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

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Abstract

This study attempts to explore the effectiveness of an ambient tax-subsidy in addressing non-point source pollution problems. This paper focuses on the effectiveness of the policy at inducing abatement as opposed to the cost effectiveness though insights regarding the latter may be found from this paper. I study the Everglades Forever Act which, among other things, imposed an ambient tax-subsidy on farmers. I use a simple two-way fixed effects model with results that are consistent with the narrative that the policy was rather ineffective at inducing abatement. This result is preliminary and there are many problems with it still as well as how to interpret it.

Introduction

Decades after the U.S. Clean Water Act of 1972 and its 1977 and 1987 amendments, the nation's water quality has improved drastically. The act was primarily aimed at regulating and reducing pollution from known and identifiable sources of discharge. However, there is still a large proportion of the nation's water bodies that still fail to meet the water quality standards set forth by the act. "In 2004 (the most recent comprehensive survey), EPA found that 'states reported that about 44% of assessed stream miles, 64% of assessed lake acres, and 30% of assessed bay and estuarine square miles were not clean enough to support uses such as fishing and swimming' ", (National Resource Defense Council, 2013). A major reason why we still see such lack of progress is due to non-point source pollution (NPSP), particularly agricultural and urban runoffs. The problem with NPSP is something that is a fundamental challenge from both a policy and academic point of view (U.S. Environmental Protection Agency, 2016).

This paper looks at how effective an ambient tax or subsidy is at reducing NPSP by evaluating the impact of a portion of the Everglades Forever Act (EFA) of 1994. NPSP is a scenario in which the regulator cannot observe individual pollution levels (or it is prohibitively costly to do so) and so the standard policy tools cannot be applied. There have been many proposed policy tools that utilize economic incentives to ameliorate these issues; the three main incentive-based tools for addressing NPSP are ambient based taxes, input taxes, and emissions proxy based taxes (Xepapadeas, 2011; Shortle and Horan, 2001). The advantage of ambient-based incentives is that it does not restrict the ways in which the polluters can abate, unlike the input-based incentives which only encourages reductions in usage of dirty inputs. The problem with emissions proxy based incentives is that it attempts to reduce the NPSP problem to being a point-source problem through some physical science modeling which comes with great uncertainty. Recently, emissions proxy methods have experienced a technological break through via satellite imaging and remote sensing. Such technologies could greatly increase the viability of emissions proxy methods in some contexts but to the best of my knowledge, there has been no sign that such technologies will allow regulators to attribute effluents to individual sources (please correct me if I'm wrong). Thus, ambient based tools are a promising candidate with which to address NPSP problems. Such tools rely on the ability to monitor ambient environmental quality (at low cost) and attribute that to a known group of polluters with little to no uncertainty. This tool will then punish and or reward everyone in the group in the same or similar manner based on group performance measured by the ambient quality.

The use of an ambient-based incentive to correct NPSP was first introduced by Meran and Schwalbe (1987) which showed how a Nash equilibrium on the efficient allocation of output and effluents could be supported. The seminal paper by Segerson (1988) independently proposed the use of such a tool showing theoretically how a linear ambient tax with a lump sum transfer can lead to the optimal emissions level while maintaining the long run optimal number of firms. Her pioneering work has led to a large literature looking at different aspects of the proposed ambient-based tool. One strand of that literature is focused on the formulation of a theoretically optimal ambient-based incentive mechanism under various contexts (Cabe and Herriges, 1992; Hansen and Romstad, 2007; Herriges, Govindasamy and Shogren, 1994; Horan, Shortle and Abler, 1998, 2002; Xepapadeas, 1991, 1992). The other strand of the literature focuses on testing various ambient 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). In the past, empirical studies of various ambient mechanisms were strictly confined to the lab. The main reason is a lack of real world implementation of ambient-based policies and the other reason is that observational studies lack individual level data due to the very nature of NPSP being individually unobservable.

Recently, some empiricists have found novel escapes out of the lab. Reichhuber, Camacho and Requate (2009) implemented a framed field experiment using an ambient-based tool to reduce harvesting of a common pool resource. The field experiment was done on villages in southwest Ethiopia. A major source of income for farmers there is honey production which requires the harvesting of lianas, a woody vine-like plant. The experiment separately tested the efficacy of a collective tax (both low and high rates) and a collective tax-subsidy mechanism (linked to aggregate output rather than aggregate liana levels) in reducing the over exploitation of lianas and found that the desired outcome can be achieved through both high and low tax rates whereas the tax-subsidy mechanism often leads to inefficiently low harvest rates due to collusion. This result is consistent with lab results such as those from Spraggon (2002) and Cochard, Willinger and Xepapadeas (2005).

Wong et al. (2019) study the effect of Brazil's Bolsa Verde program which is an environmental cash transfer. It pays low income households in certain priority areas for forest conservation measured via satellites. Forest cover is analogous to ambient environmental quality and so this program is framed as an ambient subsidy. The authors find that the program did reduce deforestation on average by about three to five percent. Both of these studies suggest that collective punishment/rewards based on aggregate performance can be a viable way to achieve environmental objectives when only group behavior is observable. However, neither study is able to disentangle the total effect between enforcement and conservation nor are they able to say anything about individual extractive behaviors.

