The Distributional Effects of Tighter Regulations: New Evidence from the Sugarcane Burning in Florida

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Abstract

Discriminatory environmental regulations can affect the distribution of pollution and therefore change who bears the cost of pollution. In south Florida, the discriminatory wind-based sugarcane burning regulation prohibits burning when winds are likely to direct pollution toward higher-income and more populated areas. In 2019, however, additional burn restrictions were implemented to prevent burning on low air quality days. Drawing on data from satellite-based active fire products and Aerosol Optical Depth (AOD) levels, I empirically evaluate the air quality and distributional effects of the new, more stringent 2019 burning restrictions using difference-in-differences and triple difference estimations. I find that on the restricted day, the number of daily fires in the major sugarcane growing region decreases by 41% relative to the protected zone. And the results may provide suggestive evidence that farmers strategically shift burnings to non-restricted days. As a result, on non-restricted days, the highly vulnerable communities around the sugarcane experience worse air quality. These results highlight an undiscussed implication of stringent regulation on top of the discriminatory regulation: its distributional consequences.

1 Introduction

Decades of work across many disciplines have acknowledged that low-income communities and people of color disproportionately experience pollution exposure (Banzhaf et al., 2019; Chakraborti and Shimshack, 2022; Mohai et al., 2009). Among the various proposed causes of this pattern, those that have received the most attention are income inequality, discrimination, firm costs (of inputs and regulatory compliance), and missing & inaccurate information about environmental quality (Hausman and Stolper, 2021). However, due to the sparse pollution monitoring networks, there's a lack of direct evidence of racial disparities in pollution exposure (Currie et al., 2020). In this paper, I present evidence of discriminatory wind-based burning regulations in the case of the sugarcane industry in Florida, where sugarcane production is substantial.

Burning sugarcane fields, a key component of sugarcane production, negatively affects local and downwind air quality. Many scientific studies have proposed that sugarcane fires are sources of $PM_{2.5}$ and linked to various diseases such as cardiopulmonary disease and asthma (Anenberg et al., 2010; Arbex et al., 2007; Brook et al., 2010; Cançado et al., 2006). So the nearby residents become more exposed than those outside the sugarcane-growing region. One suggested solution is to adopt smoke management or conduct a prescribed burn during recommended atmospheric conditions to mitigate the effects on the nearby community when using burning as a necessary harvesting method (Hiscox et al., 2015). However, Florida authorities have tried to regulate sugarcane burnings in ways that emphasize the protection of affluent communities by limiting the behaviors of people who live in the major sugarcane growing region.

Specifically, this study focuses on two adjacent south Florida regions: Zone 1 and Zone 4. Zone 1, the eastern region, has a higher average income, while most sugarcane production in the western, lower income Zone 4. To protect people living in Zone 1, a policy has been in place prohibiting sugarcane burning if the wind is from NNW, NW, W, SW, and SSW. People in Zone 4 do not have similar protections. While residents in Zone 4 have attempted to challenge the burning of sugarcane fields, it has yet to be effective. The sugarcane company, one of the area's major employers, insists the burning practice is safe, closely monitored, and complies with Clean Air Act standards. Stringent burning regulations implemented statewide in 2019 aim to reduce air quality impacts by prohibiting burning when the air quality is poor. These restrictions are implemented on top of the wind-based regulations that have existed for nearly 30 years. When the wind blows from the west, there will be burning restrictions in both zones, and the restrictions are different for Zone 1 and Zone 4, as shown in Figure 1. This design allows me to take advantage of the variation in sugarcane burning regulations in Florida across regions (Zone 1 versus Zone 4) and wind restrictions status (whether wind restrictions bind or not). This paper uses the policy interventions in 2019 as a natural experiment.

To test the impact of newly implemented burning regulations on burning behaviors and air quality, the empirical strategy in the paper includes both difference-in-differences (DD) and triple difference (DDD) estimations. The DD estimator compares the number of fires and air quality in a community on days with wind restrictions and days free of wind restrictions before and after the policy was implemented. The DDD estimator compares the number of fires and air quality in Zone 1 and Zone 4, before versus after Oct 1, 2019, and on restricted days versus non-restricted days. My approaches to evaluating the burning regulations allow me to answer three questions: (1) Do the new policies change the burning behaviors in Zone 4 relative to Zone 1? If so, to what extent? (2) Do the new regulations improve the air quality in Zone 4? (3) To what extent do the policy changes affect the highly vulnerable communities in Zone 1 and Zone 4?

