

# 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 1/4 the cost under BMPs.

# Introduction

Economics on a theoretical front, has largely succeeded in providing policy prescriptions for point-source pollution – defined as sources of pollution that are easily identifiable at the point(s) of discharge. The ability to assign economic carrots or sticks requires the ability to observe individual level pollution. Non-point source pollution (NPSP) therefore poses a unique challenge for economists and policy makers alike. 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 infeasible. Agricultural runoff is an example of such a challenge and is the main focus of this paper. 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 policies.<sup>1</sup> 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 projects and procedures 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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<sup>1</sup>Agricultural runoff can be in many forms but one important type comes from agricultural fertilizers. When such fertilizers are used in excess (i.e., any that is not absorbed by the crops), that excess will either leach into the ground and contaminate groundwater or, more important to this paper, it will get swept into the local surface water systems causing damage to ecosystems and thus costs to society.

Market incentives on the other hand, come in many forms. The primary challenge is the find something that can be observed or estimated that correlates with pollution so that incentives can be properly applied 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 where the tax base is the difference between observed ambient quality and the target. 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 achieve 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,

however (Wong et al., 2019; Reichhuber, Camacho and Requate, 2009) but 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 target always target the extractors themselves. 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.

To the best of my knowledge, this paper is the first to compare the compliance costs to polluters under a mandatory BMP policy with that under an ambient subsidy policy. I do this by studying 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 subsidy component of the EFA did cause meaningful reductions in

phosphorus discharge and that an ambient subsidy would have achieved a benchmark pollution outcome at 1/3 the cost of a mandatory BMP policy.<sup>2</sup> 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 regulatory oversight costs.<sup>3</sup>

## **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

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<sup>2</sup>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.

<sup>3</sup>See SFWMD's 2008 Budget in Brief. [Link](#).

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 Management 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.<sup>4</sup> 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<sup>5</sup>. 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.<sup>6</sup> 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

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<sup>4</sup>Map of the EAA and its sub-basins are shown in Figure 1.

<sup>5</sup>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).

<sup>6</sup>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

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.<sup>7</sup>

### 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.<sup>8</sup> Water

<sup>7</sup>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.

<sup>8</sup>Baseline TP values are acquired through a prediction model that incorporates parameter values from the

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 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)<sup>9</sup>. Farms can submit applications to further earn credits through their individual performance by proving that their TP load reductions ex-

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1980-1988 and meteorological conditions of the current year.

<sup>9</sup>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.

ceeded the target given by column 4 of Table 1.<sup>10</sup> 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.<sup>11</sup> By 2013, the ambient and individual incentive credit program will end so that all leftover credits will expire and no more credits can be earned or used to reduce the Agricultural Privilege Tax. This terminal date for the tax credit program was written into law back in 1994 and so knowledge of this terminal date was public information.

If the EAA basin is determined to be out of compliance for at least three consecutive years, then enforcement action will be taken. The SFWMD will then use the reported TP loads from each farm to target those who are not reducing their TP loads enough. If there is further non-compliance by said farms, punitive measures such as fines or arrests are possible though such measures were never required. Between 1994 and 2013, 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.

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<sup>10</sup>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.

<sup>11</sup>Individual credits can also be earned if farms show that their TP loads were below 5 ppb. However, credits earned in this manner cannot be rolled over for future use.

## Why the Everglades?

An empirical investigation of any policy that addresses NPS pollution problems would ideally have data at the individual polluter level so that polluting behavior can be analyzed. However, the very nature of NPS pollution means that individual discharge of effluents cannot be observed. The situation in Southern Florida offers an exciting opportunity to get around this problem. Due to the geographical features of the land, farms have to be hydrologically connected to large canals and drainage systems in order to continue agricultural production. Each farming parcel is surrounded by canals that channel water to one point (sometimes more) where water is then pumped out into the public canal system. When multiple farms share the same pumping infrastructure, then they're said to 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 8, 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.<sup>12</sup>

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<sup>12</sup>Political and institutional context for how this peculiar pollution management system came to be can be found in Milon (2018).

## Data

Most of the data for farms within the EAA effected by the EFA are taken from the annual Everglades Consolidated Reports and South Florida’s Environmental Reports.<sup>13</sup> These reports contain both annual TP load and estimated TP load reduction (relative to baseline), land size, baseline year, whether the farm elected to enroll in the Early Baseline Option, each farm’s baseline (pre-BMP) TP loads, acres dedicated to vegetable production, and the EAA wide incentives earned by all farms for each year. The baseline year is the water-year for which the farm established its pre-BMP base period load. Basins (farms) can enroll in the Early Baseline Option which requires farms to fast track their compliance timetables and water quality monitoring efforts and divulge more information such as soil type and other farm specific characteristics. In return, farms who elect to participate in the Early Baseline Option have less regulatory oversight and face less liabilities in the event that non-compliance occurs.<sup>14</sup> 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<sup>15</sup>. Table 3 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.<sup>16</sup>

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<sup>13</sup>URL for the reports: <https://www.sfwmd.gov/science-data/scientific-publications-sfer>

<sup>14</sup>See F.A.C. 40E-63.145(4)(g)

<sup>15</sup>Data for years 1994 through 2000 was also obtained via public records request.

<sup>16</sup>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. See Table 3 for summary statistics across units and time.

## **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.<sup>17</sup> 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,

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<sup>17</sup>It was originally aimed to achieve a concentration no greater than 50 ppb but was later amended in 2003 to 10 ppb.

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 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 6 and 7 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<sup>18</sup>.

Let  $s$  denote the ambient subsidy rate,  $Y$  denotes observed ambient pollution, and  $\bar{Y}$  denotes the ambient pollution standard. Under a standard ambient subsidy mechanism, if observed pollution  $Y$  exceeds the standard  $\bar{Y}$ , 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  $s(\bar{Y} - Y)$ . 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  $\theta_i$  is  $i$ 's business-as-usual (BAU) level of discharge (per acre) and is used to reflect firm type. Observed ambient pollution is assumed be a linear sum of each farm's total discharge  $Y_i L_i$  where  $L_i$  is acreage.

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<sup>18</sup>Uncertainty in the ambient pollution function will be introduced later.



In this static and deterministic model, farms would abate an additional unit of pollution if the marginal financial gain from doing so ( $s$ ) exceeds the marginal loss ( $\pi'(Y_i, \theta_i)$ ). 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  $\tilde{Y}_i$  and is defined in (1). Said differently, if the only way for the pivotal farm to attain compliance is by reducing discharge below  $\tilde{Y}_i$ , then the farm would not do so and instead opt to pollute at the BAU level,  $\theta_i$  (Bao, 2021).<sup>19</sup> Since  $s$  and  $\tilde{Y}_i$  are inversely related, too small of an  $s$  could result in  $\tilde{Y}_i$ 's that are too large for the Nash equilibrium to result in compliance. Lastly, we assume that agent  $i$  takes the total pollution from others ( $Y_{-i}$ ) as given.

$$\pi'(\tilde{Y}_i, \theta_i) = s \quad (1)$$

Let the profit function be defined as in (2).<sup>20</sup> Then one only needs to evaluate the values for  $\theta_i^{bmp}$  (the discharge level under mandatory BMPs but absent other policies, henceforth referred to as BMP-BAU) and  $\gamma_i$  (the slope of the marginal profit curve wrt to discharge) in order to back out the value for  $s$  (the implied static marginal incentive from the incentive credit program) necessary to achieve some pollution target.

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

A cost effective minded regulator would set  $s$  to achieve some exogenously given target,

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<sup>19</sup>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  $\tilde{Y}_i$  levels so that  $Y$  is strictly less than  $\bar{Y}$ .

<sup>20</sup>Even if the marginal profit curves are not linear, one can use a linear approximation of the function and proceed.

e.g.,  $\sum_{i=1}^n L_i \tilde{Y}_i(s) = \bar{Y}$ . However, under a pure ambient subsidy, there is no penalty for when pollution exceeds the target and therefore polluters would never collectively achieve the target exactly<sup>21</sup>. Thus, the regulator would need to set the “policy” target ( $\bar{Y}^P$ ) slightly above the “true” target ( $\bar{Y}^T$ )<sup>22</sup>. Setting the right hand side of (2) equal to the subsidy rate  $s$  gives  $i$ ’s minimum profitable pollution (3).

$$\tilde{Y}_i = \theta_i^{bmp} - \frac{s}{\gamma_i} \quad (3)$$

Then utilizing the pollution constraint (4) we get that the optimal subsidy rate, is given by (5)<sup>23</sup>.

$$\bar{Y}^T = \sum_{i=1}^n \tilde{Y}_i L_i \quad (4)$$

$$s^* = \frac{Y^{bmp-bau} - \bar{Y}^T}{\sum_i L_i / \gamma_i} = \frac{Y^{bmp-bau} \left(1 - \frac{\bar{Y}^T}{Y^{bmp-bau}}\right)}{\sum_i L_i / \gamma_i} \quad (5)$$

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

## 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 credit

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<sup>21</sup>To see this, just assume that other’s pollution is such that  $Y_{-i} = \sum_{j \neq i}^n L_j \tilde{Y}_j$ . If  $i$  were to emit  $\tilde{Y}_i$ , then he would incur a loss compared to emitting  $\theta_i^{bmp}$ .

<sup>22</sup>The “policy” target is the pollution target for which that ambient subsidy is based on. The “true” target is the pollution level that the regulator actually wants to achieve.

<sup>23</sup>The pollution target in (4) is the “true” target.

program was layered on top in an attempt to induce *additional* abatement. Importantly, the threshold for which the incentive credits are triggered is based on that same 25% reduction target, i.e.,  $\bar{Y}^P$  was set equal to 75% of BAU levels (without BMPs). Therefore, it is as if the “policy” target ( $\bar{Y}^P$ ) in the simple model above satisfies (6). Setting the pollution standard 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<sup>24</sup>. 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.

$$\bar{Y}^P \geq \sum_{i=1}^n \theta_i^{bmp} L_i \quad (6)$$

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  $\gamma_i$  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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<sup>24</sup>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,  $\gamma_i$ .

### **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).

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

see equation 25 for the technical expression of  $G_{it}$ . 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 am-

bient 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  $\gamma_i$ .<sup>25</sup> This parameter can be construed as the slope of the marginal abatement cost curve, the same as in the standard ambient subsidy model (1).

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

## 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 find a suitable upper bound for it, one that varies depending on credit-stock levels. I start 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  $D_{it} \geq G_{it}$ . The term  $M$  represents the maximum exercisable credits each period from 1998-2013<sup>26</sup> and  $(T - t + 1)$  represents the number of remaining periods in which credits are relevant, including the present. The product of which represents the maximum 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

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<sup>25</sup>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.

<sup>26</sup>See Table 1.

variable) for period  $t$ .

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

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 be able to exercise the maximum number of credits each period ( $M$ ), including period  $T$ , after which all credits become irrelevant. 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. 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 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

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  $\theta_i$  to  $\theta_i^{bmp}$ ) 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 the average of (8), 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 17 graphs a heatmap of the distribution of  $D_{it}$  across time and gives a glimpse at the identifying variation across both  $N$  and  $T$ .

