only paper so far that has tried to do this. They used a computable general equilibrium model calibrated to match estimated elasticities of input substitution to estimate the cost-effectiveness of mandated input levels and input taxes and find only a ten percent cost savings from input taxes compared with command-control. In contrast, the comparison made in this paper is between command-control and another market incentive mechanism in the NPSP context, that is, the ambient market mechanism. The cost advantages from AMMs compared to command-control is much more ambiguous and thus this comparison should be of great interest. Specifically, AMMs on

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one hand provide the greatest flexibility for firms to abate. On the other, AMMs could have too much flexibility that leads to free-riding therefore undercutting potential cost advantages.

First, I study a program called the Everglades Forever Act (EFA) which had both a mandatory BMP component and an pseudo-AMM component in the form of a subsidy to abate which was based on both group and individual performance. This empirical setting is extremely attractive for such a study because it is the only agricultural runoff setting in which the runoff from farms are actually a point-source pollution but regulated as if it were non-point source. I first estimate how farms' discharge responded to the subsidy while controlling for BMPs using fixed effects. That exercise allows me to uncover the marginal abatement cost curve which can then be used to estimate the optimal ambient subsidy and compliance costs for various pollution targets. Compliance costs under BMPs are taken from engineer estimates and validated using a two-way fixed effects model on state level agricultural expenditure panel data. I find that the subsidy component of the EFA did cause meaningful reductions in discharge and that an ambient subsidy could have achieved the same ambient pollution outcome at 1/6 the cost of a mandatory BMP policy.[2]. Lastly, the results attenuate the concerns from the literature regarding regulator expense under an ambient subsidy being prohibitively costly. I find that to achieve the same pollution outcome as that under the EFA but using only an ambient subsidy instead would have costed the regulator $20 million in subsidy expenditures. Implementing the ambient subsidy in place of the EFA could have saved a significant fraction of the $34 million in annual regulatory oversight costs.[3]

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[2]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.

[3]See SFWMD's 2008 Budget in Brief. Link.

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, 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 is consistent with the polluter-pays principle which is where policy makers are increasingly turning towards. 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). 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.[4] 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[5]. 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.[6] 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.[7]

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

[5]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).

[6]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.

[7]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.

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 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 achieve a percent TP load reduction of 25% relative to a baseline historic TP level.[8] Water quality monitoring stations are placed downstream of the main canals running through the EAA and are used to measure ambient quality attributed to EAA farmers. If the *entire* EAA basin achieves a TP load reduction by more than the 25% target for reduction, then everyone is awarded one tax credit per acre for each percentage point above 25%. Earned credits can go towards reducing future privilege tax obligations two water years from which it was earned. The rate at which a credit can reduce the tax is the same for all parcels. However, at a minimum, the tax per acre must not fall below $24.89 which implies that for each year, there is a maximum number of exercisable 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

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

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)[9]. 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.[10] 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.[11] 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,

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[9]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.

[10]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.

[11]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.

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.

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.[12]

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.[13] 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

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

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

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.[14] 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[15]. 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.[16]

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.

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

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

[16]URL: https://sfwmd.maps.arcgis.com

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.[17] 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 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 up-

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

stream 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.

Model

The purpose of this section is to introduce the most parsimonious model of a pure ambient subsidy mechanism with the goal of understanding the basic NPSP problem and guiding empirical design. 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[18].

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 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 and is given by $\pi_i(Y_i) = \pi(Y_i, \theta_i)$ where Y_i is chosen discharge and θ_i is 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 $Y = \sum_{i=1}^{n} Y_i$.

In such a setting, there are two possible Nash equilibria. One where there is compliance $(Y < \overline{Y})$ and one where there is non-compliance $(Y > \overline{Y})$. Each polluter is willing to reduce their emissions by one unit from their business-as-usual level if they are paid s for that reduction. If a farm is pivotal in the determination of compliance, then the lowest level of discharge that is profitable is (henceforth referred to as the minimum profitable pollution level) denoted as $\widetilde{Y_i}$ and is defined in (1). 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).[19] However, whether a subsidy

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

[19]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 $\overline{Y}$.

is paid out depends on others' actions. There can be two sets of policies, one that satisfies the incentive compatibility constraint for all agents thereby engendering a compliant Nash equilibrium ($Y^{NE} < \overline{Y}$) and a second, more generous one that completely eliminates the non-compliant Nash.

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

To achieve the first policy (henceforth referred to as the compliant Nash) it must be such that the incentive compatibility constraint, given by (2), holds for every agent. Note that the left hand side of (2) is the same for everyone so the policy need only hold for the agent k : $k = \arg\max_j \{\pi_j(\theta_j) - \pi_j(\widetilde{Y}_j)\}$. Here $\overline{Y}^T$ is the pollution threshold that triggers the subsidy; it represents the "true" ambient target and is set equal to $\sum_i \widetilde{Y}_i$. The term $\overline{Y}^P$ determines the subsidy base and it must be the case that $\overline{Y}^P > \overline{Y}^T$. The subsidy rate s is chosen so that the ambient pollution under a compliant Nash hits the target, $\overline{Y}^T$, while the value $\overline{Y}^P$ must be chosen so that agents are incentivized to choose their minimum profitable pollution level (chosen so that (2) holds).

$$s(\overline{Y}^P - Y) \geq \pi_i(\theta_i) - \pi_i(\widetilde{Y}_i) \tag{2}$$

Let the profit function be defined as in (3).[20] Then one only needs to evaluate the values for θ_i^{bmp} (the discharge level under mandatory BMPs but absent other policies, henceforth referred to as BMP-BAU) and γ_i (the slope of the marginal abatement cost curve wrt to

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

discharge) 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 $\overline{Y}^T$.

$$\pi(Y_{it}, \theta_i^{bmp}) = -\frac{\gamma_i}{2}(\theta_i^{bmp} - Y_{it})^2 \tag{3}$$

Setting the right hand side of (1) equal to the subsidy rate s gives i's minimum profitable pollution (4).

$$\widetilde{Y}_i = \theta_i^{bmp} - \frac{s}{\gamma_i} \tag{4}$$

Then utilizing the pollution constraint (5) we get that the optimal subsidy rate, is given by (6)[21].

$$\overline{Y}^T = \sum_{i=1}^{n} \widetilde{Y}_i \tag{5}$$

$$s^* = \frac{Y^{bmp-bau} - \overline{Y}^T}{\sum_i \frac{1}{\gamma_i}} = \frac{Y^{bmp-bau}\left(1 - \frac{\overline{Y}^T}{Y^{bmp-bau}}\right)}{\sum_i \frac{1}{\gamma_i}} \tag{6}$$

where $Y^{bmp-bau} = \sum_{i=1}^{n} \theta_i^{bmp}$.

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

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[21]The pollution target in (5) is the "true" target.

credit program was layered on top in an attempt to induce *additional* abatement. Importantly, both the threshold for which the incentive credits are triggered and the threshold that determines the subsidy base are based on that same 25% reduction target, i.e., $\overline{Y}^P = \overline{Y}^T$ were both set equal to 75% of BAU levels (without BMPs). Therefore, it is as if the both $\overline{Y}^P$ and $\overline{Y}^T$ in the simple model above are both greater than $\sum_i \theta_i^{bmp}$. Setting the pollution standards in such a way dissolves the strategic interactions between polluters. So long as polluters do not collectively exceed the BMP-BAU ambient pollution level ($\sum_{i=1}^{n} \theta_i^{bmp} L_i$), then polluters are almost guaranteed to receive a subsidy[22]. Consequently, 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

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[22]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.

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

Polluter's Decision Problem Under Incentive Credit Program

In this section, I try to model the decision problem that agents *actually* faced under the EFA policy. The incentive credit program under the EFA engendered a dynamic decision problem for the farmers in that tax credits awarded for compliance can be stored for future use, e.g., used to reduce the lump sum tax in future periods. So instead of behavior being governed by (1), it is instead governed by (7).

$$\pi'(Y_{it}^*, \theta_i) = G_{it} \tag{7}$$

The term G_{it} is simply the partial derivative of the continuation value with respect to the pollution choice variable (see equation 25 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.

Equation (7) 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 (8) which shows how a simple comparative static on the policy function can retrieve the parameter γ_i.[23] This parameter can be construed as the slope of the marginal abatement cost curve, the same as in the standard ambient subsidy model (1).

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

A Proxy for G_{it}

The problem with using G_{it} directly is that it represents the farmer's expectations about the future values of credits earned today. Additionally we have no way of knowing each farmer's discount factors. One way to proxy for G_{it} is to use something that is conceptually similar. Since the partial derivative of the continuation value hinges on the number of credits left to earn, then I can simply use that as my proxy. Specifically, I will use the proxy defined in (9), 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 $\frac{\partial Y_{it}^*}{\partial G_{it}} > \frac{\partial Y_{it}^*}{\partial D_{it}}$. Therefore, my estimates of slope γ_i using estimates of $\frac{\partial Y_{it}^*}{\partial D_{it}}$ will be a conservative estimate (biased toward zero) of the true slope term, γ. 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

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[23]Abusing terminology a bit here because equation (8) 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 (8) across farms.

are relevant, including the present. The product of which represents the maximum necessary credits to achieve minimum tax burden; it includes the present so think of it as a starting balance value. The term S_{it} represents the starting balance of credits (a stock variable) for period t.

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

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}.

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[24]. Thus, I restrict the estimation period to start on 1996 to avoid spurious correlation.[25] Furthermore, I allow for the adopted BMPs to change once every five year cycle. Farms are allowed to adjust their chosen BMPs but only during the permit renewal process which occurs every five years from when they were first issued their permit (different for each farm). I include a categorical variable that represents which cycle each farm is at for each water-year thus creating a unit-specific 5-year fixed effects for all units.

Empirical Methodology

To achieve a consistent estimate of our estimand, the average of (8), 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 (10) where Y_{it} is the phosphorus load

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[24]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)

[25]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.

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.[26]

$$Y_{it} = \alpha_i + \alpha_t + \beta_1 D_{it} + \beta_2 X_{it} + \varepsilon_{it} \tag{10}$$

The problem with estimating (10) 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 (9). 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 (10) so that consistency only requires sequential exogeneity (Hansen, 2021; Anderson and Hsiao, 1981). A variable satisfies sequential exogeneity if it is not correlated with current or future period error terms and only past ones, if at all; covariates that satisfy sequential exogeneity are said to be predetermined. Then lagged values of the predetermined variables are suitable IVs for the first differenced predetermined variable. I argue that they are suitable since the relevance condition is satisfied by (9) together with the law of motion for credit stock (23). The exclusion restriction assumption is satisfied via the sequential exogeneity as seen by first differencing equation (9). First differenced values are denoted with a $\triangle$ symbol where $\triangle r_t = r_t - r_{t-1}$. The first differenced version of (10) is given by (11).