Thus, this paper contributes to the literature by being the first observational study of a real world ambient policy in which it is possible to monitor individual polluting behavior. Based solely on speculation right now, I suspect that the setting used in this paper is one in which it is unlikely that the enforcement mechanism plays a significant role. My verbal argument is that total phosphorus runoff is universally hard to monitor, even for the acting agent himself. One could think of a way to monitor certain signals indicating the degree of compliance among one's neighbors but that seems unlikely since that is the responsibility of the regulatory agency.[1] The goal is to explore the efficacy of an ambient-based tax-subsidy using Florida's Everglades Forever Act (EFA) of 1994 as our empirical setting. In particular, this study aims at assessing how effective the ambient-based scheme was at inducing farmers to take up actions that abate nutrient runoff from their farms. I first develop a model that mimics certain relevant features of the farmer's objective. This model will allow me to make a prediction on when the ambient incentive's effects will dissipate prior to the policy's expiration, conditional on the existence of such effects. I first use a simple two-way fixed

[1] Farmer's WOD permits are required to be renewed once every five year cycle for which a compliance inspection is conducted.

effects regression model to test the responsiveness of farmer's abatement outcomes to the ambient incentive utilizing the within variation. Using data from the regulatory agency, I can see when each farm should have stopped responding to the ambient incentives. I then use a structural break test on my panel model (which I have not implemented yet and am still debating whether this is a needed/convincing way to go about it) to evaluate whether abatement behavior changed on each farm after their specific period for which the incentive is predicted to be irrelevant. The results from the two-fixed effects estimation seem to suggest that the ambient tax-subsidy had no effect on farmer's abatement decisions.

Policy Context

The Everglades Forever Act was signed into law by the Florida Legislature in 1994 to address the issue of nutrient loading into the Everglades, specifically phosphorus. The policy had three major components and the regulatory agency in charge of enforcement and oversight is the South Florida Water Managment District (SFWMD). The first component was a mandate that required all owners of commercial agricultural parcels within the Everglades Agricultural Area (EAA) to obtain a permit in order to continue conducting operations.[2] To obtain a permit, parcel owners need to develop a best management practice (BMP) plan and a water quality/quantity monitoring plan. The water monitoring plan requires a third party labratory to collect and analyze the farm-specific runoff samples though this data is not used by the regulatory agency to determine regulatory compliance. Once approved by

[2]Map of the basins and regulated areas are shown in Figure 1.

the SFWMD, applicants must achieve full implementation of both plans by the start of the 1996 water-year to remain in compliance.[3] 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.[4]

For instance, the government 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. However, applicants who wish to implement an action/strategy not offered in the menu provided can apply to do so with documented research of the proposed action/strategy's effectiveness.

The second component was the construction of storm-water treatment areas (STA's) around the five areas in which the EAA drains south towards the Everglades. The STA's are large plots of land that are planted with vegetation that absorb phosphorus. The third component charged 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 the STA's as well as an extra incentive to induce further TP load reductions. For the EAA constituents, 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 Table 1.

[3] A water-year starts on May 1st and ends on the following April 30th.

[4] 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.

[Table 1 about here.]

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.[5] Water quality monitoring stations are placed down stream of the main canals running through the EAA and are used to measure ambient quality attributed to EAA farmers. If the EAA basin achieves a TP load reduction by more than the 25% target, then all EAA parcel owners are rewarded tax credits that can go towards reducing future privilege tax obligations. Credits are awarded on a per acre basis and is the same for all parcels; each parcel owner gets the same number of credits per acre for each percentage point above the 25% target. However, at a minimum, the tax per acre must not fall below $24.89 which implies that for each year, there is a maximum number of exercisable credits that prevents one from reducing their per acre tax below the minimum. If a permitee wanted to exercise credits to reach the minimum per acre tax, they must first prove that they reached the required TP reductions in Column 4 of Table 1 or prove that their TP loads were at most 50 ppb. If farmers have more credits than they need in any given period, then the credits can be carried forward for future use but the value of a single credit changes over time and is dictated by the regulatory agency. This tax credit incentive scheme is based on ambient quality and it is this component of the EFA that we are interested in.

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

If the EAA basin is determined to be out of compliance, 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.

Why the Everglades?

An empirical investigation of any policy that addresses NPSP problems would ideally have data at the individual polluter level so that polluting behavior can be analyzed. However, the very nature of NPSP 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 connect to large canal and drainage systems in order to continue agricultural production. Because the EAA was once a part of the Everglades, during the early 20th century, a large system of canals was developed by both the Army Corps of Engineers and local farmers to reclaim land for agriculture. This infrastructure, depicted in Figure 1, is largely publicly funded and allows farmers to drain their fields as well as providing irrigation from Lake Okeechobee without which agriculture in this region would not be possible (Daroub et al., 2009). The process of drainage and irrigation via canals means that water inflows and outflows from any parcel passes through an identifiable point creating this unique situation whereby this runoff problem is actually a point-source pollution problem but is regulated as if it were NPSP.

[Figure 1 about here.]

Data

Data for all individual farms within the EAA effected by the EFA are taken from the annual Everglades Consolidated Reports and South Florida's Environmental Reports.[6] 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, and each farm's baseline (pre-policy) TP loads. The baseline year is the water-year for which the farm established its pre-BMP base period load and coincides with when the farm achieved BMP compliance. The Early Baseline Option essentially allowed farms the option to achieve compliance earlier than required, agree to better water quality monitoring by SFWMD, and divulge more information such as soil type and other farm specific characteristics. In return, farms who elect to participate in the Early Baseline Option have less regulatory oversight.[7] The data starts from 2001 to 2018 and is measured on an annual basis. I can acquire the data from 1994 to 2000 via manual digitization but it is a very tedious undertaking and I would appreciate any thoughts on how to make that procedure easier or whether it is worth embarking at all. The older data is not readable, they are scanned documents. I have also located land use data and chosen BMP's for each farm for select years, but that requires manual digitization as well. Table 2 provides summary statistics for the variables that I currently have at the farm level from 2001 to 2018. There are about 221 farms throughout the sample period with only 127 of which are balanced throughout the time period. Additionally, the SFWMD has recorded the amount of credits per acre earned by eligible farms within the EAA for water-years 1994 through 2012. I use this data to construct my variable

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

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

that captures the relevant economic incentive.