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<sup>27</sup>. Thus, I restrict the estimation period to start on 1996 to avoid spurious correlation.<sup>28</sup> 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 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

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<sup>27</sup>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)

<sup>28</sup>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.

max credits needed and 0 otherwise. The event study design in Equation (10) where  $E_i$  represents the first year in which farm  $i$  began the year with a higher stock of credits than what is needed.

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

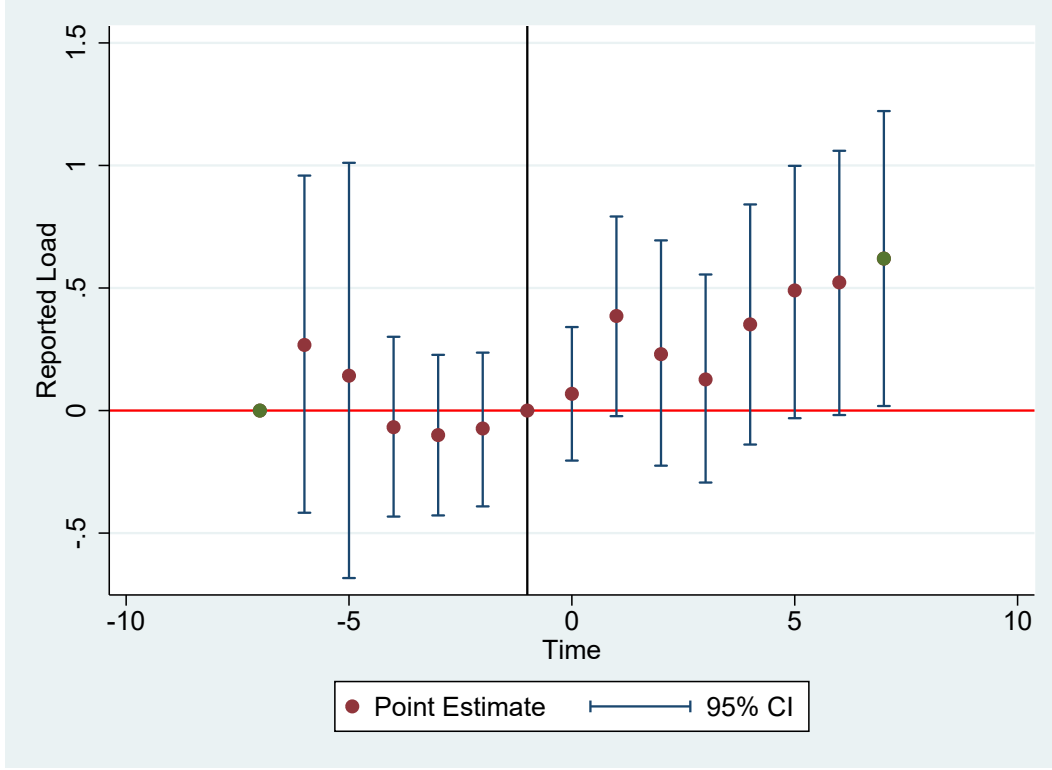
Equation (10) is used to summarize the data and the results of which are shown in Figure 1. The term  $Y_{it}$  is the farm-year specific phosphorus outcome and is measured total phosphate (TP) load measured in lbs/acre. I use three leads and lags so that there will be some farms in the study horizon 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).

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 face less 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, 2021). 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.



**Figure 1:** Event Study: Outcome is Measured TP Load (lbs/acre)



These requirements are not satisfied given 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  $\gamma_i$ . This is because of the discretisation of the variable used to represent the effects from the incentive credit program.

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 (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.<sup>29</sup>

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

The problem with estimating (11) is that  $D_{it}$  is correlated with the error term leading to bias and inconsistent estimates of  $\beta$ . This correlation is due to the fact that  $D_{it}$  is a function of the stock of credits  $S_{it}$  via (9). The stock value itself is a function of all past outcomes  $(Y_{i1}, \dots, Y_{i,t-1})$ . A known workaround is to take first differences of (11) so that consistency only requires sequential exogeneity (Hansen, 2021; Anderson and Hsiao, 1981). 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  $\Delta$  symbol where  $\Delta r_t = r_t - r_{t-1}$ . The first differenced version of (11) is then pre-multiplied by the instrument matrix  $Z_{it}$ , and stacking over  $i$  and  $t$  gives (12).<sup>30</sup>

$$\mathbf{Z}' \Delta \mathbf{Y} = \Delta \alpha_t + \mathbf{Z}' \Delta \mathbf{D} \beta + \mathbf{Z}' \Delta \mathbf{X} \gamma + \mathbf{Z}' \Delta \boldsymbol{\varepsilon} \quad (12)$$

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<sup>29</sup>Acres dedicated to vegetable production is given special treatment under the EFA.

<sup>30</sup>Bold indicates matrices.

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

$$\mathbf{Z}_i = \begin{bmatrix} [D_{i1}, \Delta\alpha_2, \Delta X_{i2}] & [0] & [0] & \dots & [0] \\ [0] & [D_{i1}, D_{i2}, \Delta\alpha_3, \Delta X_{i3}] & [0] & \dots & [0] \\ \vdots & \vdots & \ddots & & \vdots \\ [0] & [0] & [0] & \dots & [D_{i1}, \dots, D_{iT-1}, \Delta\alpha_T, \Delta X_{iT}] \end{bmatrix} \quad (13)$$

and is the instrument matrix used for  $\Delta \mathbf{D}$ . Each variable in  $X_{it}$  is treated as strictly exogenous as well as the time dummies.<sup>31</sup> The first element of the first row of (13) is the vector of instruments for  $\Delta D_{i2}$ , the second element of the second row is for  $\Delta D_{i3}$ , and so on.

The sequential exogeneity assumption in this context amounts to assuming that the number of credits left for farm  $i$  to earn at time  $t$ ,  $D_{it}$ , cannot be correlated with current or future errors in the discharge levels. From (25) and (26), current period optimal discharge is a function of today's expectations about future credit stock levels. If errors in the discharge function 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.

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<sup>31</sup>Control variables could also be treated as sequentially exogenous which I also run as a robustness check.

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

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

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

The result from estimating (12) using (13) but 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. 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. 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 17 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.<sup>32</sup> Importantly, the magnitudes of those coefficients are implausibly large since the maximum credits needed to earn in 1996 was about 180 credits. The results then imply that farms reduced their P loads by more than 100%. However, the standard errors are quite large as well suggesting that using estimated percent P load reduced as the dependent variable comes with much more noise thus limiting the usefulness of those results considerably.

## Permutation Test

To test the inference results in Table 2, I run a simple permutation test on the discretized version of equation (11). I start by discretizing  $D_{it}$  to be 1 if the current period is on or after the "break point", i.e., the point in time for which basins no longer needed additional credits and 0 otherwise. The permutation sampling is done over break points which are allowed to range between 1996 to 2013<sup>33</sup>. Then for each permuted sample of break points, a sample

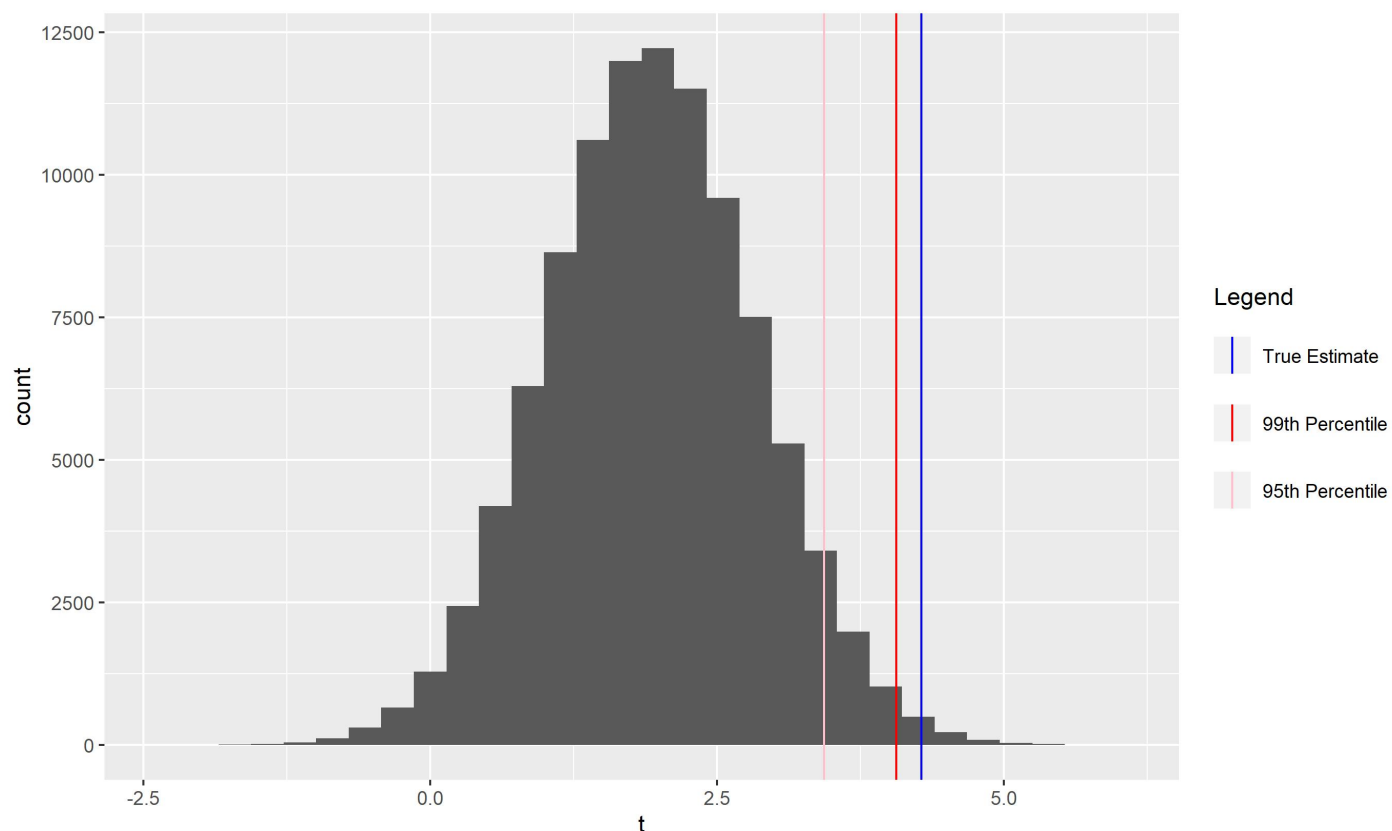
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<sup>32</sup>The percent P load reduction is estimated by SFWMD using precipitation at the farm level as the only covariate.

<sup>33</sup>This range was chosen to coincide with the range of periods for which tax credits are relevant.

of binary  $D_{it}$ 's are constructed and equation (11) is estimated. There are a total of  $18^{217}$  possible enumerations on break points of which only 100,000 are sampled. Figure 2 plots the distribution of corresponding t-statistics from the test as well as the location of the “true” t-stat<sup>34</sup>.