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

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

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 (1) 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 (11) 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 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 3 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.[27] Importantly, the magnitudes of those coefficients are implausibly

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

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 did not change the slope of marginal profit curves. However, it seems reasonable that BMPs can either steepen or flatten the slope of the pollution demand curves but it would certainly reduce θ_i from θ_i^{bau} to θ_i^{bmp}. On the one hand, there are structural BMPs such as having onsite detainment ponds which could provide a flexible way for farms to control runoffs.[28] On the other hand, BMP adoption may have left farmers with fewer options to adjust their P loads in response to incentives, i.e., θ_i^{bmp} is close to zero. 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

covariate.

[28]Detainment ponds are usually able to allow a portion of phosphorus to be retained onsite before pumping the water offsite.

in equation (12).

$$\gamma^{bmp} = \lambda \gamma^{bau} \tag{12}$$

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.[29]. 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 (6), 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 (4) for the average farmer using estimates from earlier to get (13).

$$\widetilde{Y}_i = 0.973 - 0.0117s \tag{13}$$

Equation (14) gives the ambient subsidy rate for various targets for ambient pollution. To

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[29]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).

estimate $Y^{bmp} = \sum_i \theta_i$, I estimate within-unit average total emissions (in lbs) over the post-break point years.[30] I then sum that value across farms to get 421,294.6 lbs of phosphorus for the average year under command-control only. To convert values from pounds to metric tons, I simply divide by 2205 to get 191.06 metric tons.[31][32]

$$s^* = \frac{191.06 \left(1 - \dfrac{\overline{Y}^T}{191.06} \right)}{2.457} \tag{14}$$

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 \$19.44. In other words, without the EFA in place, the regulator could have achieved, at a minimum, a 25% reduction in ambient phosphorus with an ambient subsidy rate of \$19.44.

The benchmark pollution level for cost comparison is arrived at by estimating the percent

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[30]Post break-point years refer to the years for which $D_{it} = 0$.

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

[32]Note that the denominator in (6) is also divided by 2205.

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 levels, a subsidy rate of $28.77 is needed. Taking the relevant area under the marginal abatement cost curve results in an area of about $5.32 which represents the estimated compliance cost per acre under the standard ambient subsidy policy for the average farm. Scaling this figure up using the average land size of 2550 acres means that the compliance cost for the average farm is almost $14,000/year.

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 arrived at in one of two ways.

The first way involves taking estimates from other papers. 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 per acre is roughly $638.88 (Roka et al., 2010) the data for which came from calendar years 2008-09. This figure can be interpreted as a result of 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 best that I have come across, are estimates made pre-policy intervention, such are the early days of the empirical revolution. These ex-ante estimates imply that for the evaluated set of BMPs, the estimated 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.

The second way to arrive at the BMP cost is to estimate the two-way fixed effects (10) model using data from the USDA Quick Stats portal that has 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

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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

The cost of the mandatory BMPs is estimated to be about $34.15/acre compared to the standard ambient subsidy of $5.32/acre meaning that the compliant Nash could achieve the same pollution outcome as the BMPs but at a sixth of the cost.[33] If we relax the assumption that the slope of the marginal abatement cost curve is unchanged after adopting BMPs, then the compliance cost under only the standard ambient subsidy policy can look quite different. For instance, if BMPs flattened the slope then our estimate of that slope, which is based on a data-generating process that has BMPs in practice, is biased down. Depending on that bias, the compliance cost under an ambient subsidy (and a compliant Nash) may be greater than that of the command-control. Specifically, if the mandatory BMPs resulted in a MAC curve with a slope that is smaller by a factor of 0.16, then the compliance costs under either command-control or ambient subsidy are equal. Any flatter then the compliance cost is higher whereas if the BMPs increased the slope, then the slope under no policy is flatter meaning that the compliance cost is lower than estimated.

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[33]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, under the simulated ambient subsidy scenario, the regulator would incur an annual cost of about $20 million in order for the compliant Nash to achieve the same annual ambient reductions under the EFA of 55%. The cost to regulator under the EFA is estimated to be about $13 million (citation needed). Though this represents an almost 50% increase in regulator expenditure compared to that under the EFA, the EFA policy provides idea on how to reduce this regulatory burden. For starters, one could apply a lump sum tax to polluters and offer the subsidy in the form of tax credits similar to the EFA. Thereby creating the same marginal incentives to abate as that under an ambient subsidy but without actually paying out real money which significantly reduces government expenditure.

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.[34]

Finally, the author would like to caution those who view this work as evidence that ambient

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

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.[35] 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.

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[35]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.[36]

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[36]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
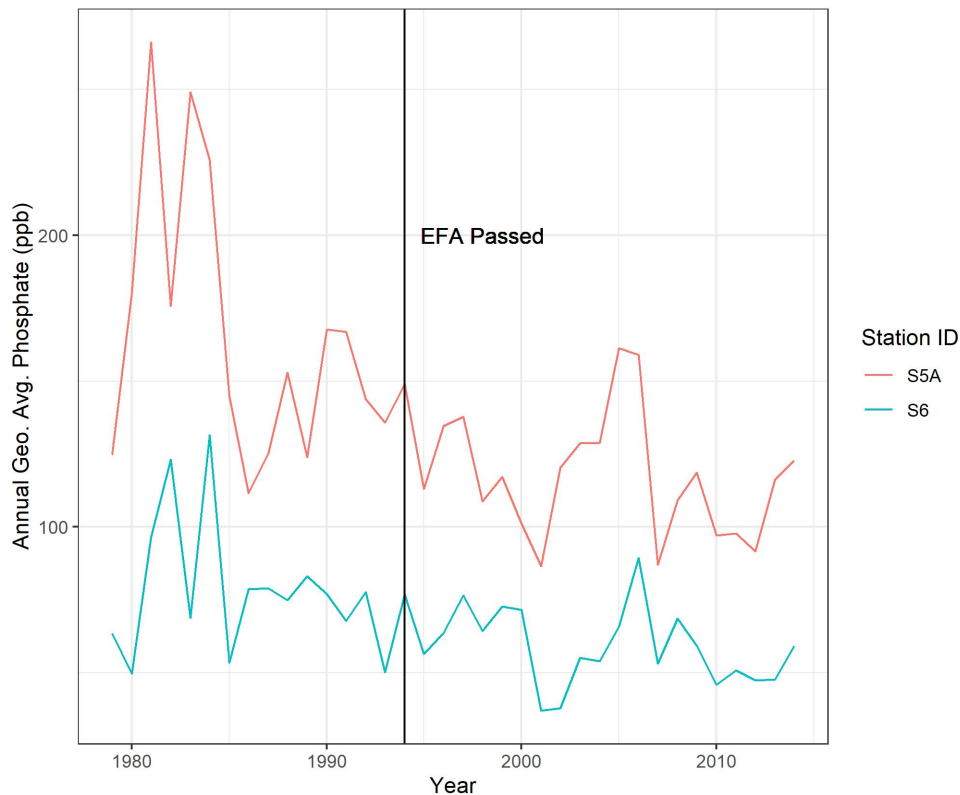
The unit of analysis is at the water quality monitoring station level with a total of 21 potential donors and 2 treatment units (map of locations of donors and hydrological flow is shown in Figures 5 and 6 found in Appendix B). A station is assigned to be in the treated group if it resides immediately downstream of the EAA area and is used to monitor water quality coming out of the EAA.[37] 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

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[37]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.

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

X_{it} denotes the annual geometric average phosphorus levels for station i and no other co-variates are used.[38] 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 2.

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

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[38]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
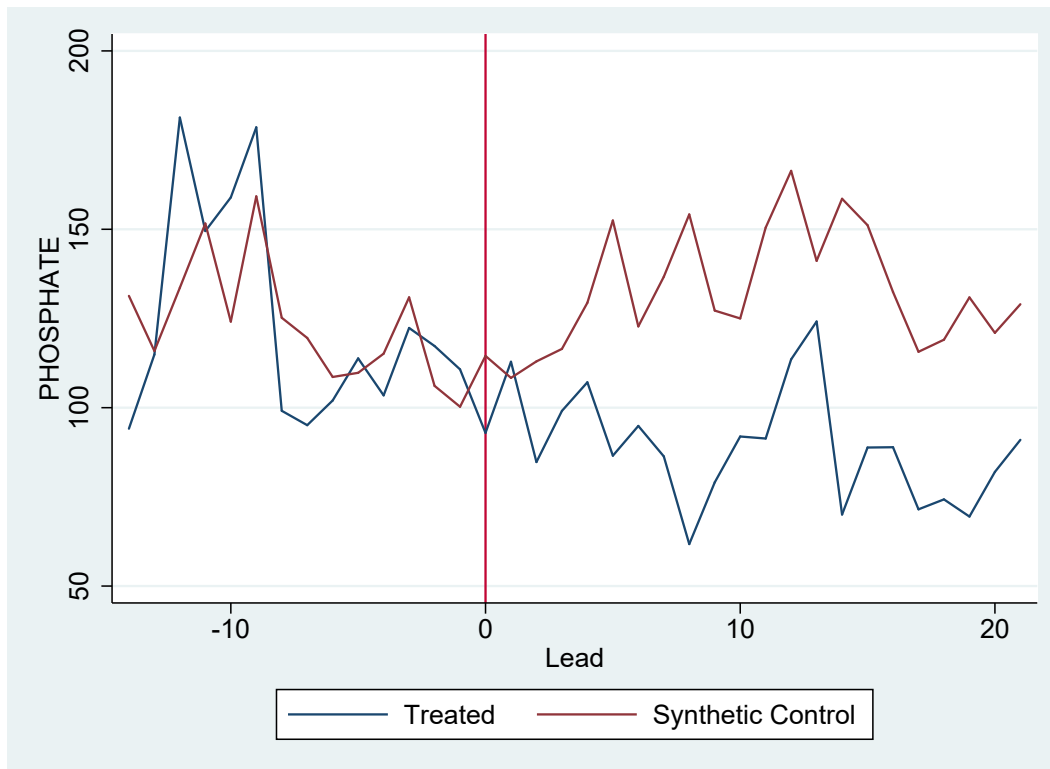
Inference is done by using a permutation-placebo test where a control unit is randomly sampled from the donor pool with replacement. The randomly chosen control unit is then assigned as "treated", synthetic control weights are calculated and the corresponding estimated treatment effect is then calculated. 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
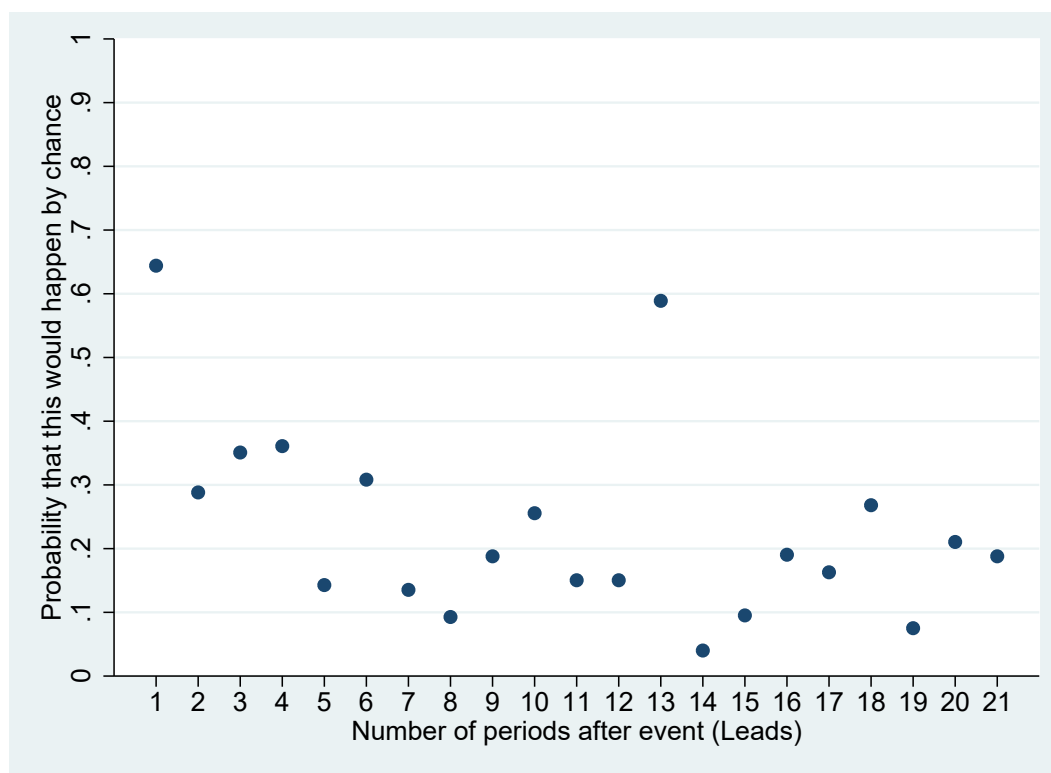
There are a number of robustness I have implemented and the results are shown in Appendix A. First, I try to incorporate anticipatory effects by treating the "effective" policy implementation date as *if* it were in 1992. The actual policy implementation date was 1994 but the policy is a culmination 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 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