I also have data from water quality monitoring stations (WQMS) located around the EAA as well as other areas in Florida. I could potentially utilize that to estimate the effectiveness of the *overall* policy on aggregate TP loads though I have yet to find a compelling specification for this.

[Table 2 about here.]

Model

In this section, I attempt to model the problem faced by a farmer in the EAA after the passage of the EFA to find potential insights to my problem. There are a few deviations from reality that are worth mentioning here. First, I abstract from strategic behavior and pretend that firms behave non-strategically thus avoiding the need to solve a dynamic Markov Equilibrium solution. Since I only care about the ambient tax-subsidy component of the EFA, I model only that part and ignore BMP considerations.[8] In addition, firms are homogeneous in all aspects except for their land size. Lastly, I assume the maximum exercisable credit is constant over time which clearly contradicts the last column in Table 1.

Firms are rewarded tax credits per acre for each unit in which the basin wide abatement level is above the minimum required abatement denoted as $\underline{A}$. Here, I define abatement as

[8]The STA component of the EFA should not affect abatement decisions since water quality measures attributed to the EAA is done upstream of the STAs.

the ratio between the amount of abated effluents and the effluent level without the policy. I assume the effluent discharge function per acre $e(x_{it}, \omega_{it})$ is equal to $\omega_{it} e(x_{it})$ where $\omega_{it} \in [0, 1]$ is the firm specific stochastic term meant to represent weather variability and differs between firms due to differences in land characteristics. Think of $e(x_{it})$ as the amount of phosphorus that is sitting on farmer i's land and either all, none, or a fraction of it gets discharged. The basin wide abatement level is then

$$A_t = \frac{\sum_{j=1}^{n} w_{jt} L_j a_{jt} e(x_{it})}{E_t}$$

where $a_{it} \in [0, 1]$ is firm i's chosen abatement (as a percent) per acre and E_t is what the counterfactual effluent level would have been absent the policy.[9] Conditional on the current period's ambient quality being better than the standard, each firm i is allocated $[A_t - \underline{A}]$ per acre in tax credits. Each period, firms are charged a per acre tax equal to T_t which evolves exogenously given by column 2 of Table 1. Firms have a stock of tax credits per acre, S_{it}, which they can choose to exercise or not in each period. The amount of credits exercised per acre in period t is given by Q_{it}. The per acre benefit (farming profit) function $B(x_{it})$ is a function of only the dirty input x_{it}. The per acre abatement cost function is $c(a_{it})$ where a_{it} is the abatement level. I am implicitly assuming that the cost of abatement is additively separable from the benefit function and that everything can be written in terms of per acre which includes x_{it} and a_{it}, and L_i is total acres. Figure 2 depicts the timing of the decisions and state variable realizations.

[9]For a detailed explanation of how SFWMD calculates E_t every year, see Figure 3 in the Appendix. The calculated limit is equal to $(4/3) \times E_t$.

[Figure 2 about here.]

[Figure 3 about here.]

Thus, firms solve the following Bellman equation

$$V(S_{it}) = \max_{x_{it},a_{it},Q_{it}} \Big[B(x_{it}) - c(a_{it}) - (T_t - Q_{it}R_t)\Big]L_i + \delta\mathbb{E}\Big[V(S_{i,t+1})\Big|S_{it}\Big] \tag{1}$$

$$\begin{aligned} \text{s.t.} \quad & S_{i,t+1} = S_{it} - Q_{it} + (A_t - \underline{A})\mathbb{1}\{A_t > \underline{A}\} \\ & T_{t+1} = h(t) \\ & R_{t+1} = g(t) \\ & Q_{it} \leq \overline{Q} \end{aligned}$$

where δ is the discount factor. The choice of a dynamic model is not entirely necessary from a behavioral point of view. The problem faced by farmers could easily be framed by a static problem whereby the value from abatement is taken to be the discounted value of the expected credits earned. However, the gain from forumlating the problem dynamically is that it allows a better utilization of the panel data structure at hand and allows me to make a sharp prediction.

Prediction: Let $t = 0$ be the start of the policy and $t = \tau$ be the end of the policy for which all credits expire and no more credits are issued after τ. For all individuals i, let there exist a value k_i such that $S_{i,\tau-k_i} > (k_i + 1)\overline{Q}$. Denote the sequence of solutions for abatement decisions under the policy as $\{a^*_{it}\}_{t=0}^{\tau}$. Then, if the ambient policy was effective for i (i.e., $\{a^*_{it}\}_{t=0}^{\tau} \neq \{0\}_{t=0}^{\tau}$), then we have

$$\{a^*_{it}\}_{t=0}^{\tau} = \Big\{\{a^*_{it}\}_{t=0}^{\tau-k_i-1},\ \{0\}_{t=\tau-k_i}^{\tau}\Big\}$$

where $\{a^*_{it}\}_{t=0}^{\tau-k_i-1} \neq \{0\}_{t=0}^{\tau-k_i-1}$. The point $\tau - k_i$ is referred to as the breakpoint and the sudden change in the agent's abatement policy function is referred to as the break.

Restating the prediction intuitively, if the ambient-based policy was effective at inducing any level of abatement at any point in time, then we should see a break for the period in which the agent has more credits than she needs for the remaining duration of the policy. The proof is tedious but simple enough that I think I can get away with not providing it for now. To see the intuition for the proof, turn again to (2) and notice that if the stock of credits exceed what is needed (i.e., $S_{i,\tau-k} > k\overline{Q}$ where τ is the point in time in which afterwards all credits expire and the ambient policy terminates), then there is no incentive to further abate. This means that $a^*_{i,t} = 0$ for all $t \geq \tau - k$ and this is method I use to test this ambient-based policy's effectiveness. I calculate the predicted breakpoint for each farm and the distribution is show in Figure 4.