**Figure 2:** Histogram of Permuted t-stats



The corresponding p-value from this comes out to be about .00496 or almost 0.5% which would lead to the rejection of the null hypothesis that the break points, and subsequently, the tax incentive credits, had no effect on TP loads. The result strengthens confidence that the incentive credits did result in measurable difference in TP load outcomes. For a similar

<sup>34</sup>The “true” t-stat here is simply the one for  $\hat{\beta}$  from estimating (11) using the true values for  $D_{it}$ .

histogram on the estimate values alone, see Figure 18.

## **Cost Effectiveness**

For this section I compare the cost of the mandatory BMPs to farms compared to the cost per farm to the regulator under an ambient subsidy to gauge relative efficiency. Using some back of the envelope calculations, I am able 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. However, it is reasonable to assume that BMPs steepened the slope of the marginal profit curves if one believes that the BMP adoption left farmers with fewer options to adjust their P loads in response to incentives. In which case, the calculated subsidy schedules would likely represent an upper bound for settings without BMP adoption.

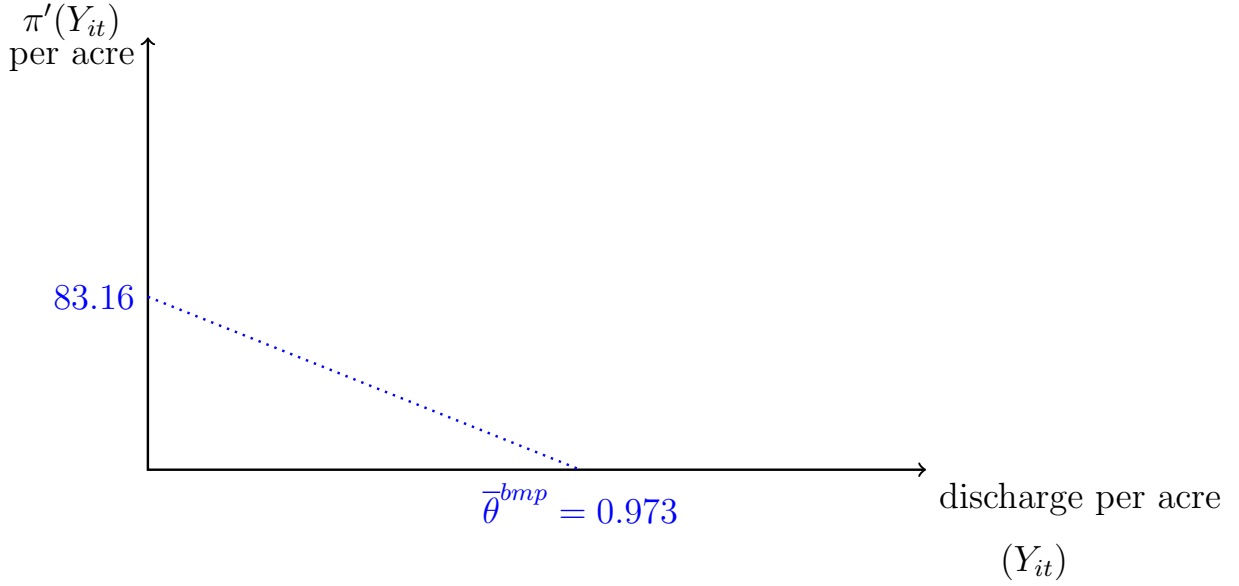
### **Optimal Ambient Subsidy Rate**

The previous section presented evidence that the incentive credit program of the EFA had reduced 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 estimate Equation (5) using estimates from the last column of Table 2 to produce the marginal profit curve for the average farmer in the EAA



shown in Figure 3.<sup>35</sup> To get an estimate of the average BMP-BAU discharge per acre ( $\theta_i$ ), I average the TP loads over farms and over each period after farms' corresponding break points when all farms no longer needed any more credits (see Figure 17).

**Figure 3:** Estimated Marginal Profit Curve for the Avg. Farm



Using the functional form assumptions under the static model for the optimal subsidy rate (not per acre) from Equation (5), I can map out what optimal subsidy should be for different targets. Without individual level estimates for  $\gamma$ , I approximate (3) for the average farmer using estimates from earlier to get (14).

$$Y_i^* = 0.973 - 0.0117s \quad (14)$$

This then implies that the equation for the optimal subsidy as a function of the ambient

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<sup>35</sup>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).

pollution target is given by (15). To estimate  $Y^{bmp-bau} = \sum_i \theta_i L_i$ , I estimate within-unit average P loads over the years post-break point years and multiply that by the corresponding farm's acreage. I then sum that value across farms to get 428,112.2 lbs of phosphorus under a BMP-BAU scenario for the average year. To convert values from pounds to metric tons, I simply divide by 2205 to get 194.16 metric tons.<sup>3637</sup>

$$s^* = \frac{191.06 \left( 1 - \frac{\bar{Y}}{191.06} \right)}{2.82} \quad (15)$$

Figure 4 plots Equation (15) for various pollution targets (expressed as a fraction of BMP-BAU levels). 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. Additionally, the true BMP-BAU value also varies with time.

The horizontal intercept in Figure 4 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% relative to BMP-BAU levels using *only* the ambient subsidy, then the subsidy needs to be roughly \$20.80. 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 per acre subsidy rate of \$20.80. On average, under 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 mandatory BMPs and the incentive credit program. In order to estimate

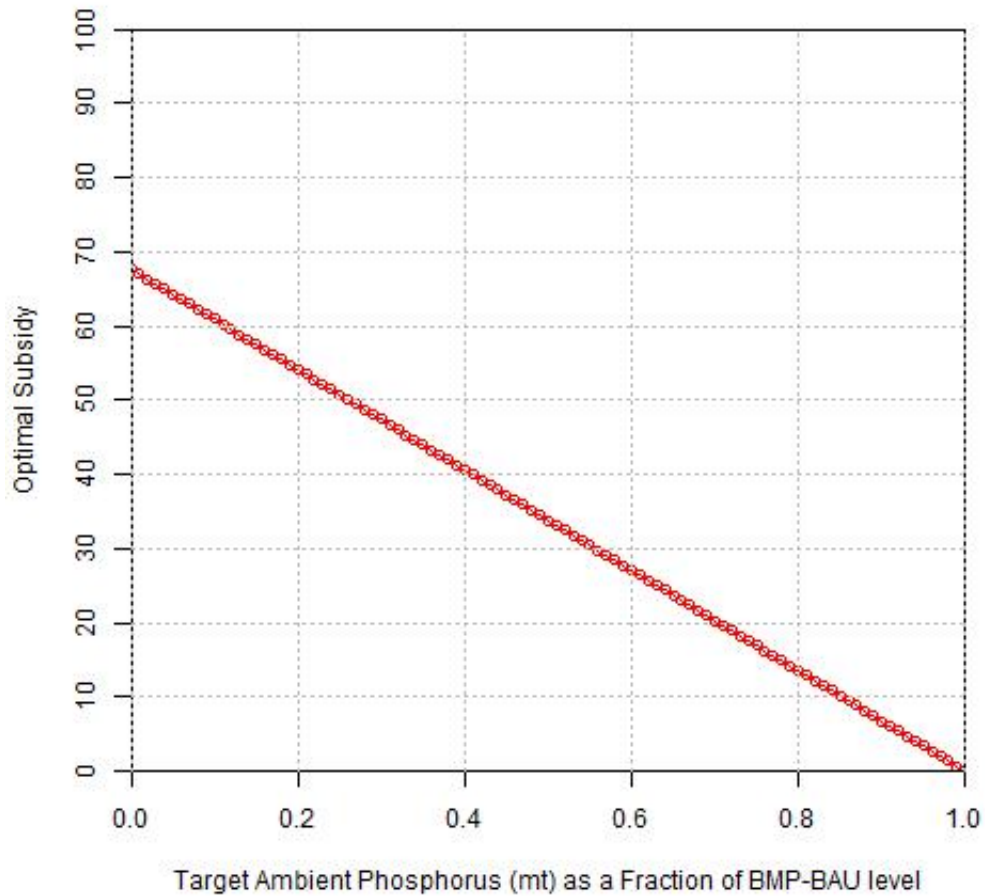
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<sup>36</sup>Metric tons is unit used in determining compliance by the SFWMD regulator.

<sup>37</sup>Note that the denominator in (5) is also divided by 2205.

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 19. On average, the estimated counterfactual basin-wide TP loads were 42.1% higher when compared to the estimated basin-wide TP loads using the true EFA data. After some back of the envelope calculations, I estimate that the average TP load reductions under a BMP-only regime would have been about 36%. Therefore if the regulator instead opted for a pure ambient subsidy rate to achieve the same abatement levels, a subsidy rate per acre of \$24.36 is needed. Taking the relevant area under the marginal abatement cost curve results in an area of about \$10.49 which represents the estimated compliance cost per acre under the standard ambient subsidy policy for the average farm.

**Figure 4:** Optimal Subsidy as a Function of Ambient P Target



### 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 aim here is to compare the cost of achieving pollution reductions similar to what was seen

under the EFA using an ambient subsidy (\$33.93 number found above) with the cost of the mandatory BMPs. I arrive at the cost for the mandatory BMPs in two separate 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 a simple two-way fixed effects (TWFE) 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 TWFE 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 BMP and incentive credit program. 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 7% which comes out to about \$44.72 if the figure from Roka et al. (2010) is used as the base. The 95% confidence interval for these estimates ranges from 6% to 9%. Thus, I combine the 5% figure from the above into the relevant range of estimates for the BMP cost estimate.

## Results and Conclusion

The cost of the mandatory BMPs ranged somewhere between \$34-\$44 according to the two methods used and the hypothetical ambient subsidy resulted in a cost of about \$10.50 meaning that the ambient subsidy would achieve the same pollution outcome as the BMPs but at 1/3 the cost.<sup>38</sup>

Further, under the simulated ambient subsidy scenario, the regulator would incur an annual cost of about \$20 million 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

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<sup>38</sup>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.

abate as that under an ambient subsidy but without actually paying out real money which significantly reduces government expenditure.

Secondly, the estimated subsidy schedule from Figure 4 is a lower bound on the true optimal subsidy rate under the assumption that the mandatory BMPs *decreased* the slope of the marginal abatement cost curve under standard theories involving improved abatement technologies.

Lastly, 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 mechanism 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.<sup>39</sup>

Finally, the author would like to caution those who view this work as evidence that ambient mechanisms can reduce NPSP in the agricultural runoff context for two reasons. First, this paper does not test the behavioral assumptions under standard AMM theory but rather assumes they hold and simulates the outcomes. Secondly, external validity limited by the

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<sup>39</sup>Figure 6, Yoder, Chowdhury and Hauck (2020).

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  $\gamma$  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.<sup>40</sup> Taken together these facts suggest that average behavior, as indicated by our estimate for  $\gamma$ , 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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<sup>40</sup>Table 1, Yoder (2019).