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			
2027-2029	$20.00	Tax Credits No Longer Available		
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

Figure 5: Map of Donors for Synthetic Ctrl
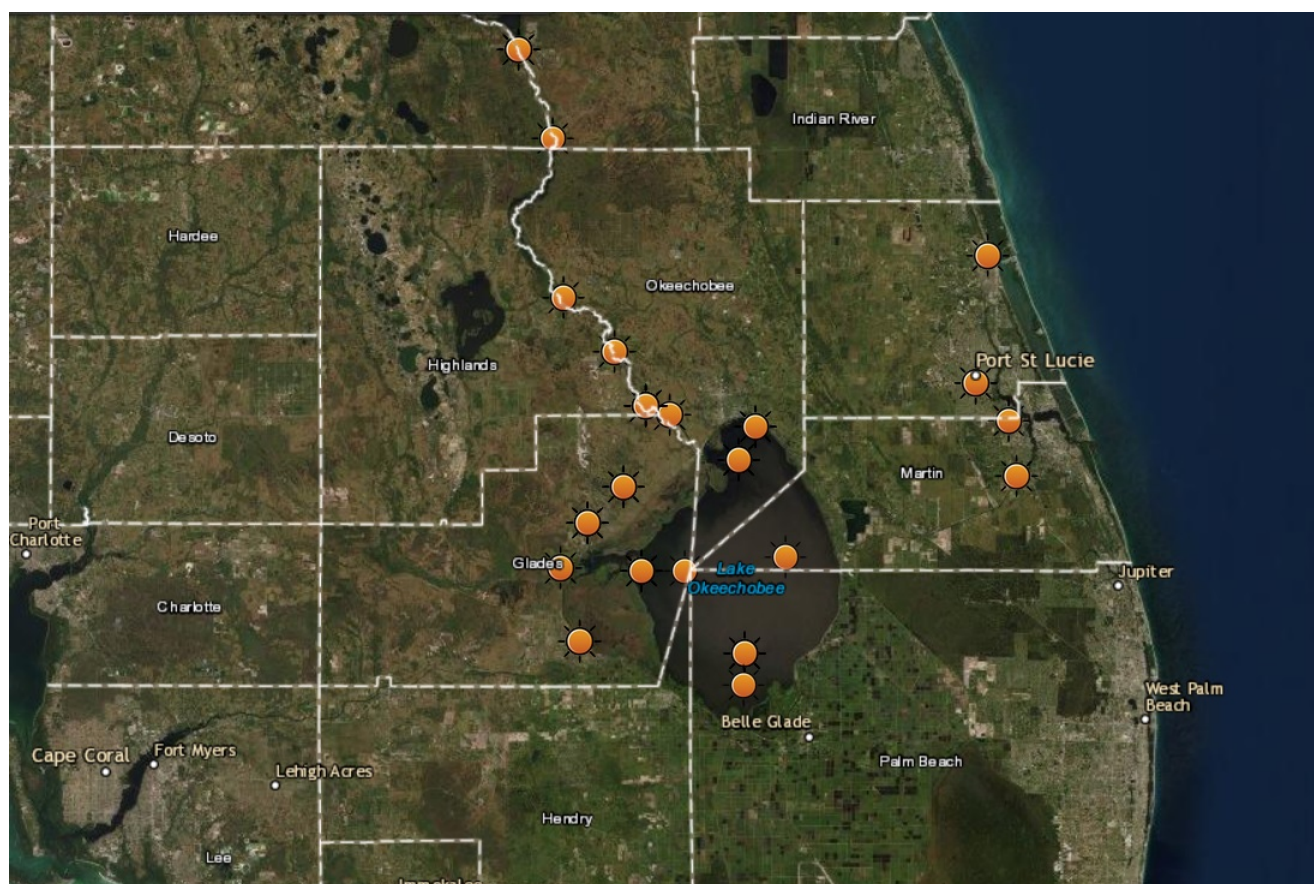
Source: DBHYDRO's Map Browser

Figure 6: Hydrological flow in Southern Florida
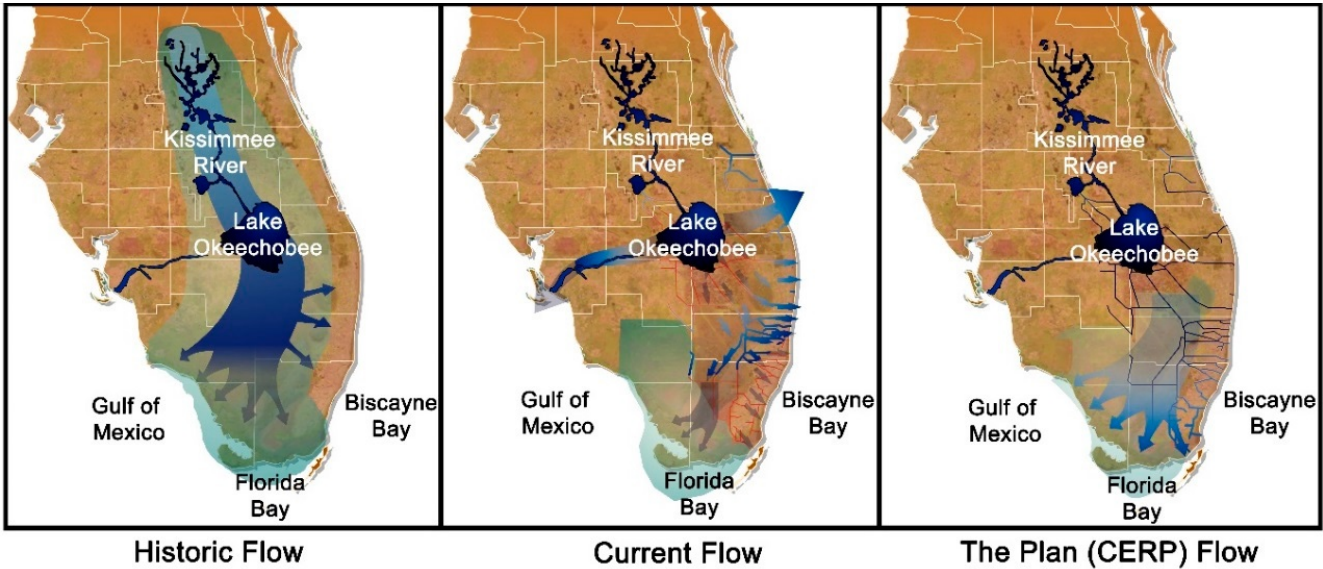
Source: Schade-Poole and Möller (2016)