[Figure 4 about here.]

Another important takeaway from the model is that it illuminates what the ambient-based incentive is so that we can empirically isolate its effect on abatement and test for the existence of a breakpoint in that relationship. Equation (2) provides such insights and is arrived at by taking the first order condition from (1) with respect to a_{it}. The derivation for (2) can be found in the appendix.

$$c'(a_{it}^*) \geq \underbrace{\left(L_i \sum_{k=0}^{\tau-1-t} \mathbb{P}\Big(S_{t+k+1} < \overline{Q} \Big| S_t\Big) R_{t+k+1}\delta^{k+1} \right)}_{(i)} \underbrace{\mathbb{E}\left[\frac{\omega e(x_{i,t}^*)}{E_t} \middle| S_{i,t}, A_t > \underline{A} \right]}_{(ii)} \mathbb{P}(A_t > \underline{A}) \tag{2}$$

If we assume that the marginal abatement cost is strictly increasing in abatement levels (i.e., $c''(a_{it}) > 0$), then a_{it}^* ought to increase with land size. Equation (2) also tells us that an individual's abatement per acre decision is implicitly a function of the expected product between (i) the sum of future discounted credit values resulting from increasing A_t by one unit relative to the standard and (ii) the increase in A_t as a result of increasing a_{it} by one unit.

Notice that the (i) term, the sum of future discounted credit values resulting from increasing basin-wide abatement by one unit, has these conditional cumulative distribution terms. In principle, all future stock *levels* are unknown, but their lower bounds are somewhat past dependent meaning that if we know $S_{i,t} > (k+1)\overline{Q}$, then we know that $S_{i,t+h} > \overline{Q}$ for all $h \in [0, k]$ which implies that $\mathbb{P}(S_{i,t+h} < \overline{Q} | S_{i,t}) = 0$ for all $h \in [0, k]$. So in this sense, the expected sum of future discounted values from a marginal increase in S_{t+1}, and thus the relevant economic incentive, only captures the credit values (or rates) from periods for which we are not guaranteed a sufficient stock of credits to reach $\overline{Q}$. For values $h > k$, these conditional CDFs are no longer guaranteed to be zero.

Empirical Strategy

This section details my approach in answering how much additional TP load reduction by the ambient tax-subsidy component of the EFA? To empirically evaluate the effectiveness of the ambient-based incentive policy, I run a two-way fixed effects model with the variable of interest being D_{it} which equals the (i) term from Equation (2) but allowing $\overline{Q}$ to change over time according to column 5 of Table 1. The calculation for D_{it} is given by Equation (3). For this section, I simply replaced the conditional densities with indicator terms and ignore individual's subject probability evaluations.

$$D_{it} = L_{it} \sum_{k=0}^{\tau-1-t} \delta^{k+1} R_{t+k+1} \mathbb{1} \left\{ S_{it} < \sum_{\ell=t}^{t+k+1} \overline{Q}_{\ell} \right\} \tag{3}$$

The indicator variable in Equation (3) equals one whenever the current period stock levels for farmer i is not enough to cover a future period's maximum excercisable credit. For the purposes of exposition, I just assume that all farmers discount at the same rate of $\delta = 0.98$. However, I can just omit the discounting and measure the incentive in terms of nominal rather than present value. Equation (4) illustrates my main specification.

$$y_{it} = \gamma_i + \delta_t + X_{it}'\alpha + \beta D_{it} + \varepsilon_{it} \tag{4}$$

Where y_{it} is the rain and unit-area adjusted TP load for farm i water-year t, γ_i and δ_t are individual and time fixed effects respectively. The farm fixed effects captures differences in soil type and other time-invariant characteristics. Originally, I thought that this fixed effect can capture differences in BMP practices but, upon further investigation it seems that BMPs can and do change over time. This is why I must go back and gather such data manually to be included in X_{it}, a vector of controls which I do not completely have yet but I am in the process of gathering land use data that will vary across time and farms. I do have land size data for each farm and water-year and there is some slight variation over time in size. This is also captured in our X_{it} vector.

[Table 3 about here.]

There are three identifying assumptions that I (think I) need (though may not be a comprehensive list). First, I assume that there is no ommited variable that varies both over time and individuals and that correlates with our dose variable, D_{it}. This is clearly violated as of now and I hope to remedy this moving forward. Secondly, I assume that land size does not change endogenously either by reducing land size to reduce tax burden or by increasing land size to take advantage of economies of scale in their abatement practices. To address this second assumption, I run the same specification for various subsamples of the data subsetted based on various values of maximum land size changes calculated as $\max_{L_{it}}\{L_{it}\} - \min_{L_{it}}\{L_{it}\}$ (done separately for each i). The results from my main specification for the whole sample and the various subsamples are shown in Table 3. Column label "All" means the whole sample and column labels with "LEQ X" means it is only for observations with max land size change less than or equal to X. The "No Change" column is for the subsample for which no land size change occurred. Lastly, I assume conditional independence between the potential outcomes and the realized dosage. Borrowing the notation from the potential outcomes framework, I need the following to hold

$$\{y_{it}(D)\}_{D\in[0,\overline{D}]} \quad \perp\!\!\!\perp \quad D_{it} \quad |X_{it}$$

where D is the evaluation point for the dosage level whose support is $[0, \overline{D}]$ and D_{it} is the realized dosage value. The ambient incentive variable is based on how large the farm is and when the farm's baseline year is. So the earlier a farm's baseline year is the more credits it has accrued since it has been around longer which decreases its D_{it} term. What the CIA says then, is that the farms who are relatively larger and who implemented BMPs later should be independent to its pre-BMP loads conditional on X_{it}. And since X_{it} includes farm size and baseline year, this assumption appears to be innocuous. Still, we test whether our setting is consistent with the CIA assumption via estimation of Equation (5). The variable $y_i(0)$ is the baseline load measured before the farms were required to have implemented BMPs and before any incentive credits were issued to that specific farm. This not a perfect counterfactual outcome because the ambient incentive is forward looking and so it is not zero as long as the agent is aware of the tax credit structure of the EFA policy. However, since baseline loads are pre-BMP, even if is technically exposed to a nonzero D_{it} value, it is not clear whether they have the means to abate without implementation of any BMPs. Thus it seems that the baseline loads adequately capture pre-incentive TP loads to the extent that farmers need the adoption of BMPs to abate at all.