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## Appendix A

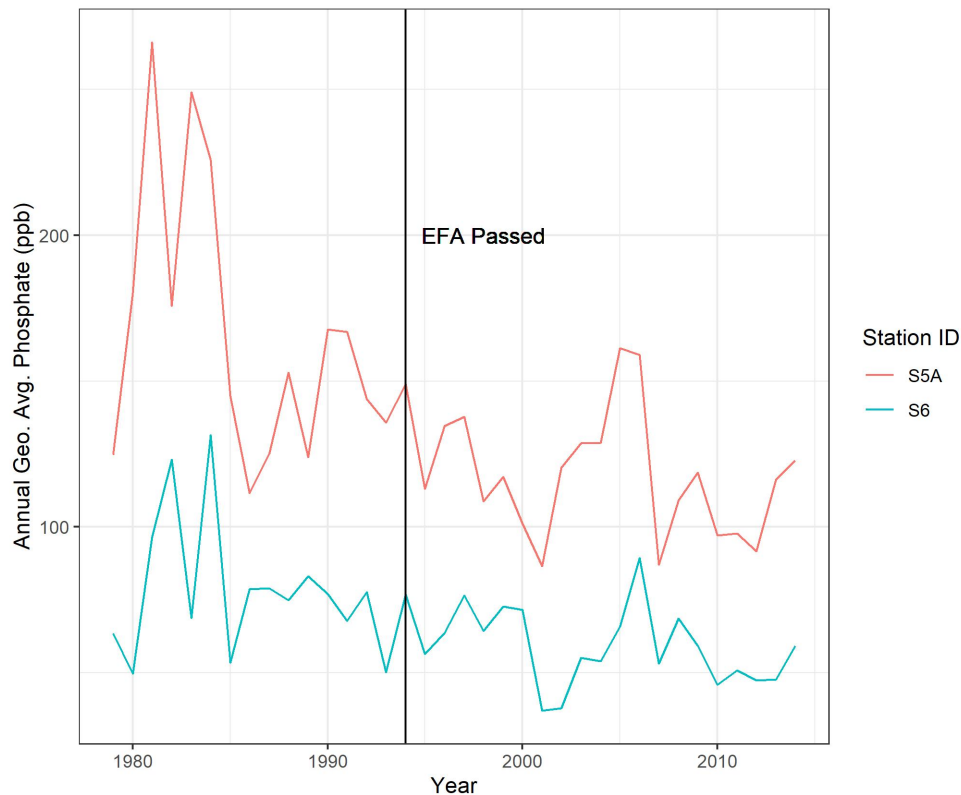
In this section, I attempt to show that overall the EFA did reduce average total phosphorus loads attributable to the EAA. First, I plot a simple time series of the water quality readings from stations within the EAA before and after the EFA implementation shown in Figure 5. This is suggestive evidence 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 solely 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 downstream of our treated EAA region) as the potential control (donor) pool.<sup>41</sup>

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<sup>41</sup>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 5:** 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 9 and 10 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.<sup>42</sup> 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

<sup>42</sup>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 (16) is minimized over the pre-treatment periods between 1979 and 1993. Here I am assuming that only  $i = 1$  belongs in the treatment group with  $i = 2, \dots, J + 1$  belonging to the donor group. However in this setting, there are two treated units and so (16) is done separately for both treated units.

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

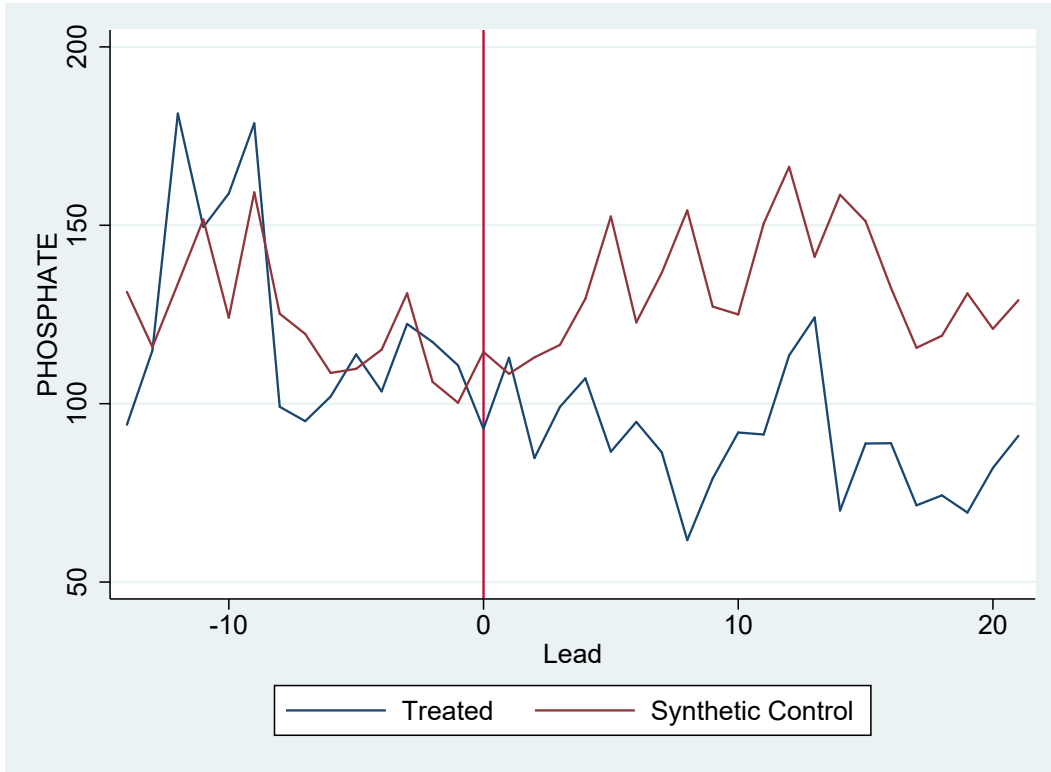
$X_{it}$  denotes the annual geometric average phosphorus levels for station  $i$  and no other covariates are used.<sup>43</sup> Once the optimal weights are computed, average treatment effect,  $\alpha_t$ , is calculated via (17) and the results of which are implicitly shown in Figure 6.

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

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<sup>43</sup>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.

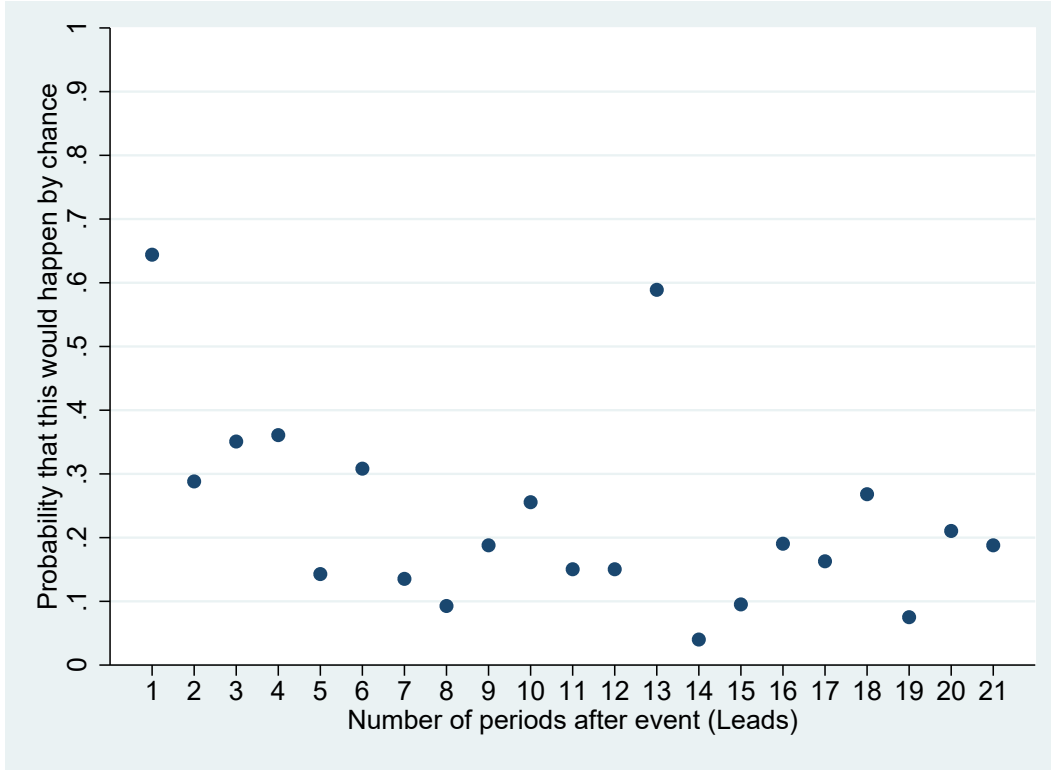
**Figure 6: Synthetic Control Result**



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 7. 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 7:** P-Values for Treatment Effects