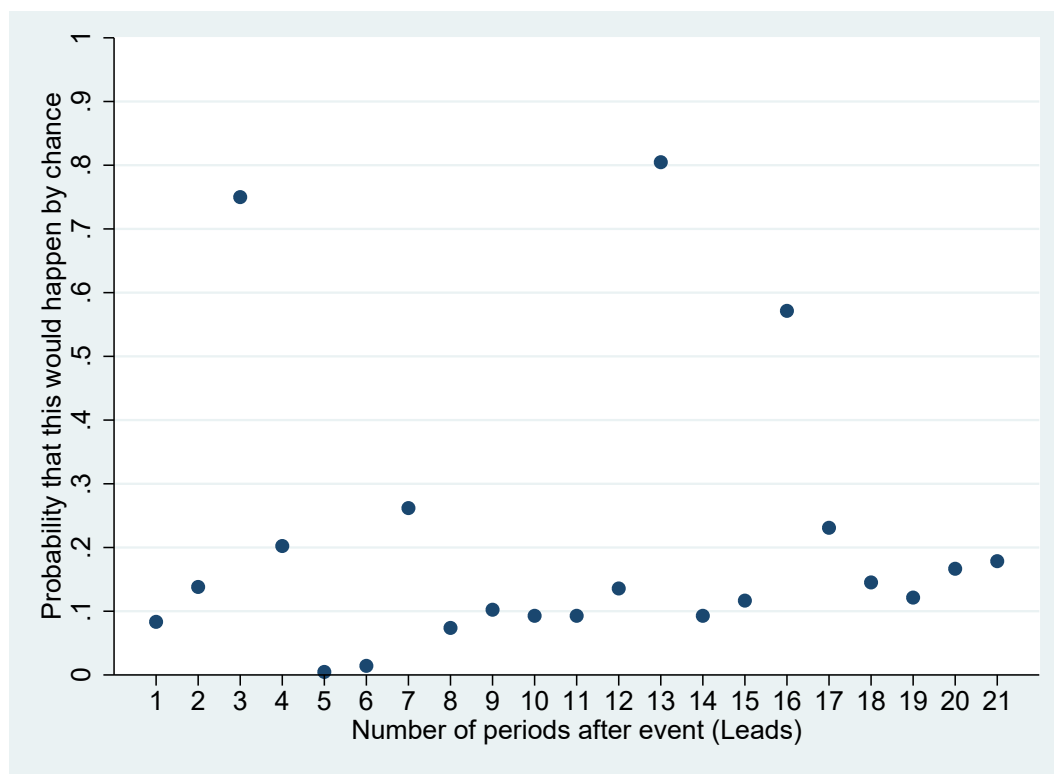**Figure 7:** Synthetic Control Result: Robustness to Anticipatory Effect
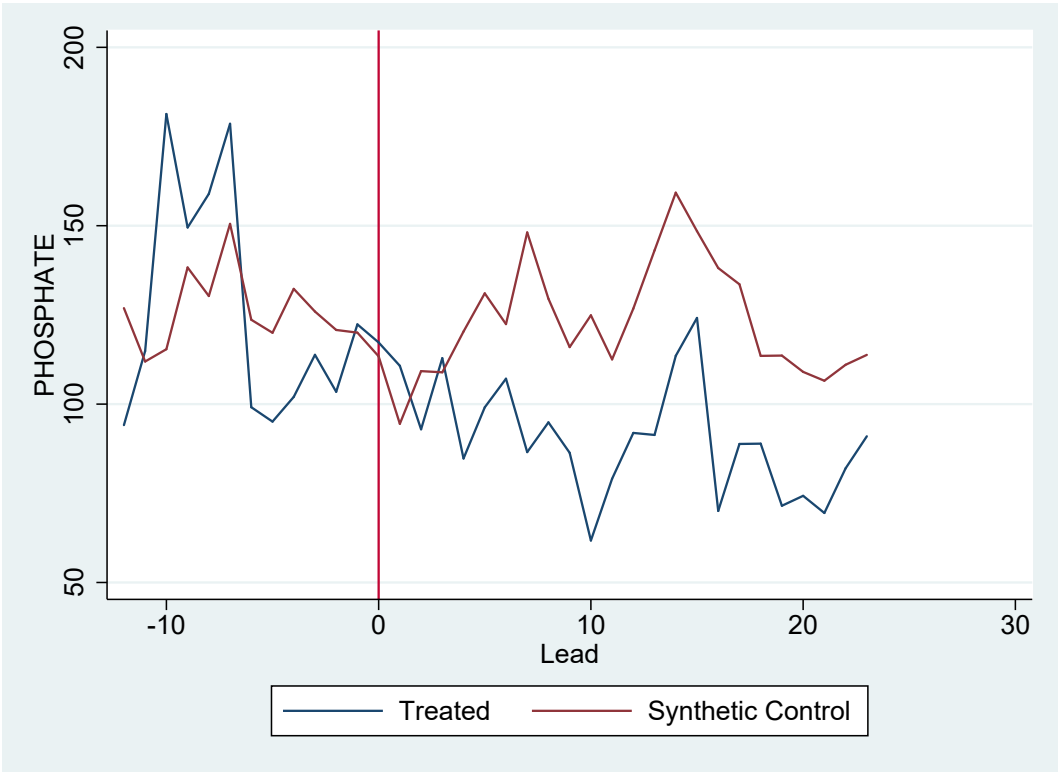
Figure 8: P-Values for Treatment Effects: Robustness to Anticipatory Effect
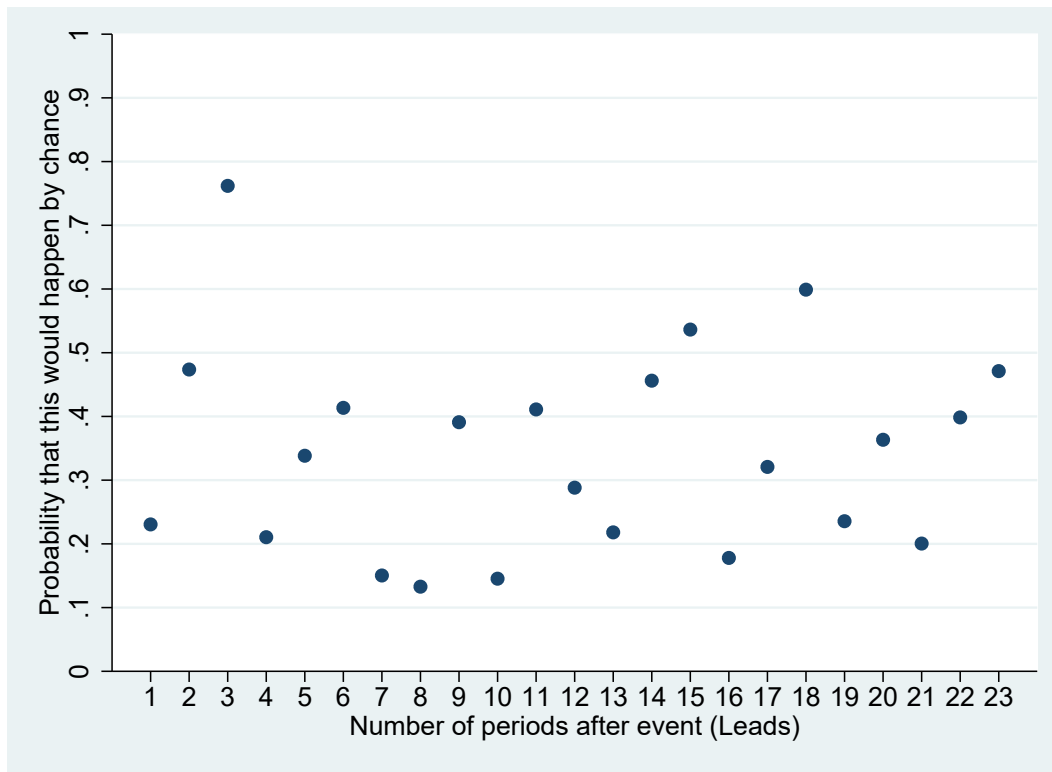
Figure 9: Synthetic Control Result: Robustness to Demeaning
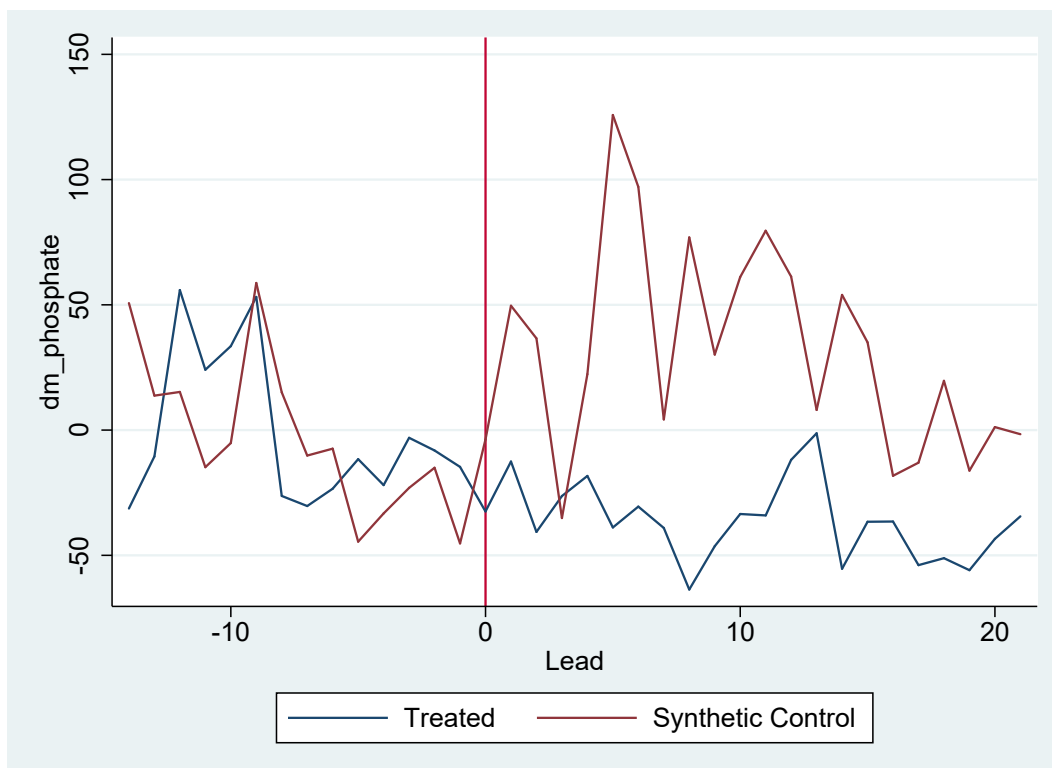
Table 2: Two-step Difference GMM Results: Outcome is Measured TP Loads

	(1) exogenous controls	(2) predetermined controls	(3) 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	287.72	53.23
0.2	427.35	143.86	26.61
0.6	142.45	47.95	8.87
1.0	85.47	28.77	5.32
1.4	61.05	20.55	3.80
1.8	47.48	15.98	2.96
5.0	17.09	5.75	1.06
10.0	8.55	2.88	0.53

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

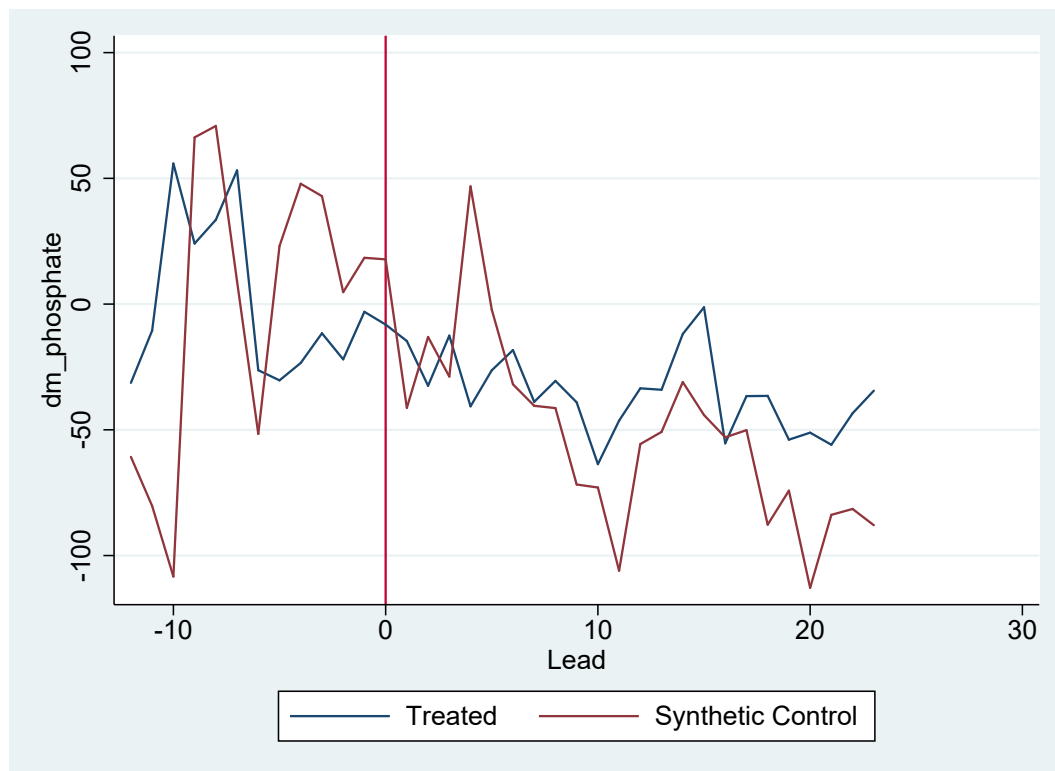**Figure 11:** Synthetic Control Result: Robustness to Anticipatory Effect & Demeaning