$$y_i(0) = b_0 + X_i' b_1 + b_2 D_{i,t} + e_i \tag{5}$$

The results from Equation (5) are shown in Table 4 which suggests that the test is somewhat consistent with our CIA assumption. I say somewhat because the this consistency in the test result changes slightly depending on how I adjust my standard errors. I think clustering on the sub-basin level, a geographical partition based on hydrological closeness, makes a lot of sense. However, it also makes sense to cluster at the baseline year level since there is likely some selection happening that determines when a farm achieves full implementation of BMPs. I am currently working on whether multiway clustering is appropriate and how to implement it in STATA. Since D_{it} changes over time, I simply use the values from the earliest sample period in my data (2001) to estimate (5). This is convenient since it is closest to the start of the policy and for most of the farms in our sample, $D_{it} = 0$ for periods after 2001.[10]

[Table 4 about here.]

I originally wanted to implement some type of structural break test where the breakpoint is allowed to be different for each farm. Despite the fact that my D_{it} term is indirectly testing the existence of breakpoints since its value is zero at and after the breakpoint, there might still be value in conducting a formal breakpoint test. I would have to reconstruct an incentive variable similar to D_{it} but it would not have zero values until after the policy end date. I would then replace D_{it} in (4) with the newly constructed incentive variable and estimate it to run my breakpoint test on. This might be a nice complement to the existing empirical approach.

[10] This is evident in Figure 4.

Concluding Thoughts

This paper attempts to measure the effect of EFA's ambient tax-subsidy on farmer's phosphorus runoff. The results suggest that the policy did not have any effect on farmer's marginal decisions to abate. However, there are many issues that are worth mentioning. First, if the results prove true, it might still be the case that the policy induced farmers to increase fixed inputs in their abatement production function. In other words, farmers could have been induced to build a bigger reservoir to treat water runoff before discharging to the Everglades as a result of the ambient tax-subsidy. Our empirical strategy here would not be able to capture such adjustments.

Secondly, if the ambient tax-subsidy had no effect at all on abatement decisions, this paper is currently not well suited to answer why. My original hypothesis is that the mandatory BMPs pushed farmers towards the right of their marginal abatement cost curves which reduce the effectiveness of any economic incentive mechanism. One possible way to address this is to see whether the entire EFA policy had an effect on basin-wide phosphorus runoff. A comparison of the averages in baseline loads and reported loads in Table 2 suggests that, on average, farmers did reduce their TP loads by a lot after both implementation of BMPs and introduction of an ambient tax-subsidy. To test this, I think synthetic controls is the way to go since I only have one treated unit (the EAA) and no clear control unit or group. If it turns out that the entire policy reduced basin-wide runoff but the ambient component failed to induce farmers to further abate, then it would be clear that the BMPs alone would have sufficed to achieve the environmental outcomes that occurred. Such an outcome would lend credence to my narrative but not quite confirm it. Any thoughts on this would be greatly appreciated.

Lastly, and quite possibly the most important is the estimation procedure. First off, for most of the farms, the breakpoint occurs in the second year of my sample period which greatly reduces the statistical power of my results. Secondly, it turns out that farms can apply for a part or their whole farm to be classified as vegetable acreage. Vegetable acreages under the EFA do not earn tax credits and are charged only the minimum per acre tax meaning those acres are not treated with the ambient tax-subsidy. I just got that data in non readable form as of February 5th, 2020 so I had no time to incorporate it into this proposal but it is on my to-do list. This revelation is promising since it means that I might be able to implement a fuzzy DiD approach however, there is a selection problem. Farms are required to apply for this vegetable acreage classification so selection into the control may be endogenous.

I hope that my results from this paper can provide crucial insights to individual abatement behavior in response to an ambient tax-subsidy policy. I might also be able to weigh in on the efficacy of mandatory BMPs which is a popular command and control policy used to address agricultural runoff problems. This would naturally lead to a discussion related to the prices versus quantities debate from Weitzman (1974) but in the context of NPSP. The prices mechanism in our case would be the ambient policy and the quantities would be the mandatory BMPs.