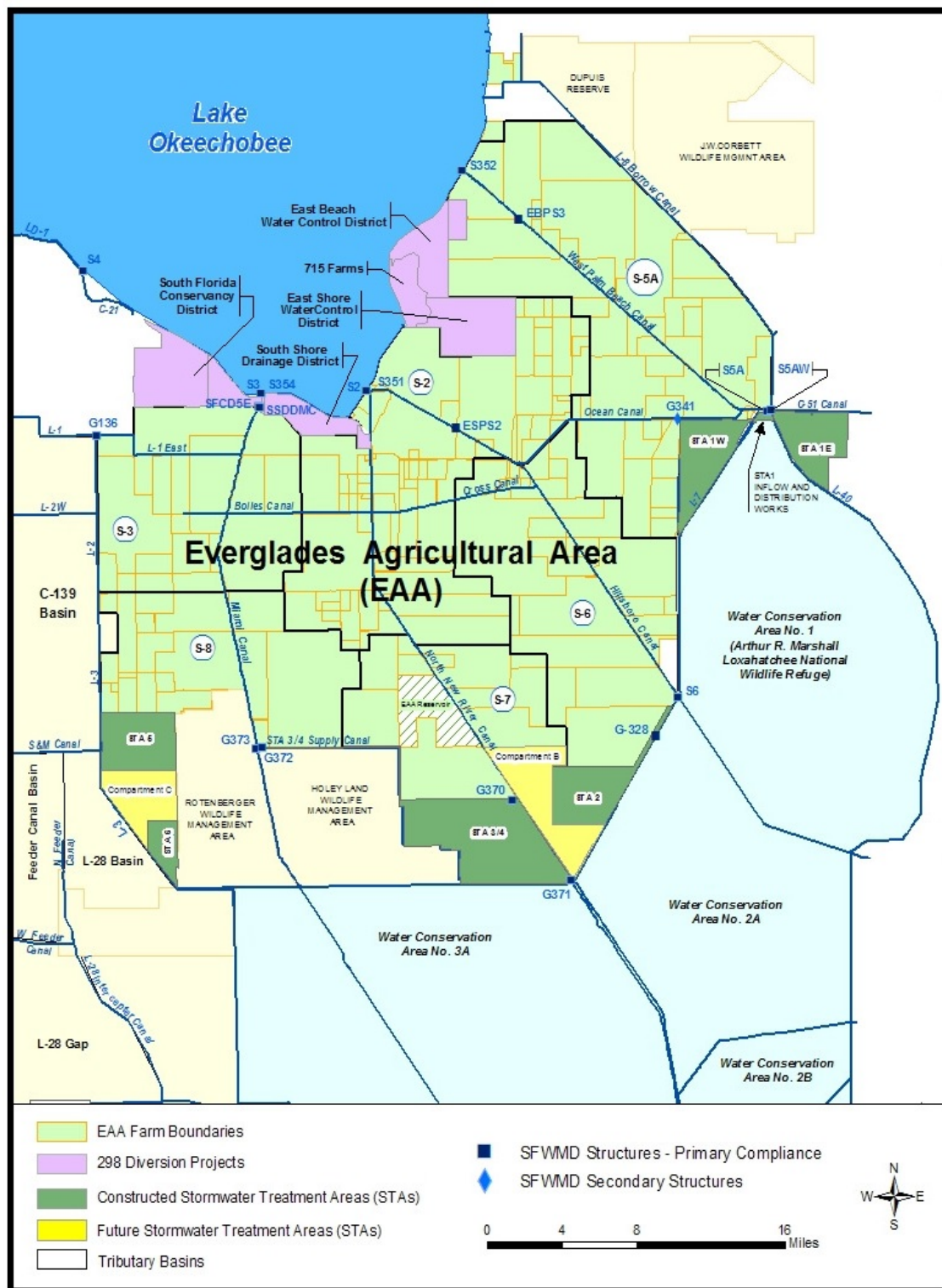


There are a number of robustness I have implemented and the results are shown in Appendix A. First, I try to incorporate anticipatory effects by treating the “effective” policy implementation date as *if* it were in 1992. The actual policy implementation date was 1994 but the policy is a culmination of legal proceedings that occurred with public attention starting in 1992. The results of changing the intervention date are shown in Figures 11 and 12. 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 13 through 16 in Appendix B). The results seem to be largely unaffected in these checks except for the demeaned version with captured anticipatory effects. Another explanation 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 8: EAA Area with Canals/Drainages

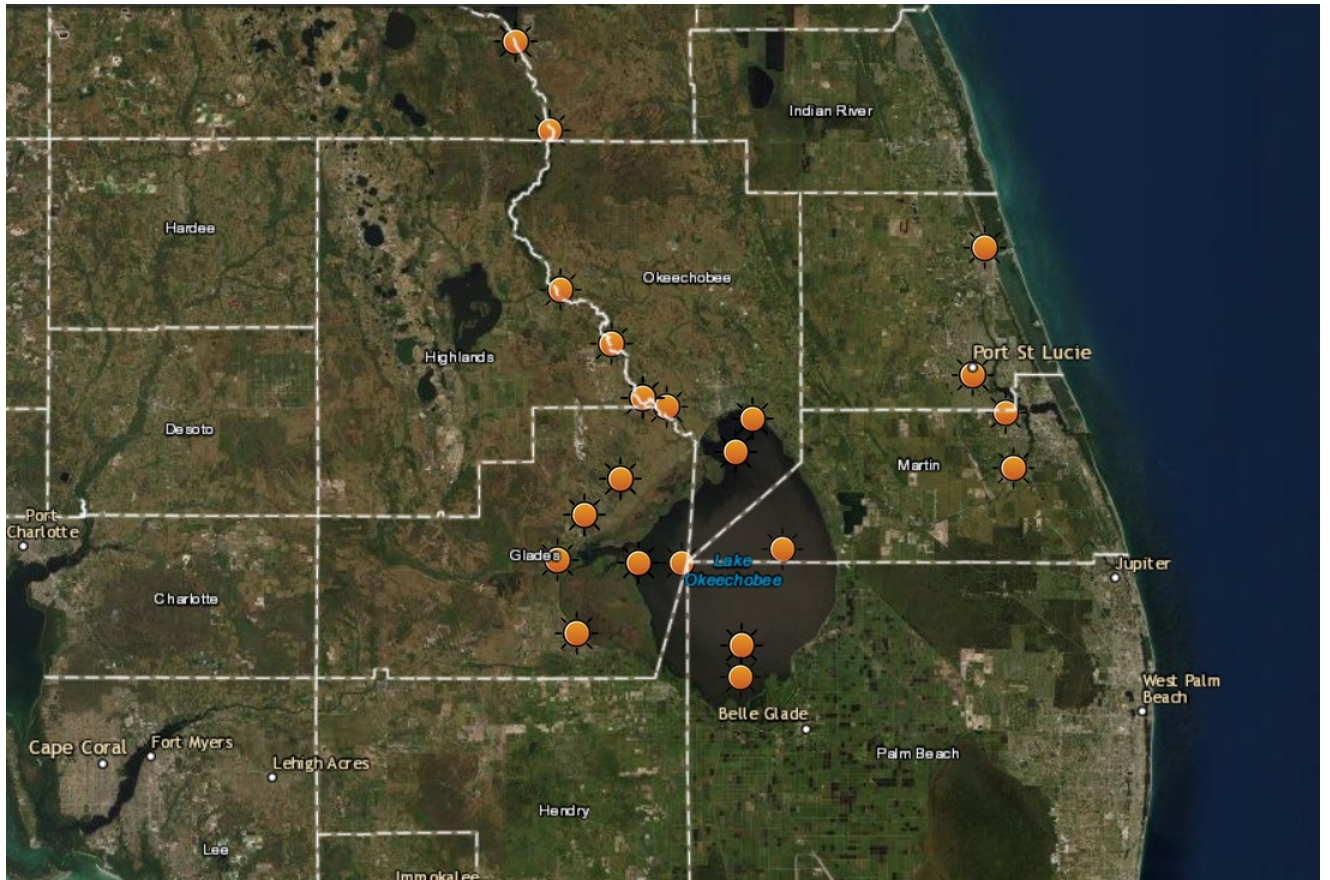


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**Table 3:** Individual Farm Data: Summary Statistics

	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

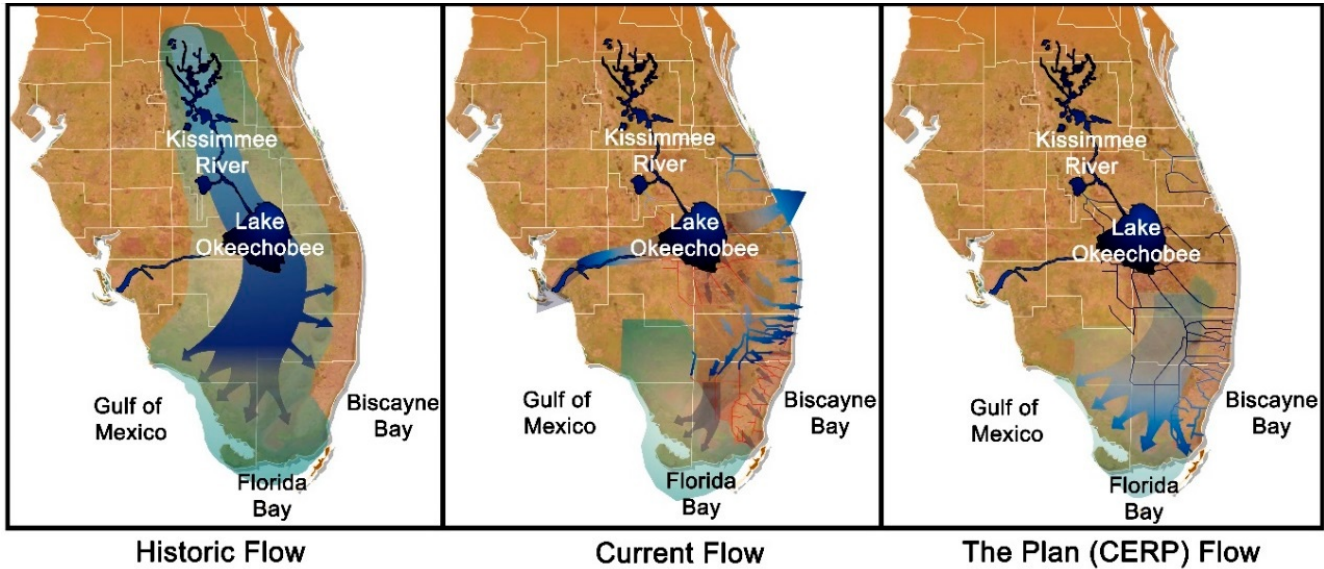
**Figure 9:** Map of Donors for Synthetic Ctrl