Figure 12: P-Values for Treatment Effects: Robustness to Anticipatory Effect & Demeaning
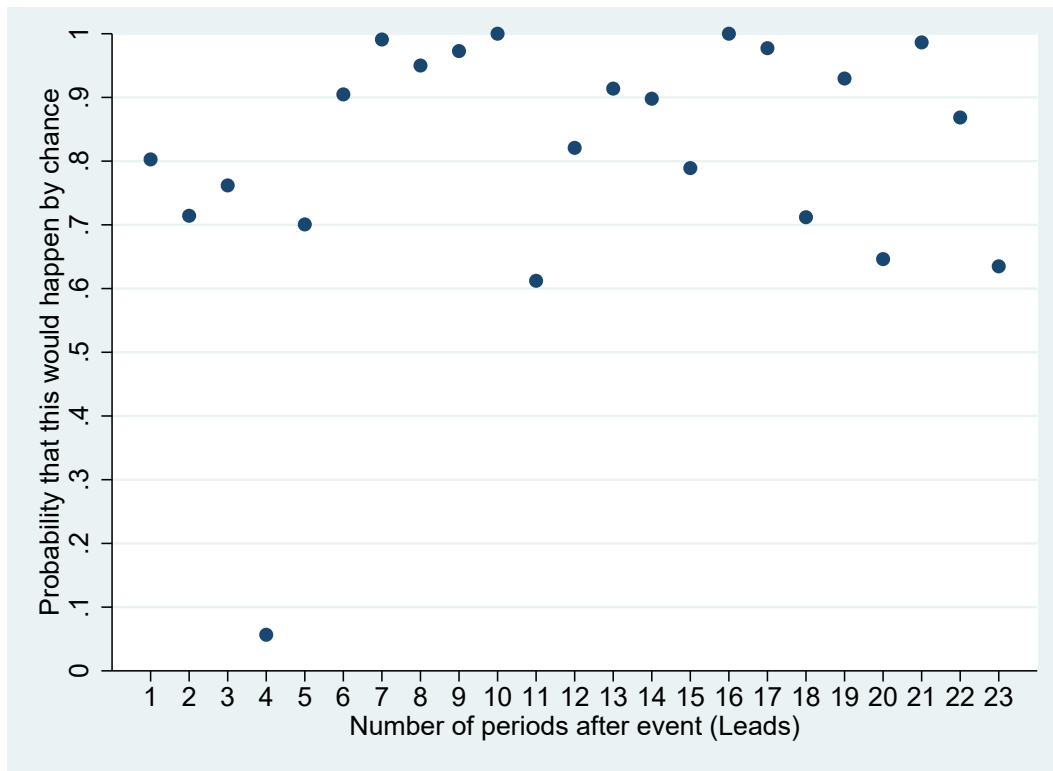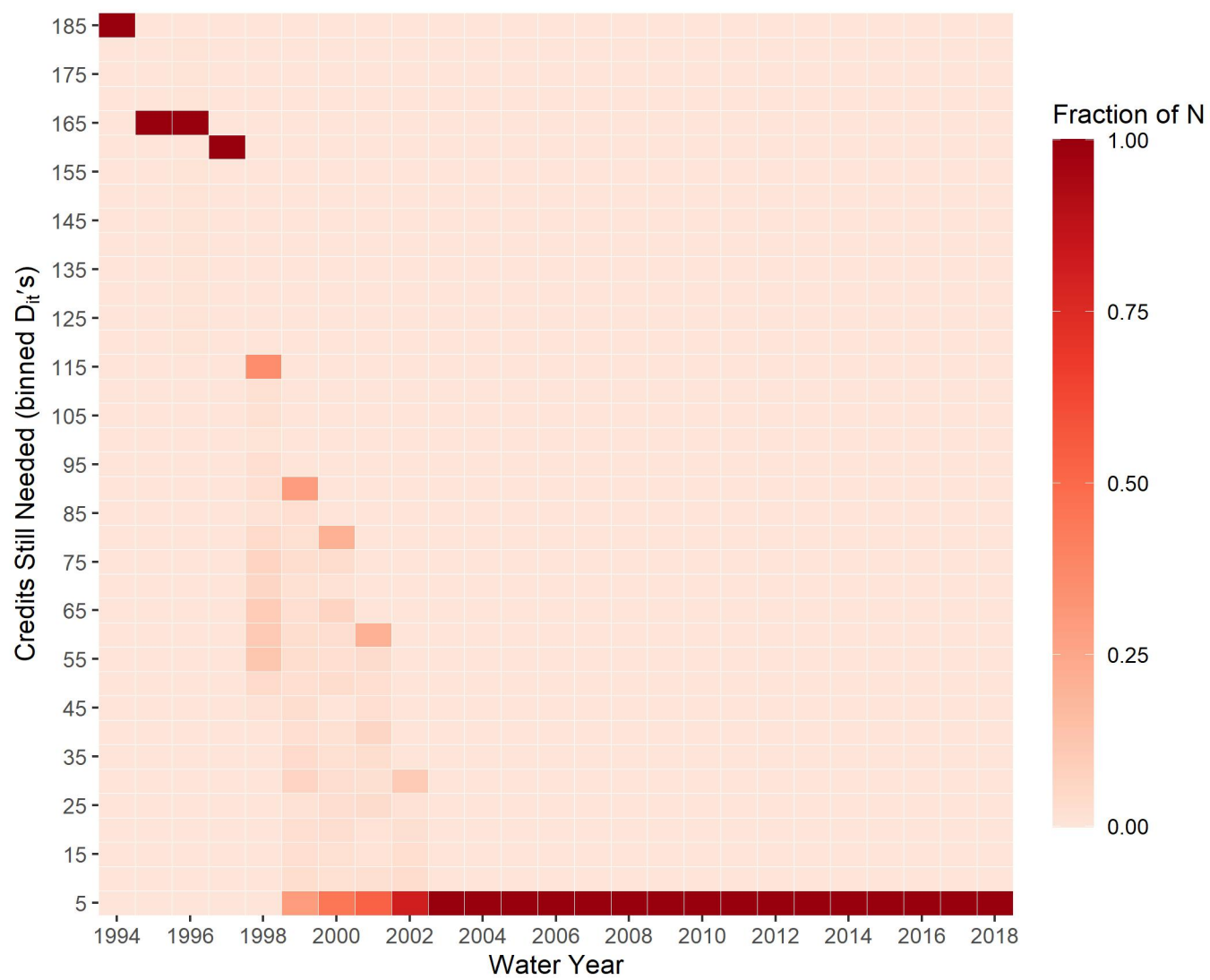
Figure 13: Heatmap Distribution of D_{it}'s

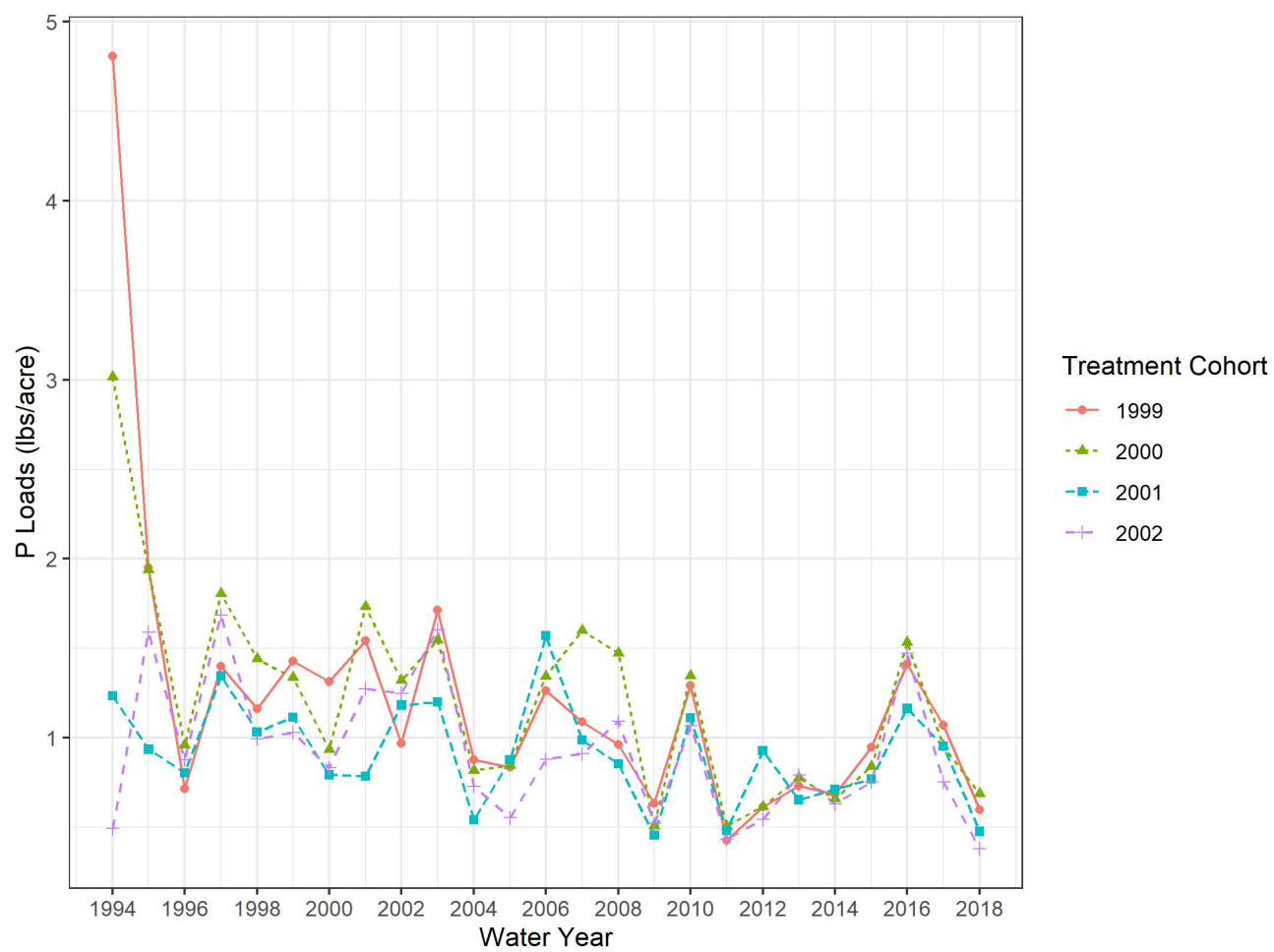**Figure 14:** Annual Average Phosphorus Loads by Cohort