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Appendix

Solving For Equation (2)

Note, I drop all i subscripts for simplicity. The FOC of (1) with respect to a_{it} without assuming interior solution is

$$c'(a_t)L \geq \delta \frac{\partial \mathbb{E}[V(S_{t+1})|S_t]}{\partial a_t}$$

assuming regularity conditions so that we can push the derivative inside the expectation we get

$$c'(a_t)L \geq \delta \mathbb{E}\left[\frac{\partial V(S_{t+1})}{\partial S_{t+1}} \frac{\partial S_{t+1}}{\partial A_t} \frac{\partial A_t}{\partial a_t} \middle| S_t \right]$$

Evaluating each partial term separately:

1. $\dfrac{\partial V(S_{t+1})}{\partial S_{t+1}}$

   First, recognize that the optimal Q_t is given by $Q_t^* = \overline{Q} + (S_t - \overline{Q})\mathbb{1}\{S_t < \overline{Q}\}$ which comes from assuming that people discount enough so that they always choose to exercise credits today rather than tomorrow. This also appears to be the case in reality and I remember seeing this in one of SFWMD's reports but I will need to find that again. So we substitute Q_t^* into (1) to get

$$\frac{\partial V(S_t)}{\partial S_t} = \mathbb{1}\{S_t < \overline{Q}\}R_t L + \delta \frac{\partial \mathbb{E}[V(S_{t+1})|S_t]}{\partial S_t} = \mathbb{1}\{S_t < \overline{Q}\}R_t L + \delta \mathbb{E}\left[\frac{\partial V(S_{t+1})}{\partial S_t}\middle| S_t\right]$$

$$\begin{aligned}
\implies \frac{\partial V(S_{t+1})}{\partial S_{t+1}} &= \mathbb{1}\{S_{t+1} < \overline{Q}\}R_{t+1} L + \delta \mathbb{E}\left[\frac{\partial V(S_{t+2})}{\partial S_{t+2}}\frac{\partial S_{t+2}}{\partial S_{t+1}}\middle| S_{t+1}\right] \\
&= \mathbb{1}\{S_{t+1} < \overline{Q}\}R_{t+1} L + \delta \mathbb{E}\left[\frac{\partial V(S_{t+2})}{\partial S_{t+2}}\middle| S_{t+1}\right] \\
&\qquad\qquad\qquad\qquad\qquad\qquad (\text{since } \partial S_{t+2}/\partial S_{t+1} = 1) \\
&= \mathbb{1}\{S_{t+1} < \overline{Q}\}R_{t+1} L + \delta \mathbb{E}\left[\mathbb{1}\{S_{t+2} < \overline{Q}\}R_{t+2} L + \delta \frac{\partial \mathbb{E}[V(S_{t+3})|S_{t+2}]}{\partial S_{t+2}}\middle| S_{t+1}\right]
\end{aligned}$$

Through continual substitution and use of expectation of Bernoulli, we have that

$$\frac{\partial V(S_{t+1})}{\partial S_{t+1}} = L \sum_{k=0}^{\tau-1-t} \mathbb{P}(S_{t+k+1} < \overline{Q}|S_{t+1}) R_{t+k+1} \delta^k$$

where τ is the date of expiration for the ambient policy and thus the continuation value at time τ does not depend on credit stocks.

2. $\dfrac{\partial S_{t+1}}{\partial A_t} = \mathbb{1}\{A_t > \underline{A}\}$

3. $\dfrac{\partial A_t}{\partial a_t} = \dfrac{\omega L e(x_t)}{E_t}$

Thus we have

$$c'(a_t)L \geq \delta \mathbb{E}\left[\left(L\sum_{k=0}^{\tau-1}\mathbb{P}(S_{t+k+1} < \overline{Q}|S_{t+1})R_{t+k+1}\delta^k\right)(\mathbb{1}\{A_t > \underline{A}\})\left(\frac{\omega L e(x_t)}{E_t}\right)\middle| S_t\right]$$

$$\iff c'(a_t) \geq \mathbb{E}\left[\left(L\sum_{k=0}^{\tau-1}\mathbb{P}(S_{t+k+1} < \overline{Q}|S_{t+1})R_{t+k+1}\delta^{k+1}\right)\frac{\omega e(x_t)}{E_t}\middle| S_t, A_t > \underline{A}\right]\mathbb{P}(A_t > \underline{A})$$

$$\iff c'(a_t) \geq \left(L\sum_{k=0}^{\tau-1}\mathbb{P}(S_{t+k+1} < \overline{Q}|S_t)R_{t+k+1}\delta^{k+1}\right)\mathbb{E}\left[\frac{\omega e(x_t)}{E_t}\middle| S_t, A_t > \underline{A}\right]\mathbb{P}(A_t > \underline{A})$$

(smaller info set wins rule)