Source: DBHYDRO's Map Browser

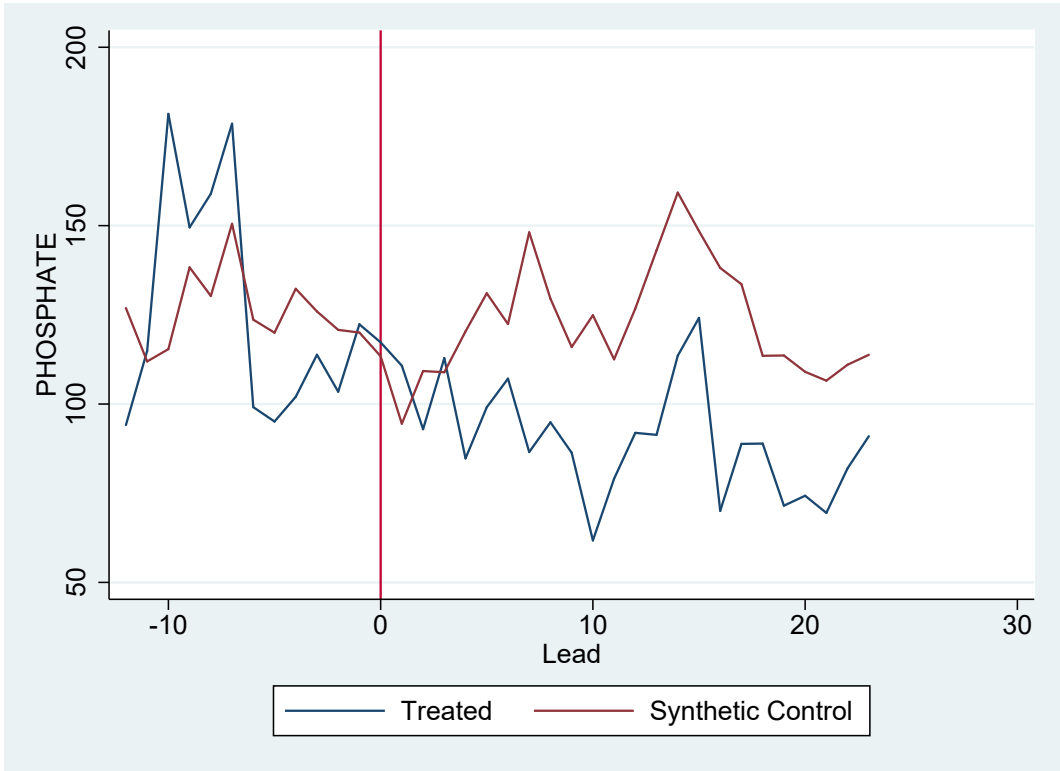


Figure 10: Hydrological flow in Southern Florida



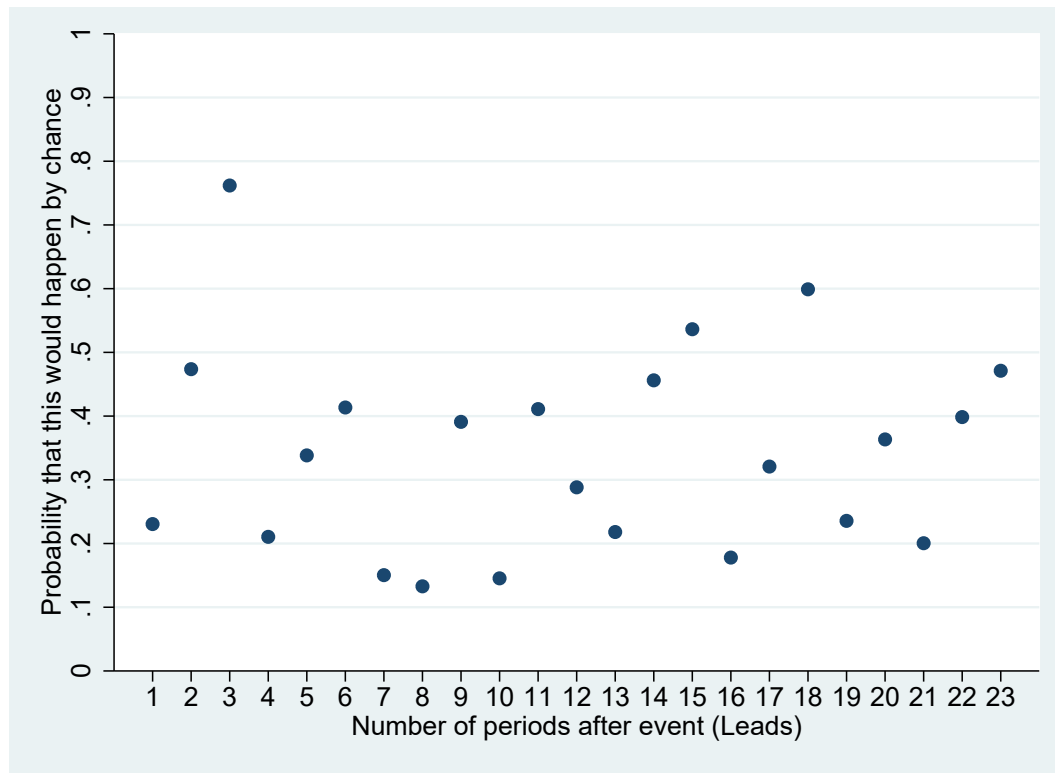
Source: Schade-Poole and Möller (2016)

Figure 11: Synthetic Control Result: Robustness to Anticipatory Effect

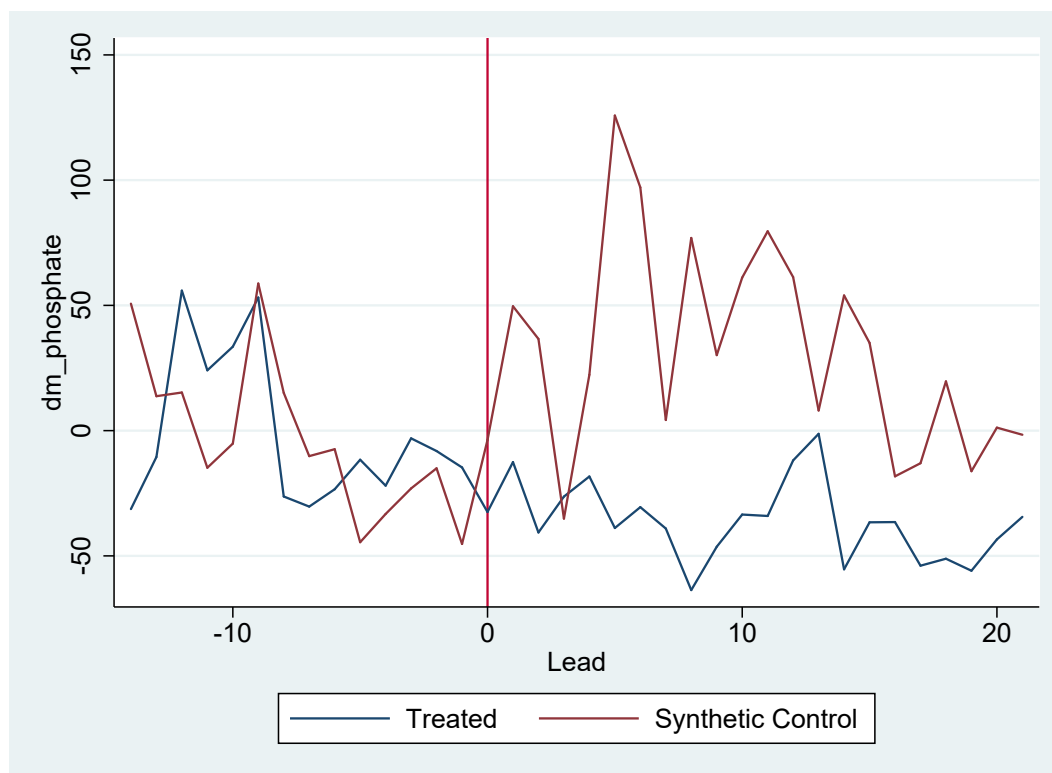




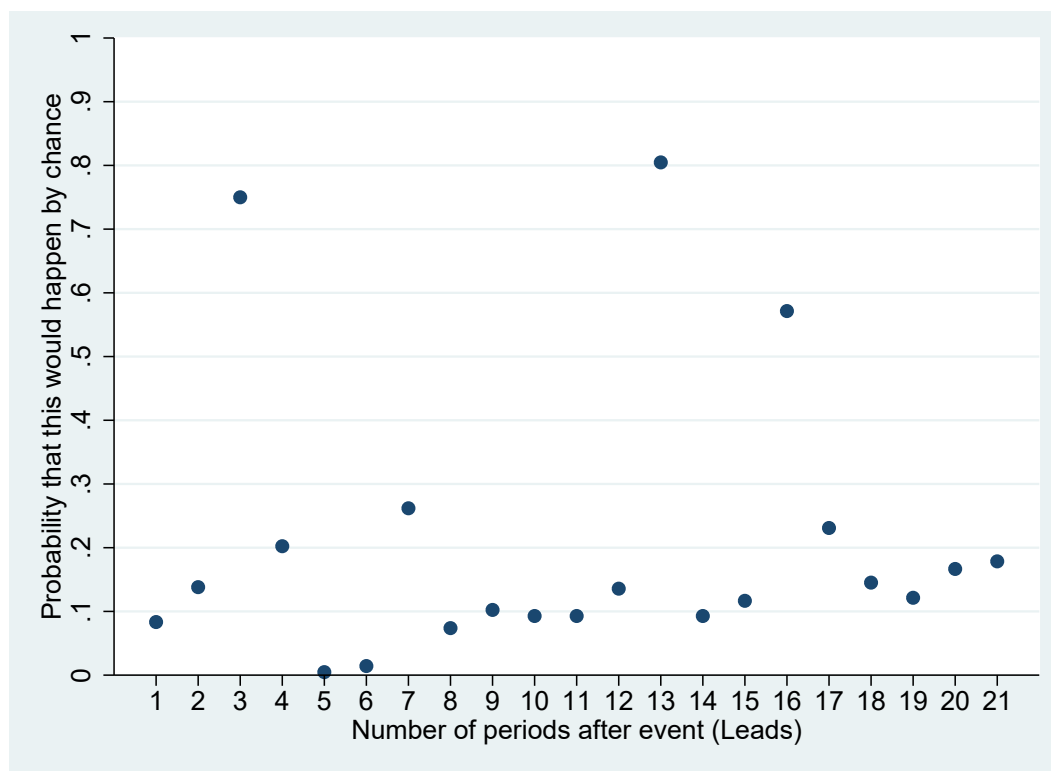
**Figure 12:** P-Values for Treatment Effects: Robustness to Anticipatory Effect



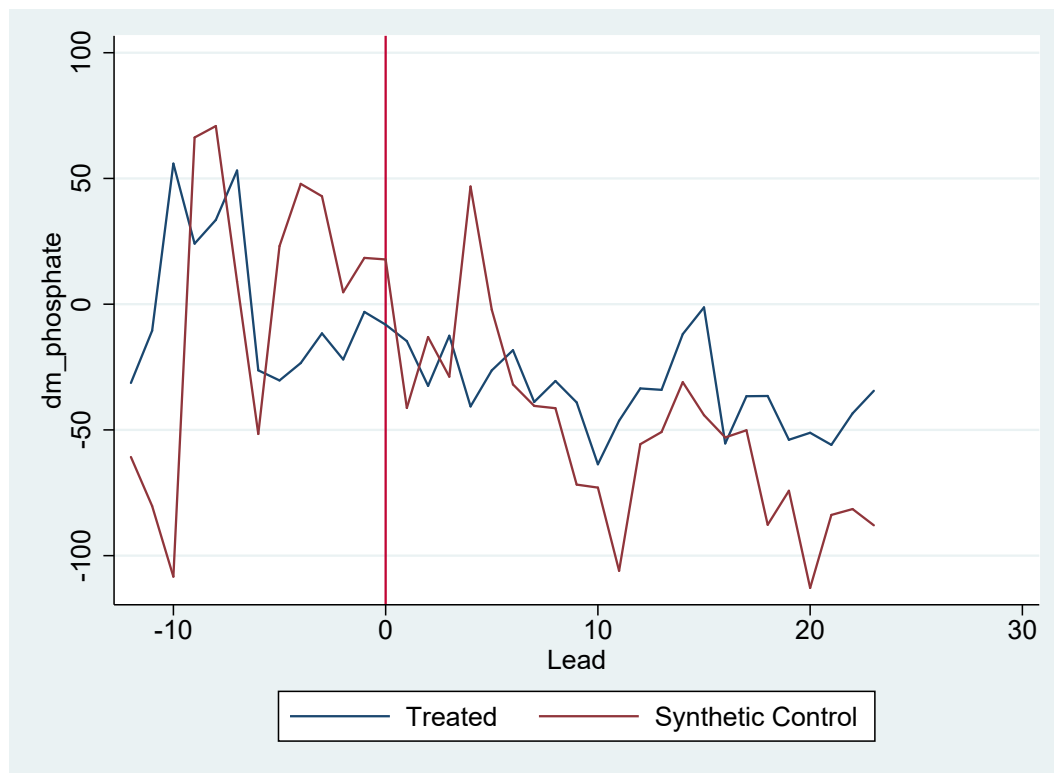
**Figure 13:** Synthetic Control Result: Robustness to Demeaning