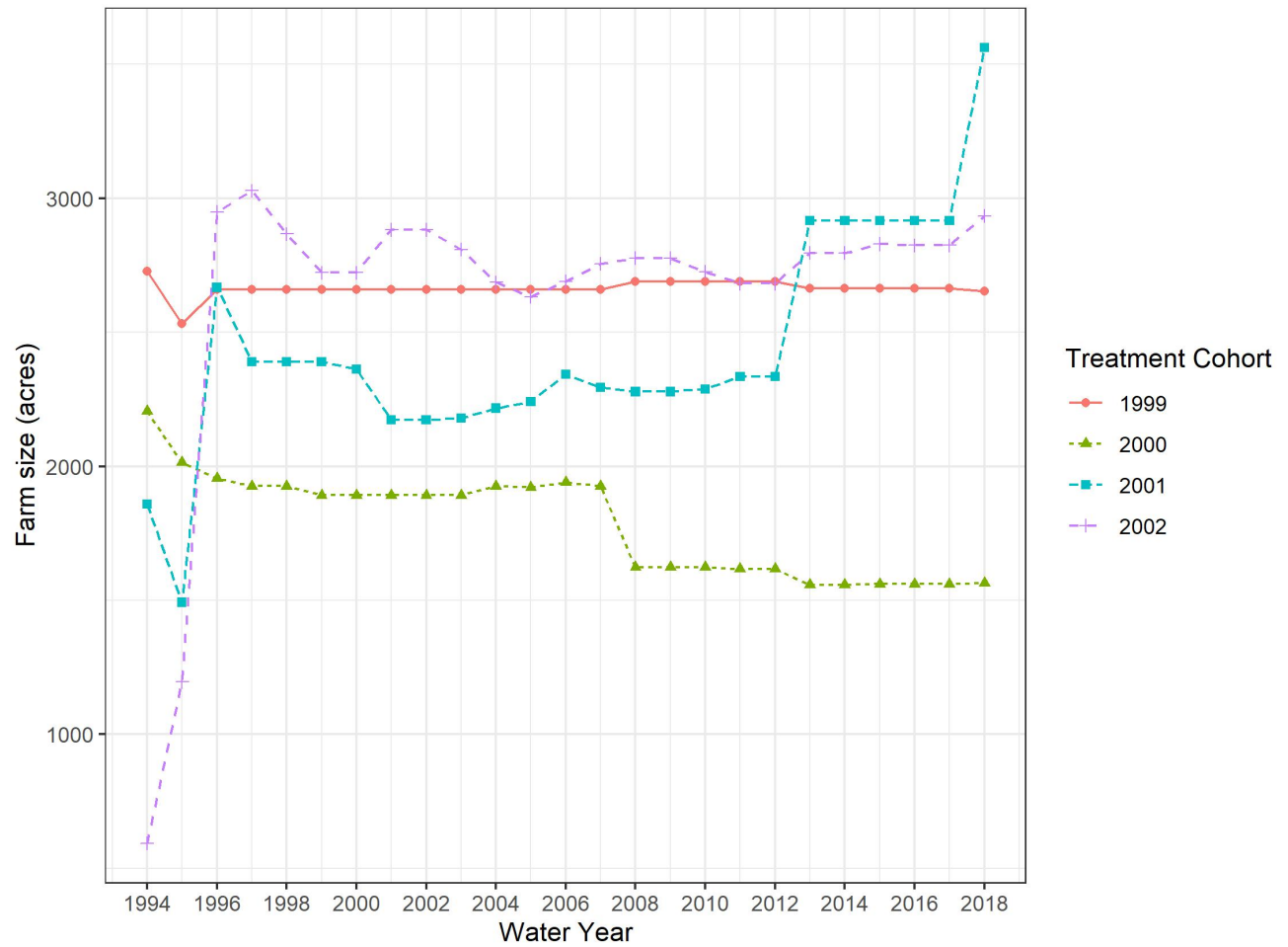**Figure 15:** Annual Average Land Size by Cohort

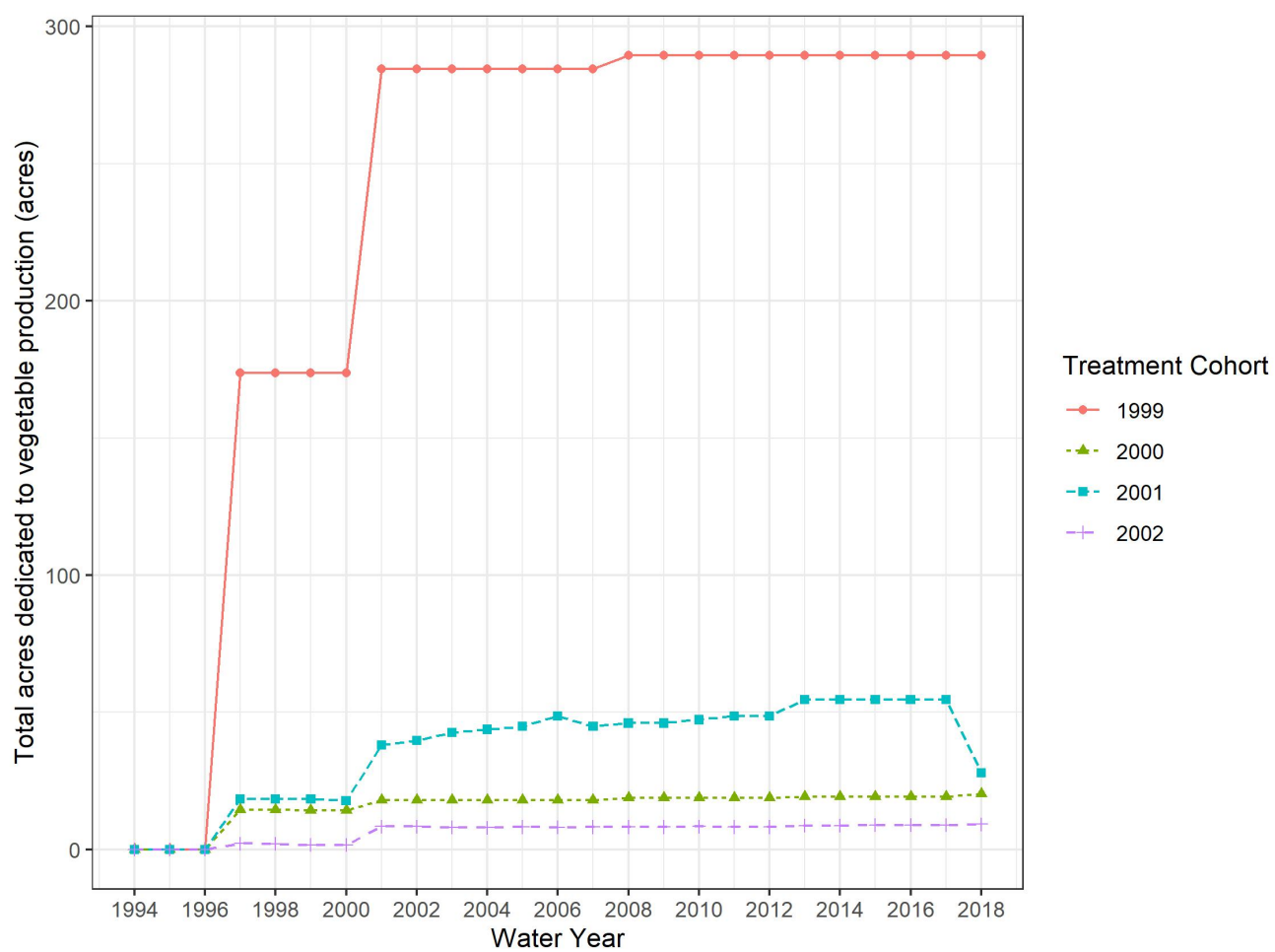**Figure 16:** Annual Average Acres Dedicated for Vegetable Production by Cohort