■

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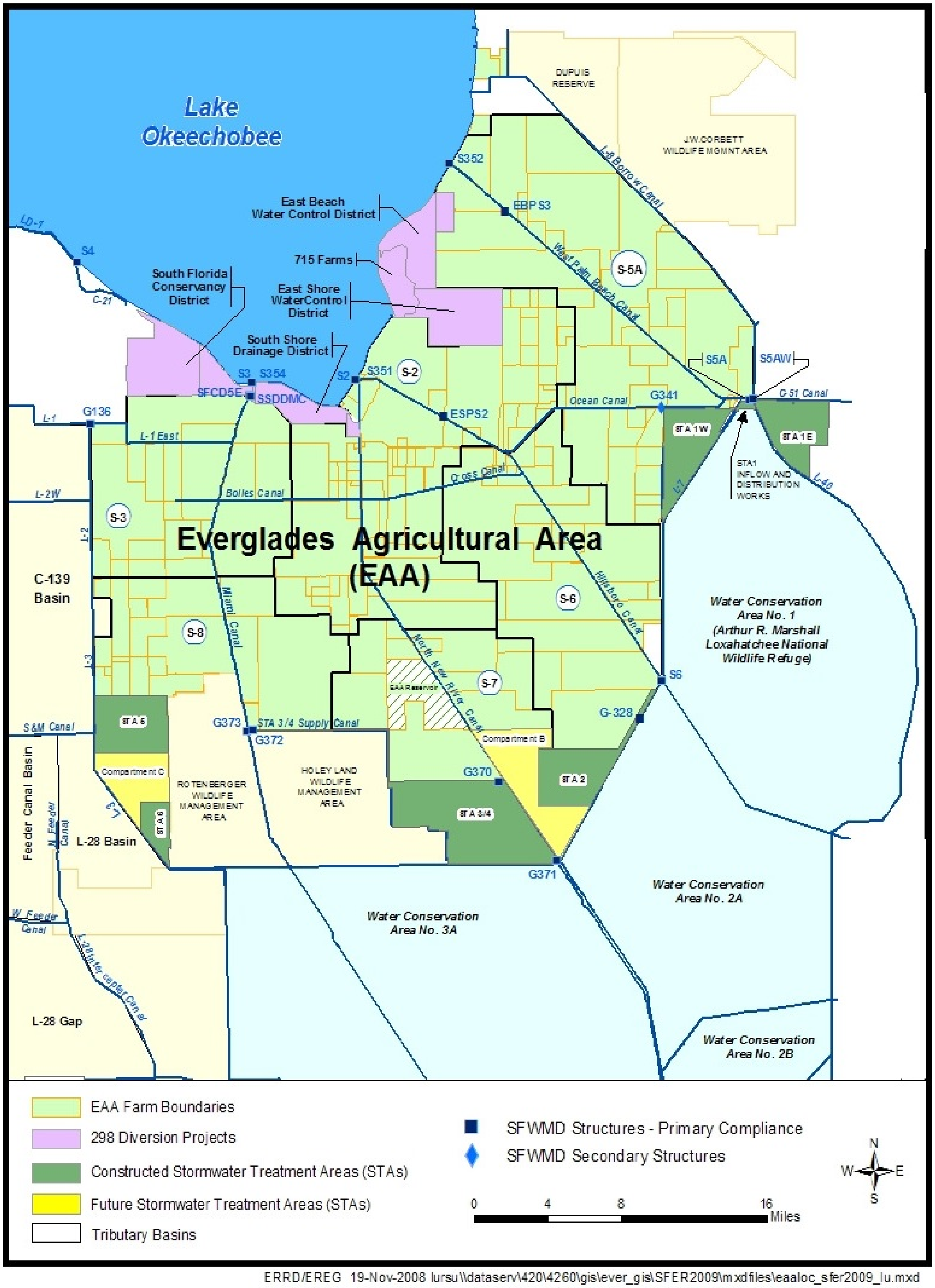


Figure 1: EAA Area with Canals/Drainages

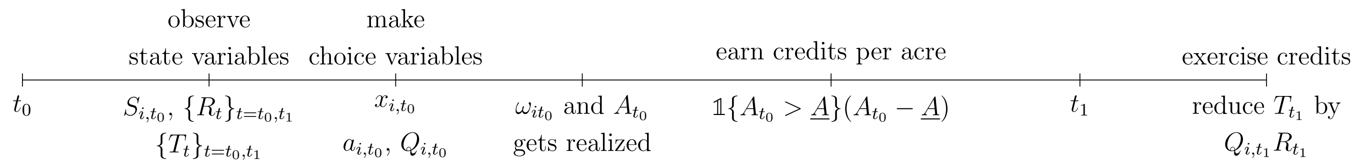


Figure 2: Timeline

Figure 3: Calculation for E_t

RULE 40E-63 EAA BASIN COMPLIANCE MODEL (from Chapter 40E-63, F.A.C.)

The target and limit must be calculated according to the following equations and explanation.

To reflect the required 25% reduction, TP loads are multiplied by 0.75 before performing the following regression:

Target = exp (-7.998 + 2.868 X + 3.020 C - 0.3355 S)

Explained Variance = 90.8%, Standard Error of Estimate = 0.183

Predictors (X, C, S) are calculated from the first three moments (m_1,m_2,m_3) of the

12 monthly rainfall totals (r_i, i=1 to 12, inches) for the current year:

m_1 = Sum [r_i] / 12

m_2 = Sum [r_i - m_1]^2 / 12

m_3 = Sum [r_i - m_1]^3 / 12

X = ln (12 m_1)

C = [(12/11) m_2] $^{0.5}$/m_1

S = (12/11) m_3 / m_2 $^{1.5}$

Limit = Target exp (1.476 SE F)

SE = standard error of predicted ln(L) for May-April interval

SE = 0.1833 [1 + 1/9 + 5.125 (X-X_m)^2 + 17.613 (C-C_m)^2 + 0.5309 (S-S_m)^2 +

8.439 (X-X_m) (C-C_m) - 1.284 (X-X_m) (S-S_m) - 3.058 (C-C_m) (S-S_m)]$^{0.5}$

F = factor to reflect variations in model standard error as a function of month (last in 12-month interval), calculated from base period.

Where:

Target = predicted load for future rainfall conditions (metric tons/year)

Limit = upper 90% confidence limit for Target (metric tons/year)

X = the natural logarithm of the 12-month total rainfall (inches)