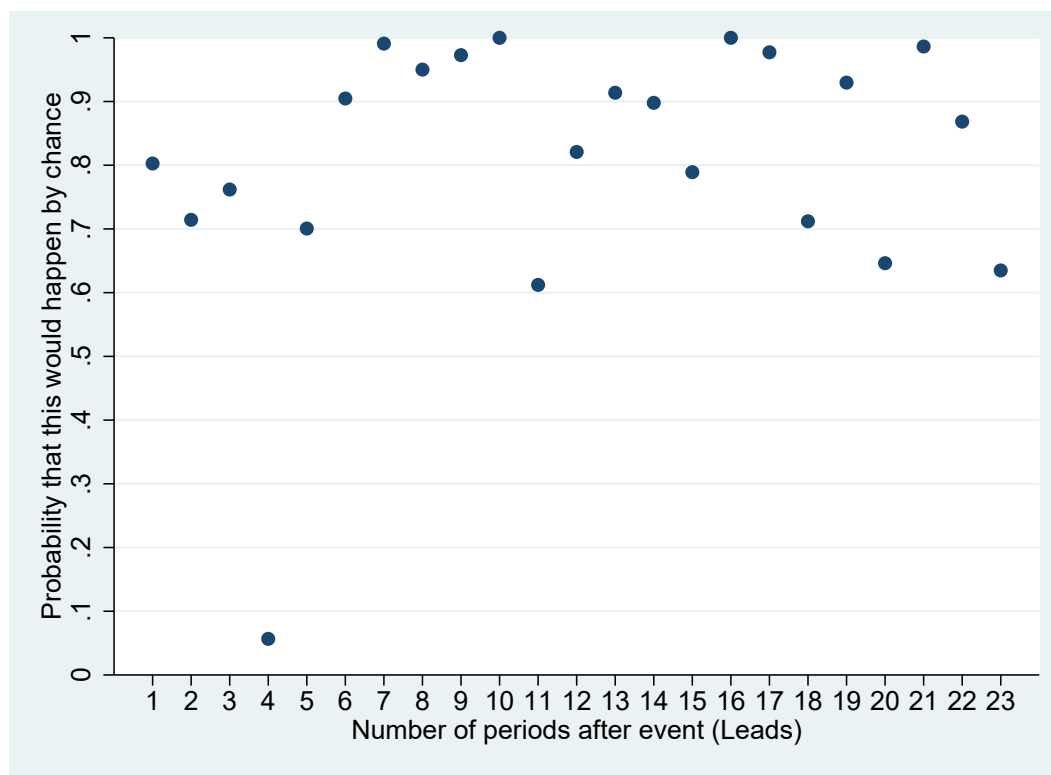
**Figure 14:** P-Values for Treatment Effects: Robustness to Demeaning



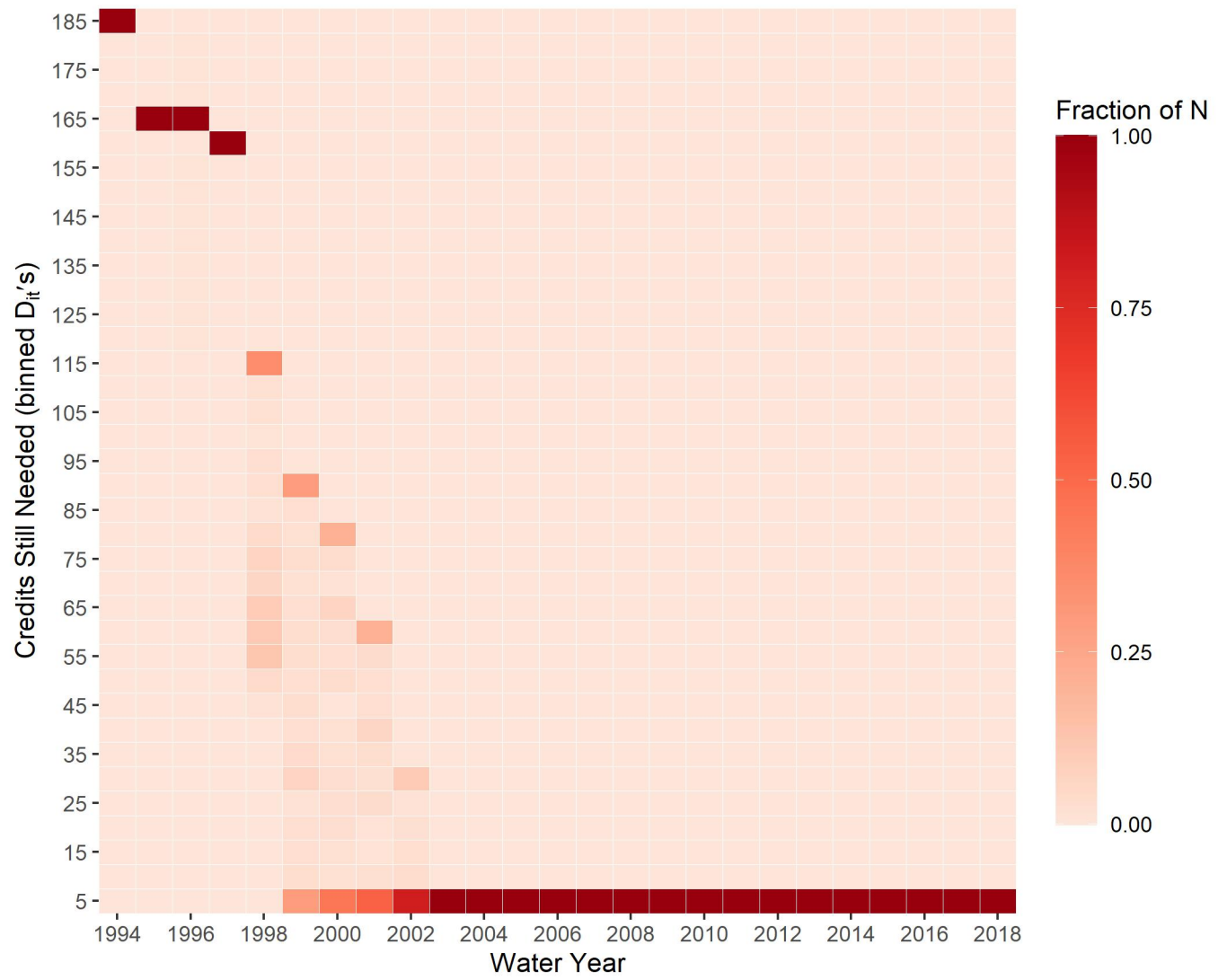
**Figure 15:** Synthetic Control Result: Robustness to Anticipatory Effect & Demeaning



**Figure 16:** P-Values for Treatment Effects: Robustness to Anticipatory Effect & Demeaning



**Figure 17:** Heatmap Distribution of  $D_{it}$ 's



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

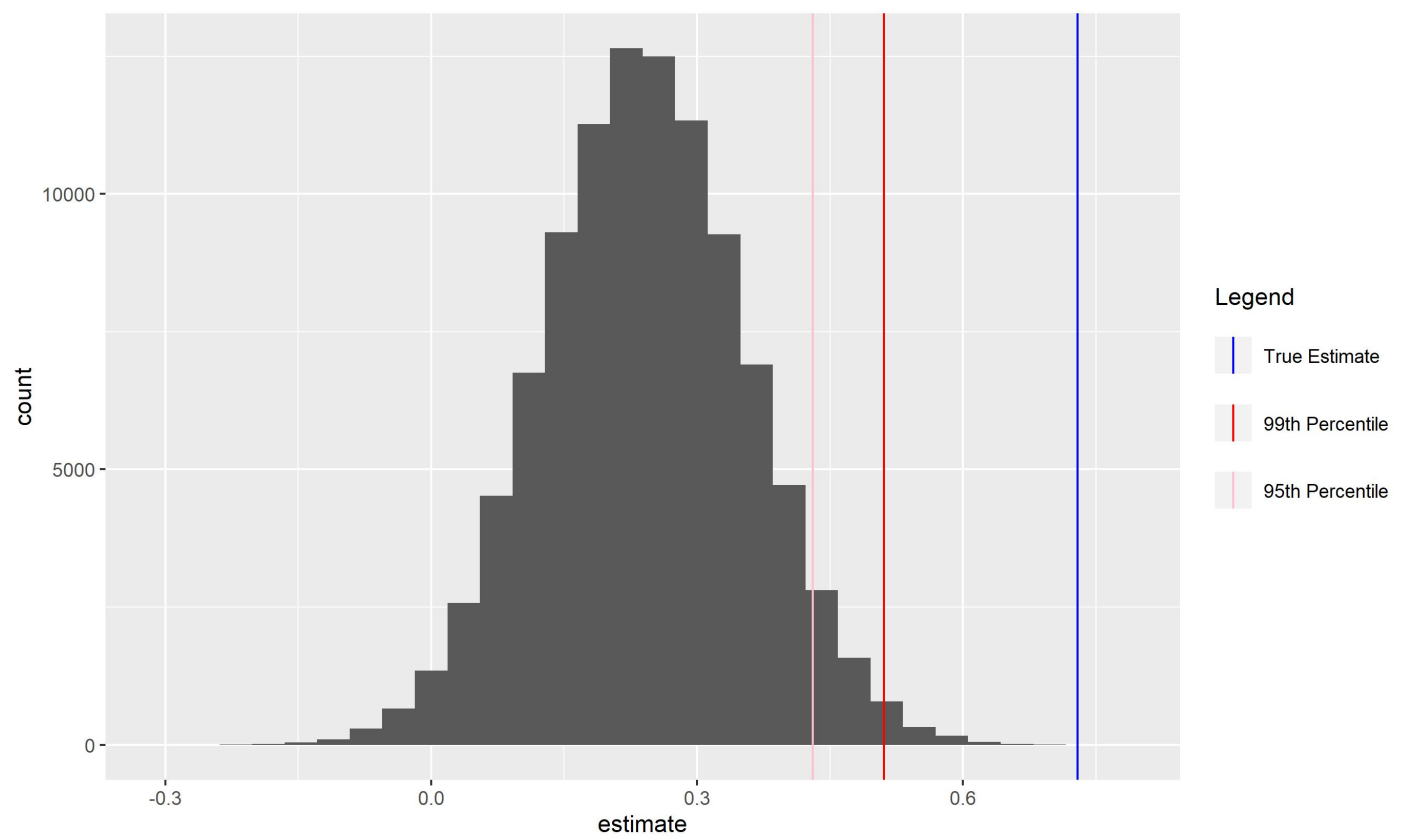
	exogenous controls	predetermined controls	Veg Acres Predetermined
rolling_incentives2	1.670 (0.285)	1.922 (0.267)	1.675 (0.279)
interact2	-0.0000343 (0.141)	-0.0000334 (0.121)	-0.0000345 (0.128)
Total Acres Dedicated to Vege	0.0226 (0.231)	0.0529 (0.423)	0.0142 (0.468)
Basin Acreage	-0.00107 (0.692)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