Figure 17: Annual Average Distance from Lake Okeechobee by Cohort
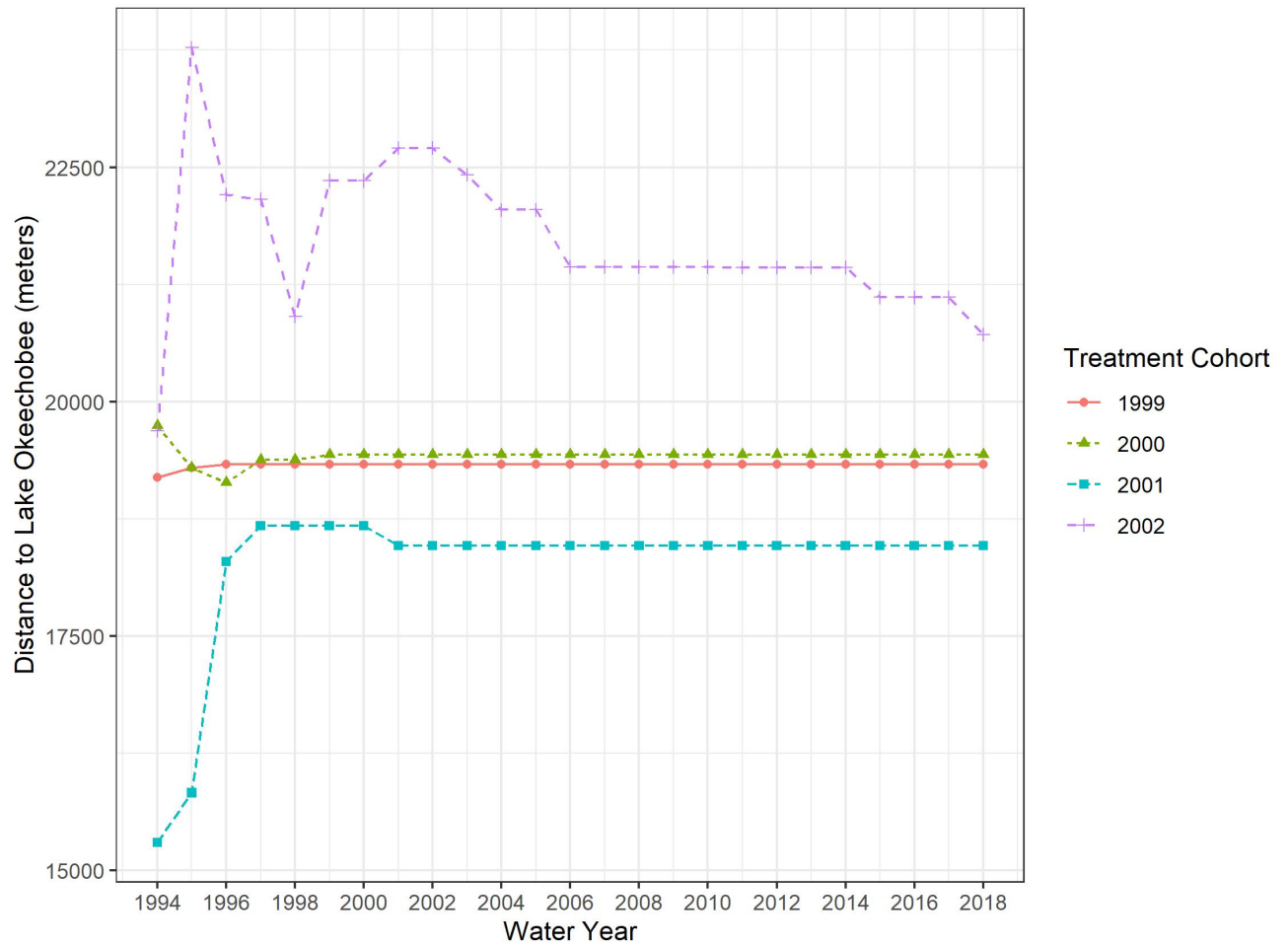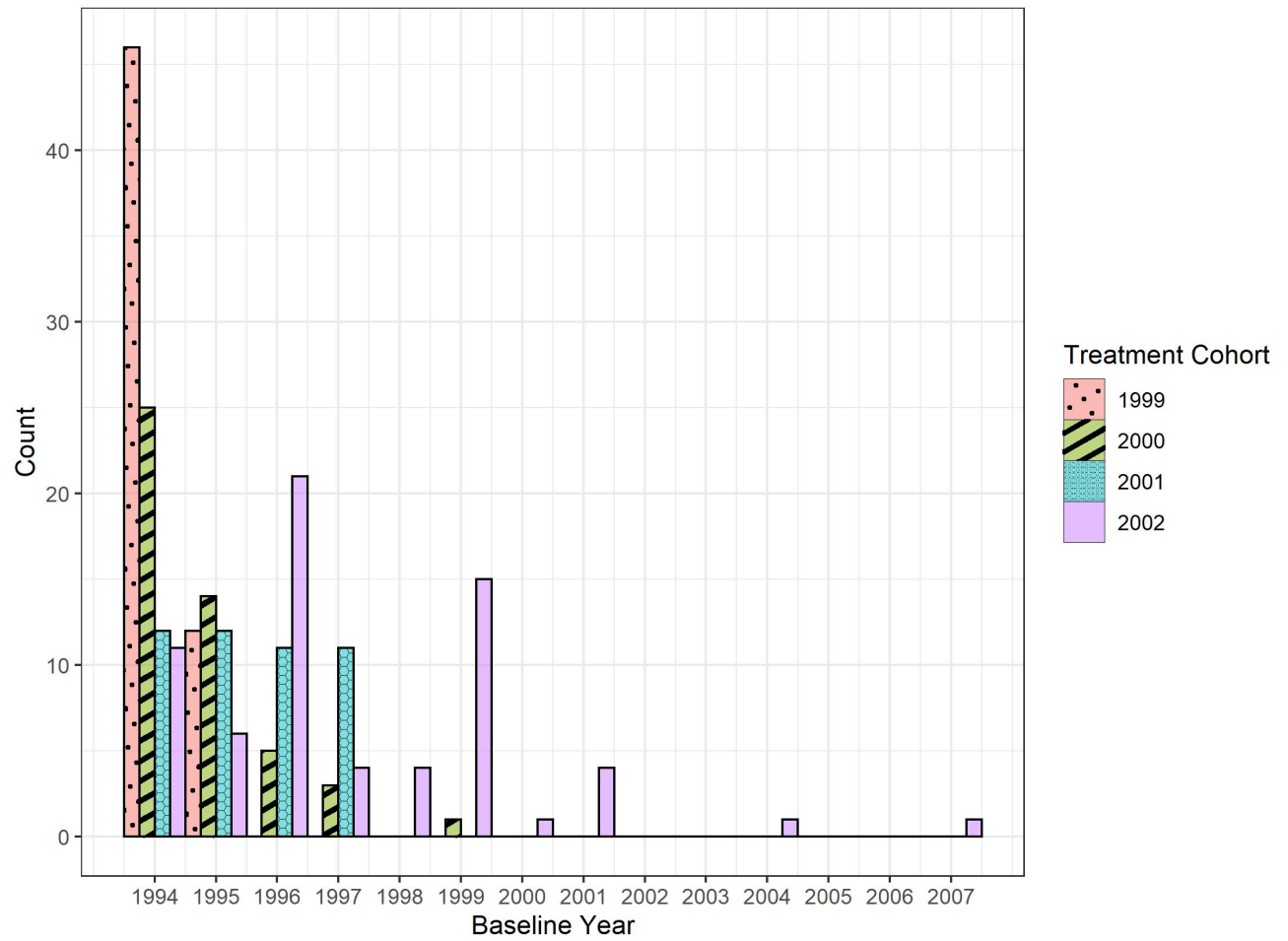
Figure 18: Distribution of Baseline Year by Cohort

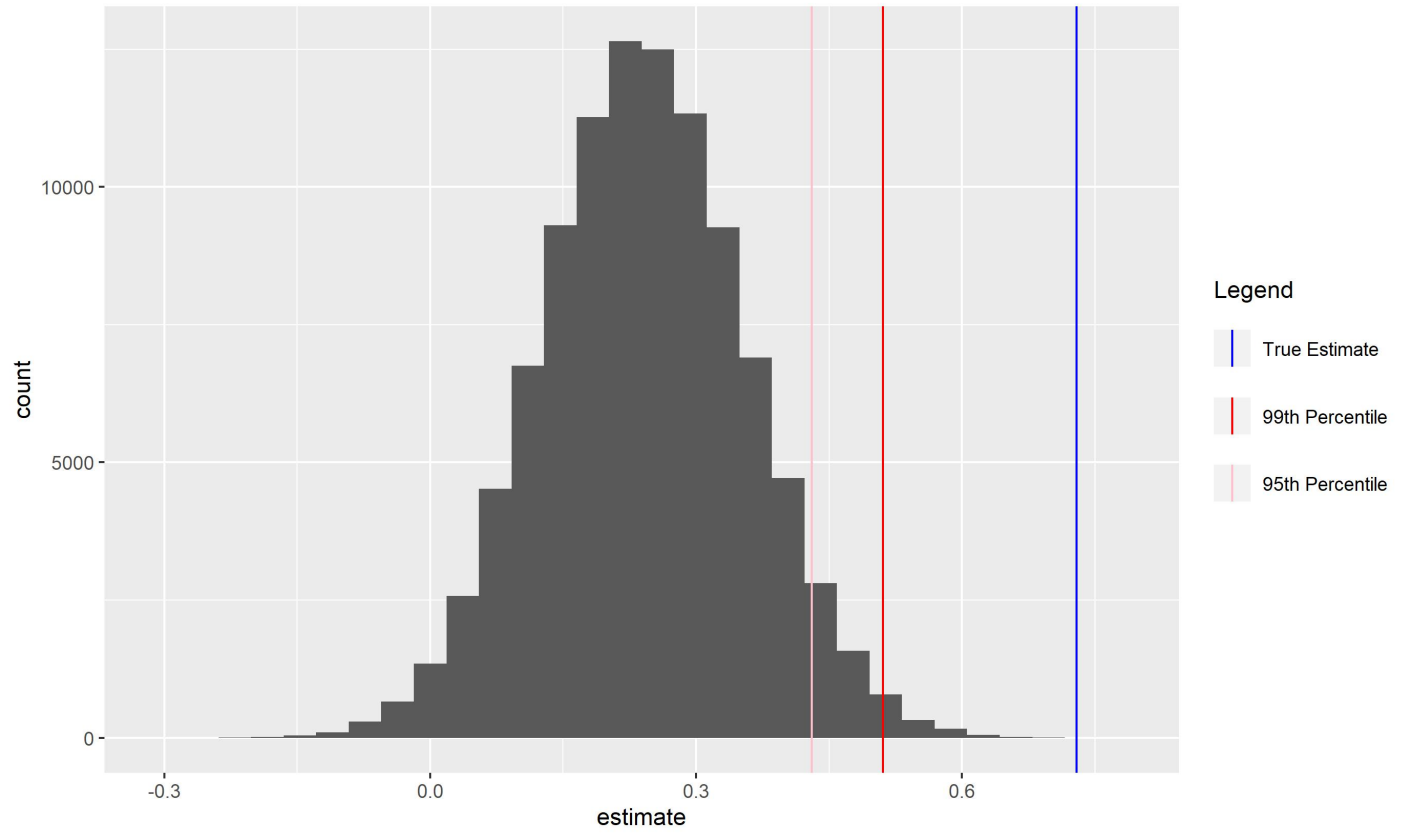**Figure 19:** Histogram of Permuted $\widehat{\beta}$'s

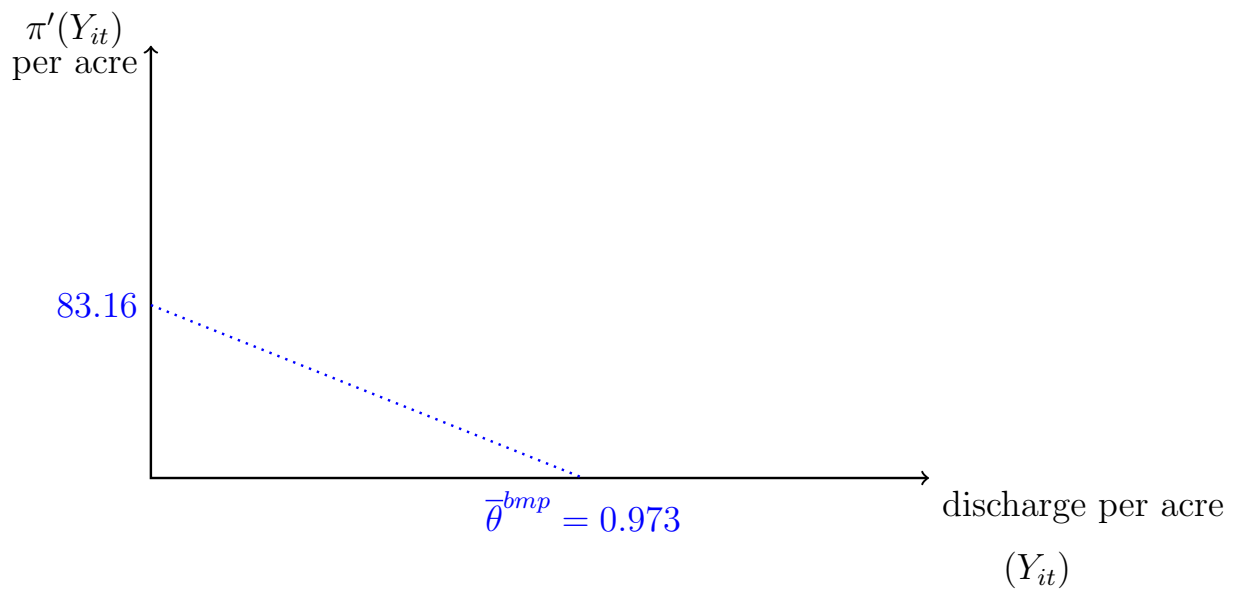**Figure 20:** Estimated Marginal Profit Curve for the Avg. Farm