C = coefficient of variation calculated from 12 monthly rainfall totals

S = skewness coefficient calculated from 12 monthly rainfall totals

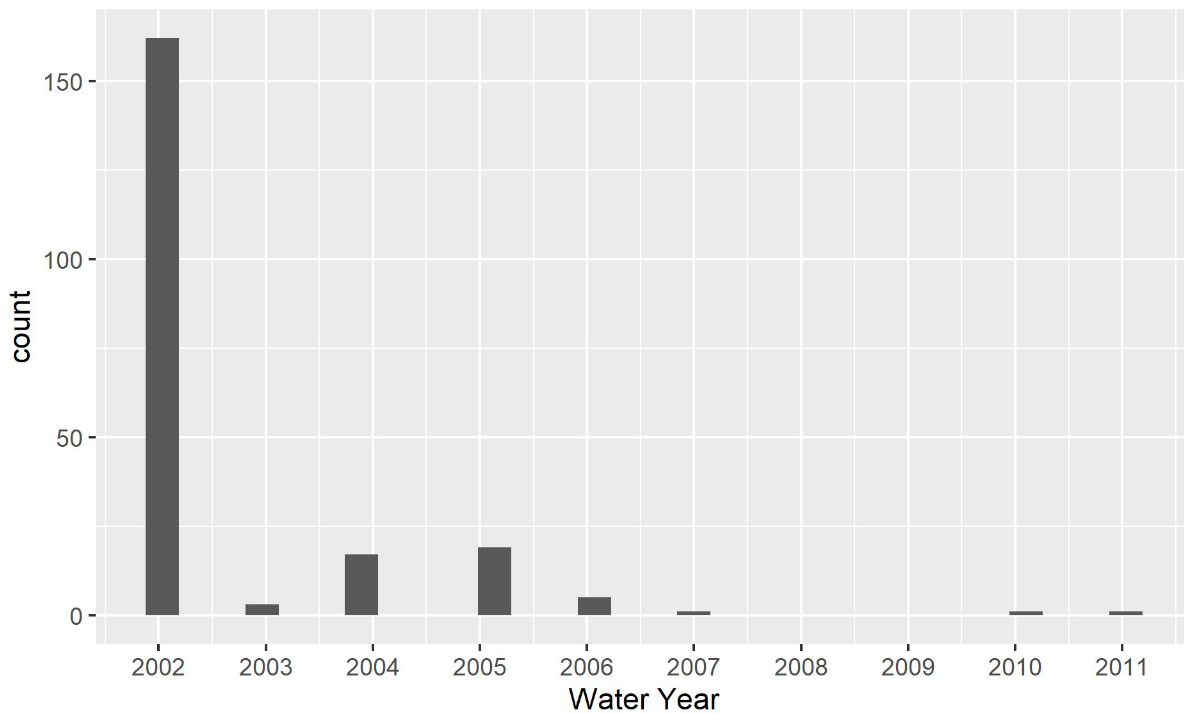
X_m = average value of the predictor in base period = 3.866

C_m = average value of the predictor in base period = 0.7205

S_m = average value of the predictor in base period = 0.7339

F = 1.0

Figure 4: Distribution of Predicted Breakpoints



List of Tables

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

Table 2: Individual Farm Data: Summary Statistics

	mean	sd	min	max	p25	p50	p75
Reported Load (lbs/acre)	0.95	1.28	0.00	22.24	0.31	0.60	1.14
% TP Reduction	17.25	349.21	-12379.00	100.00	33.00	67.00	84.00
Basin Acreage	2,533.21	3,568.92	35.00	32,535.10	453.90	1,059.60	3,434.30
Baseline TP Load (lbs/acre)	3.03	4.05	0.02	35.32	0.84	1.81	3.61
Ambient Incentive	356.08	2,097.41	0.00	45,668.00	0.00	0.00	0.00
Ambient Incentive, no L	0.16	0.57	0.00	4.38	0.00	0.00	0.00
Max Land Size Change (acres)	330.05	1,814.63	0.00	21,780.90	0.00	1.50	30.90
Baseline_Year	1,995.31	1.74	1,994.00	2,008.00	1,994.00	1,995.00	1,996.00

Table 3: Main Specification for Various Land Size Changes (acres)

	All	LEQ 1000	LEQ 100	No Change
Ambient Incentive	-0.00000140	0.00000350	0.00000296	-0.00000261
	(0.0000101)	(0.0000120)	(0.0000128)	(0.00000347)
Early Baseline (=1)	0.384	0.395	0.401	-0.338*
	(0.231)	(0.256)	(0.267)	(0.0958)
Basin Acreage	0.0000190	0.000765	0.000504	0
	(0.0000245)	(0.000862)	(0.00480)	(.)
Constant	0.336	-1.236	-0.603	1.323***
	(0.387)	(2.147)	(9.392)	(0.133)
N	3226	3035	2735	1581
Rsqr	0.428	0.425	0.414	0.431
A-Rsqr	0.384	0.382	0.369	0.382
Fstat	5.40	16.83	0.87	8.47

Standard errors in parentheses

Standard errors are clustered at the sub-basin level

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

Table 4: Placebo Test Results

	All	LEQ 1000	LEQ 100	No Change
Ambient Incentive	-0.0000444	0.00000120	-0.00000929	0.0000573
	(0.0000377)	(0.0000521)	(0.0000533)	(0.0000745)
Basin Acreage	-0.0000639	-0.000149	-0.000118	-0.000310
	(0.000116)	(0.000165)	(0.000198)	(0.000297)
Early Baseline (=1)	2.781**	2.612*	3.201*	3.223**
	(0.539)	(0.617)	(0.770)	(0.545)
Baseline_Year	0.117	0.0952	0.197	0.154
	(0.290)	(0.317)	(0.287)	(0.337)
Sub_basin	-0.457			
	(0.238)			
NA		0	0	0
		(.)	(.)	(.)
S-5A		1.434*	1.139*	0.801**
		(0.312)	(0.295)	(0.117)
S-6		0.955*	0.874	0.894
		(0.338)	(0.371)	(0.328)
S-7		-0.533	-0.427	0.215
		(0.460)	(0.471)	(0.508)
S-8		-0.880*	-0.841**	-1.070*
		(0.216)	(0.177)	(0.282)
Constant	-231.5	-190.5	-393.8	-309.2
	(579.9)	(632.9)	(573.7)	(672.7)
N	197	186	168	102
Rsqr	0.115	0.133	0.142	0.121
A-Rsqr	0.092	0.094	0.098	0.045
Fstat	.	.	.	.
df_r	4	4	4	4
bic	1118.5	1056.2	961.2	596.5

Standard errors in parentheses

Standard errors are clustered at the sub-basin level.

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