*p*-values in parentheses

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

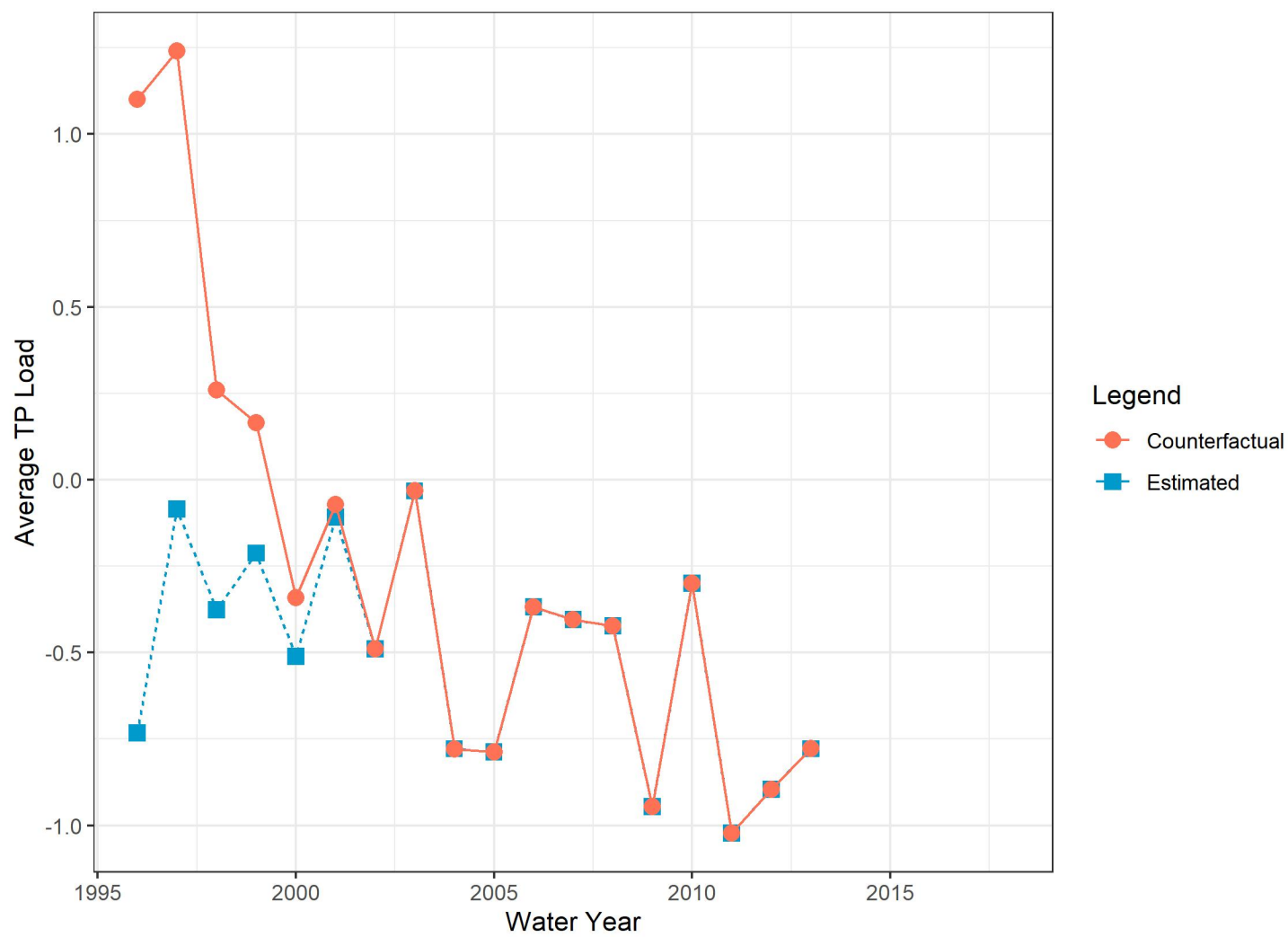
\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

**Figure 18:** Histogram of Permuted  $\hat{\beta}$ 's





**Figure 19:** Estimated and Counterfactual TP Loads



## Appendix C

First, I use the law of motion for credit stock from (23) with the fact that  $Q_{it}^* = \min\{M, S_{it}\}$  to get (18) where  $k > t + 1$  and  $\mathbb{1}\{S_{ih} < M\} = 1$  when  $S_{ih} < M$ .<sup>44</sup>

$$\frac{\partial Q_{ik}^*}{\partial Y_{it}} = -\left(1 - \mathbb{1}\{S_{i,t+1} < M\}\right) \cdots \left(1 - \mathbb{1}\{S_{i,k-1} < M\}\right) \mathbb{1}\{S_{ik} < M\} \quad (18)$$

Thus, we can rewrite equation (18) as (19). The interpretation for (19) 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  $M$ .

$$\frac{\partial Q_{ik}^*}{\partial Y_{it}} = \begin{cases} -1 & \text{if } S_{ih} > M \quad \forall h \in [t+1, k-1] \quad \text{and} \quad S_{ik} < M \\ 0 & \text{if } S_{ih} < M \quad \text{for some } h \in [t+1, k-1] \quad \text{or} \quad S_{ik} > M \end{cases} \quad (19)$$

Because equation (19) 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

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<sup>44</sup>If  $k = t + 1$ , then we have  $\frac{\partial Q_{i,t+1}^*}{\partial Y_{it}} = -\mathbb{1}\{S_{i,t+1} < M\}$ .

credit demands for all periods between  $t$  and  $k$ . In this case, we then know that  $S_{ik} > M$  so that equation (19) 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 (19) 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 (25) so that I can define  $\widehat{G}_{it}$  as (20).

$$\widehat{G}_{it} = - \sum_{k=t+1}^T \frac{\partial Q_{ik}^*}{\partial Y_{it}} \quad (20)$$

Then I substitute each  $\frac{\partial Q_{ik}^*}{\partial Y_{it}}$  term using (18) 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 (21).

$$\widetilde{G}_{it} = \sum_{k=t+1}^T \mathbb{1}\{S_{ik} < M\} \quad (21)$$

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 (21) 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 (22) where  $r_{it} \in \mathbb{Z}^+$  and  $e_{it} \in [0, 1)$  is just a remainder term.

$$\frac{S_{it}}{M} = r_{it} + e_{it} \quad (22)$$

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

$$\begin{aligned}\tilde{G}_{it} &= (T - t) - (r_{it} - 1) \\ &= (T - t + 1) - r_{it} \\ &= (T - t + 1) - \left\lfloor \frac{S_{it}}{M} \right\rfloor\end{aligned}$$

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

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

Define  $D_{it}$  as

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

So then we get that

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

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

$$\begin{aligned}
D_{it} - \tilde{G}_{it} &= (T - 1 + 1)(M - 1) - S_{it} + r_{it} \\
&= (T - 1 + 1)(M - 1) - S_{it} + \frac{S_{it}}{M} - e_{it} \\
&= (T - t + 1 - r_{it})(M - 1) - e_{it} \geq 0
\end{aligned}$$

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  $D_{it} > \tilde{G}_{it}$ . When  $r_{it} < 2$ , then  $D_{it} - \tilde{G}_{it}$  gets more positive. When  $r_{it} \geq (T - t + 1)$ , then both  $D_{it}$  and  $\tilde{G}_{it}$  are forced to be zero since the original term  $G_{it}$  is also zero in that case. 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,  $\theta_i$ , which also represents the business as usual level of discharge *after* BMPs are adopted (aka,  $\theta_i^{bmp}$  which will henceforth be referred to as BMP-BAU or  $\theta_i$ ).<sup>45</sup> The  $\bar{T}$  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  $t$ ,  $\delta$  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 per acre discharge decision *after optimally deciding*  $Q_{it}$  is given by

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<sup>45</sup>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).<sup>46</sup>

$$\begin{aligned}
V_t(S_{it}) &= \max_{Y_{it}} \pi(Y_{it}, \theta_i) - (\bar{T} - Q_{it}^*) + \delta \mathbb{E}V_{t+1}(S_{i,t+1}) \\
\text{s.t.} \quad S_{i,t+1} &= S_{it} - Q_{it}^* + (\bar{Y}^P - Y_t) \\
Y_t &= \alpha_t + \sum_i Y_{it} L_i \\
\bar{Y}^P &\geq \alpha_t + \sum_i \theta_i L_i \\
\alpha_t &\overset{iid}{\sim} F(0, \sigma_\alpha^2) \\
Q_{it}^* &= \min\{M, S_{it}\}
\end{aligned} \tag{23}$$

The timing of events in this dynamic problem is as follows: farms first make decisions about discharge ( $Y_{it}$ ), then uncertainty parameter  $\alpha_t$  is resolved and ambient quality  $Y_t$  is observed.<sup>47</sup> 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).

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

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

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<sup>46</sup>The model presented in (23) intentionally ignores the rates presented in column 3 of Table 1 for notational simplicity.

<sup>47</sup>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).

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

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

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

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

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

means that

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

$$\text{FOC: } \pi'(Y_{iT}^*) = 0 \quad (28)$$

$$\implies Y_{iT}^* = \theta_i^{bmp}$$

$$\implies V_T(S_T) = -(\bar{T} - Q_{iT}^*)$$



Then next iteration we have

$$\begin{aligned}
V_{T-1}(S_{i,T-1}) &= \max_{Y_{i,T-1}} \pi(Y_{i,T-1}, \theta_i^{bmp}) - (\bar{T} - Q_{i,T-1}^*) - \delta \mathbb{E}(\bar{T} - Q_{iT}^*) \\
\text{s.t.} \quad S_{iT} &= S_{i,T-1} - Q_{i,T-1}^* + (\bar{Y} - Y_{T-1}) \\
\text{FOC:} \quad \pi'(Y_{i,T-1}^*, \theta_i^{bmp}) &= -\delta \mathbb{E} \left[ \frac{\partial Q_{iT}^*}{\partial S_{iT}} \right] L_i \\
\implies \pi'(Y_{i,T-1}^*, \theta_i^{bmp}) &= \delta \mathbb{P}(S_{iT} < M) L_i
\end{aligned} \tag{29}$$

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

Then the next iteration

$$\begin{aligned}
V_{T-2}(S_{i,T-2}) &= \max_{Y_{i,T-2}} \pi(Y_{i,T-2}, \theta_i^{bmp}) - (\bar{T} - Q_{i,T-2}^*) + \delta \mathbb{E} \left[ \pi(Y_{i,T-1}^*, \theta_i^{bmp}) - (\bar{T} - Q_{i,T-1}^*) - \delta (\bar{T} - Q_{iT}^*) \right] \\
\text{s.t.} \quad S_{i,T-1} &= S_{i,T-2} - Q_{i,T-2}^* + (\bar{Y} - Y_{T-2}) \\
S_{i,T} &= S_{i,T-1} - Q_{i,T-1}^* + (\bar{Y} - Y_{T-1}) \\
\text{FOC:} \quad \pi'(Y_{i,T-2}^*, \theta_i^{bmp}) &= -\delta \mathbb{E} \left[ \frac{\partial Q_{i,T-1}^*}{\partial S_{i,T-1}} \right] L_i - \delta^2 \mathbb{E} \left[ \frac{\partial Q_{iT}^*}{\partial S_{iT}} \right] L_i
\end{aligned} \tag{30}$$

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

$$\pi'(Y_{it}^*, \theta_i^{bmp}) = - \sum_{k=t+1}^T \delta^{k-t} L_i \mathbb{E} \left[ \frac{\partial Q_{ik}^*}{\partial S_{ik}} \right] \tag{31}$$

Equation (31) is the same as (24) except  $\frac{\partial Q_{ik}^*}{\partial Y_{it}}$  is replaced with the equivalent value of

$$\frac{\partial Q_{ik}^*}{\partial S_{ik}} L_i.$$