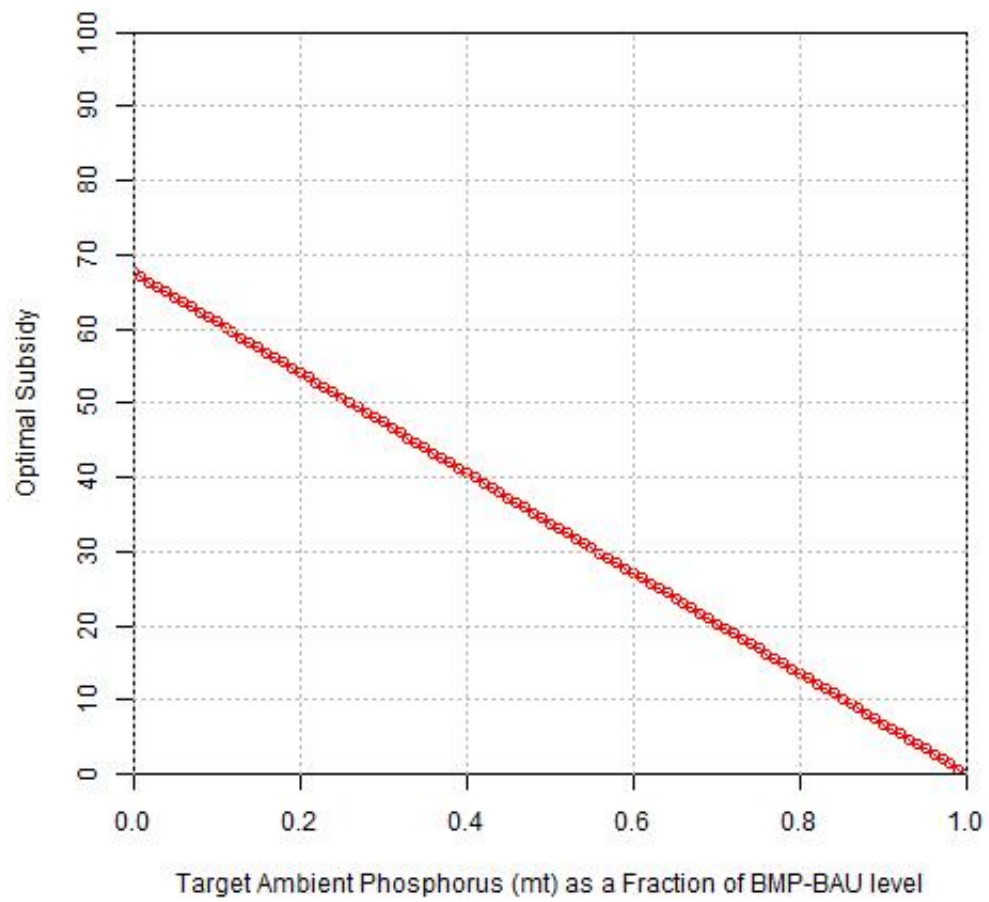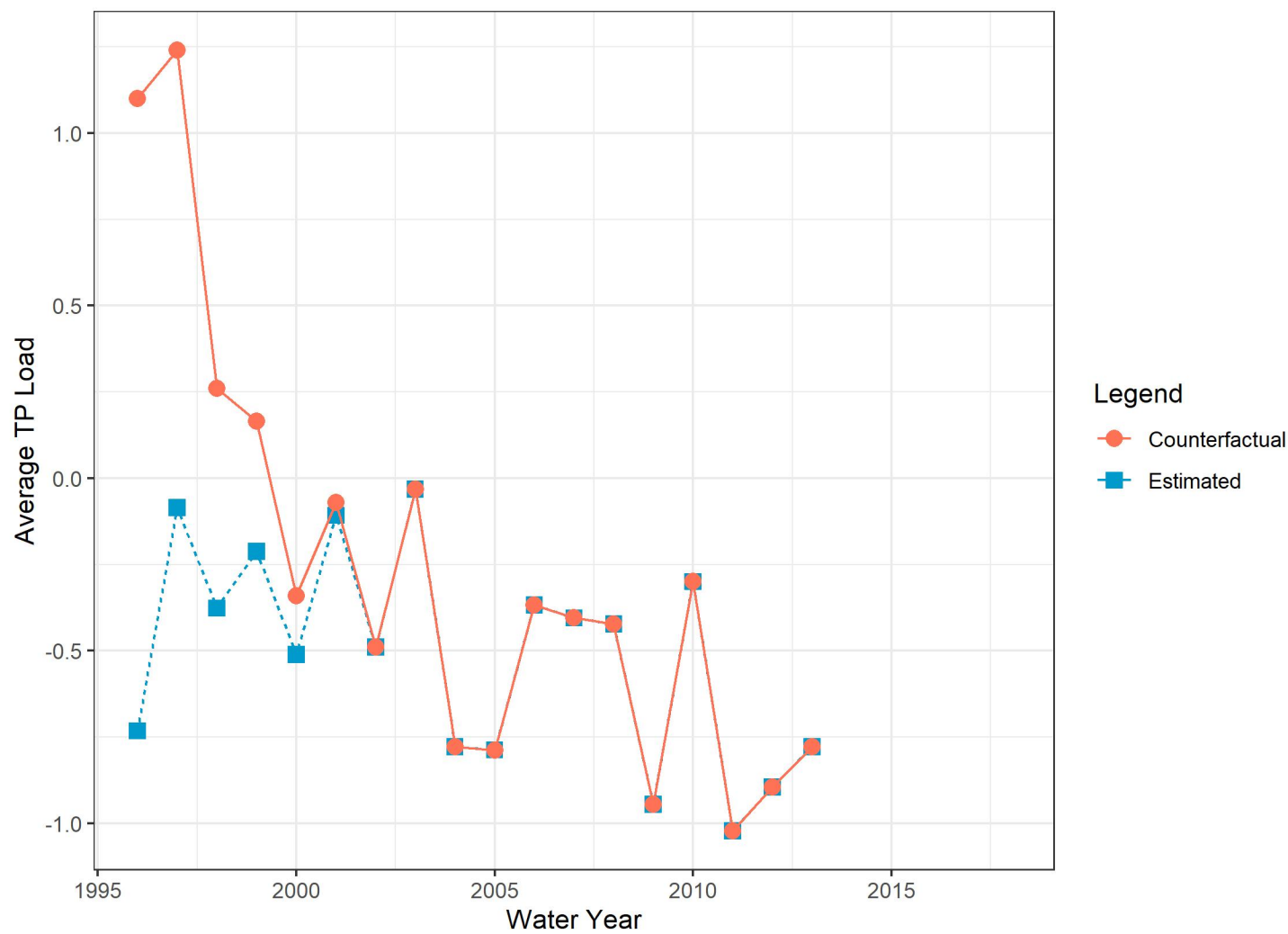**Figure 21:** Compliant Nash Subsidy as a Function of Ambient P Target

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 (17).

$$\frac{\partial Y_{it}^*}{\partial D_{it}} = \left(\frac{\partial Y_{it}^*}{\partial G_{it}} \right) \left(\frac{\partial G_{it}}{\partial S_{it}} \right) \left(\frac{\partial S_{it}}{\partial D_{it}} \right) \tag{17}$$

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 (18) instead of (25).

$$G_{it} = -\frac{d}{dY_{it}} \delta \mathbb{E} \big[V_{t+1}(S_{it+1}) \big] \tag{18}$$

Then we can apply Young's Theorem and standard regularity conditions to get (19).

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

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

$$\frac{\partial V_t(S_{it})}{\partial S_{it-1}} = \frac{\partial Q_{it}^*}{\partial S_{it}} = \mathbb{1}\{S_{it} < M\}. \tag{20}$$

Since $Q_{it}^* = \min\{M, S_{it}\}$. Thus (19) becomes (21)

$$\frac{\partial G_{it}}{\partial S_{it}} = -\frac{d}{dY_{it}} \delta \mathbb{P}(S_{it+1} < M) \tag{21}$$

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 (22).

$$\frac{\partial G_{it}}{\partial S_{it}} = -\frac{d}{dY_{it}} \delta \mathbb{P}(\alpha_t > \Gamma_t) = \frac{\partial \mathbb{P}(\alpha_t \leq \Gamma_t)}{\partial \Gamma_t} \tag{22}$$

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 (17), 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).[39] 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

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[39]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 (23).[40]

$$V_t(S_{it}) = \max_{Y_{it}} \ \pi(Y_{it}, \theta_i^{bmp}) - \left(\overline{T} - Q_{it}^*\right) + \delta \mathbb{E} V_{t+1}(S_{i,t+1})$$

$$\text{s.t.} \quad S_{i,t+1} = S_{it} - Q_{it}^* + \left(\overline{Y}^P - Y_t\right)$$

$$Y_t = \alpha_t + \sum_i Y_{it}$$

$$\overline{Y}^P \geq \alpha_t + \sum_i \theta_i^{bmp} \tag{23}$$

$$\alpha_t \overset{iid}{\sim} F(0, \sigma_\alpha^2)$$

$$Q_{it}^* = \min\{M, S_{it}\}$$

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.[41] Then credits owed can be calculated and issued out for use in the next period. In Appendix F, I solve (23) backwards under finite time with T being the terminal date and normalizing the terminal value to zero. The FOC is given by (24).

$$\pi'(Y_{it}^*, \theta_i^{bmp}) = G_{it} \tag{24}$$

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

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[40]The model presented in (23) intentionally ignores the rates presented in column 3 of Table 1 for notational simplicity.

[41]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 (25).

$$G_{it} = -\sum_{k=t+1}^{T} \delta^{k-t} \mathbb{E}\left[\frac{\partial Q_{ik}^*}{\partial Y_{it}}\right] \tag{25}$$

Note that since Y_{it} denotes discharges, the partials in (25) 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 (1) and (24). 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

$$Y_{it}^* = g^{-1}(G_{it}, \theta_i^{bmp}) \tag{26}$$

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

$$V_{T+1}(S_{i,T+1}) = \sum_{k=0}^{\infty} \delta^k \pi(\theta_i^{bmp}, \theta_i^{bmp}) = 0 \tag{27}$$

means that

$$V_T(S_{iT}) = \max_{Y_{iT}} \ \pi(Y_{iT}, \theta_i^{bmp}) - (\overline{T} - Q_{iT}^*)$$

$$\text{FOC:} \quad \pi'(Y_{iT}^*) = 0$$

$$\Longrightarrow \ Y_{iT}^* = \theta_i^{bmp} \tag{28}$$

$$\Longrightarrow \ V_T(S_T) = -(\overline{T} - Q_{iT}^*)$$

Then next iteration we have

$$V_{T-1}(S_{i,T-1}) = \max_{Y_{i,T-1}} \pi(Y_{i,T-1}, \theta_i^{bmp}) - (\overline{T} - Q_{i,T-1}^*) - \delta\mathbb{E}(\overline{T} - Q_{iT}^*)$$

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

(29)

$$\text{FOC:} \quad \pi'(Y_{i,T-1}^*, \theta_i^{bmp}) = -\delta\mathbb{E}\left[\frac{\partial Q_{iT}^*}{\partial Y_{iT-1}}\right]$$

$$\implies V_{T-1}(S_{i,T-1}) = \pi(Y_{i,T-1}^*, \theta_i^{bmp}) - (\overline{T} - Q_{i,T-1}^*) - \delta\mathbb{E}(\overline{T} - Q_{iT}^*)$$

Then the next iteration

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

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

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

$$\text{FOC:} \quad \pi'(Y_{i,T-2}^*, \theta_i^{bmp}) = -\delta\mathbb{E}\left[\frac{\partial Q_{i,T-1}^*}{\partial Y_{i,T-2}}\right] - \delta^2\mathbb{E}\left[\frac{\partial Q_{iT}^*}{\partial Y_{iT-2}}\right]$$

(30)

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

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

(31)

Thus we have (25).