The empirical analysis produces several interesting results. Firstly, I point out the burning authorization data from the Florida Department of Agricultural and Consumer Service are spatially aggregated at the county level and may not provide credible evidence of the effect of the policy on the authorized fires. So I reconstruct the number of observed fires via satellite imagery. Before breaking up by sugarcane burning zones, I find the number of fires decreases and the air quality improves after the policy at the aggregate level. Then by separating the two zones, I find that on the restricted day, the policy reduces the number of fires, and specifically, the number of daily fires in Zone 4 decreases by 41% relative to Zone 1. However, on the non-restricted day, the policy increases the number of fires in Zone 4 but reduces the number of fires in Zone 1 again. Therefore, the number of fires in Zone 1 decreases after the policy changes, regardless of the wind restriction status. In contrast, the policy effect in Zone 4 may imply farmers strategically shift burning to non-restricted days in response to the stringent regulations. One thing to keep in mind when interpreting the results is that I am slightly simplifying the policy by coding restriction days based on wind direction. In reality, other factors may restrict burning, but I cannot capture those considerations into the regression. In this sense, my paper gives a conservative estimate of the policy effect.

I further examine how the wind restrictions in Zone 4 affect the air quality in Zone 1 after the new policy. Consistent with a decrease in fire, the daily AOD levels decrease by 1.9% - 4.8% in Zone 1. Recall that Zone 1 is east and Zone 4 is west. Looking at the results when limiting the sample to non-harvest season, when the wind blows from the west, the air pollution from Zone 4 will be directed to and concentrated in Zone 1. In contrast, during sugarcane harvest season, wind-based regulations work when the wind blows from the west, and the pollution exposure in Zone 1 decreases. These results show the burning regulations benefit Zone 1 by restricting the burning in Zone 4.

Finally, I examine whether the change in pollution disproportionately affects highly vulnerable communities in Zone 1 and Zone 4 separately. I use CDC Social Vulnerability Index to classify whether a census tract is highly vulnerable. I find all communities in Zone 1 experience better air quality on a restricted day. And the highly vulnerable communities in Zone 1 experience a larger improvement in air quality compared to non-highly vulnerable communities. However, on the non-restricted day, I see higher pollution in Zone 4. In particular, the highly vulnerable communities experience higher pollution than the non-highly vulnerable communities. These results highlight an unintended consequence of the stringent environmental policy, that is, to redirect pollution to already highly vulnerable communities, that is, Zone 4.

This paper makes three key contributions. First, to the best of my knowledge, this is the first paper to develop plausibly causal estimates of the relationships between the 2019 burning policy changes with burning behaviors and air pollution by combing remote sensing data and administrative data. Prior work in sugarcane burning in Florida is in atmospheric science and has focused on quantifying the geographic distribution and health consequences of the sugarcane fires by using the atmospheric dispersion model and simulating emissions from fires (Nowell et al., 2018, 2022). In contrast to these authors, I use a rigorous research design to study sugarcane burning from the perspective of burning regulations. Furthermore, their work has pointed out that the smoke from sugarcane burning disproportionately impacts the lower-income and minority residents of the sugarcane growing regions due to the wind criteria. This paper complements the previous studies by finding the tighter regulations that, on top of the wind-based regulations, further reduce air pollution in affluent eastern communities by limiting the burning behaviors of residents in the main sugarcane-growing region but increase the pollution in highly vulnerable communities in the sugarcane-growing area.

Second, this paper contributes to the literature about the distributional impacts of environmental policies. By reducing the number of fires when the wind blows toward the east, these stringent regulations decrease the pollution in eastern communities. However, at the same time, the new burning regulations increase the number of fires when the wind blows toward the western region, which degrades the air quality in the highly vulnerable communities in the area of the west. These findings are consistent with the study that direct discrimination on the part of firms or government, by race or other demographic factor, could produce inequalities in pollution exposure (Mohai et al., 2009). Hernandez-Cortes (2022) studies sugarcane burning in Mexico, the world's sixth-largest sugarcane exporter, and finds that incomplete environmental regulation can increase the number of fires and pollution in disadvantaged areas. This paper finds another source of environmental justice: discriminatory wind-based regulations. In the literature on environmental justice, poor places tend to be more polluted. Environmental justice consequences of environmental policies may exacerbate or decrease the pollution in poor communities (Currie et al., 2020; Fullerton and Muehlegger, 2019; Hernandez-Cortes, 2022; Hernandez-Cortes and Meng, 2020; Holland et al., 2019). The findings here have more general implications in that the government may ask people who live in more polluted places to alter their behaviors for the sake of those who live in less polluted areas. And the less polluted places are communities with more political power. Therefore, the results suggest that policymakers should be aware that tighter uniform regulations may burden the already vulnerable communities in the context of long-time discriminatory regulations as environmental justice problems need environmental justice policies (Hernandez-Cortes and Meng, 2020).

Third, this paper joins a growing literature that exploits pollution variation from wind direction in the U.S. (Anderson, 2020; Deryugina et al., 2019; Rangel and Vogl, 2019; Schlenker and Walker, 2016). All these papers use wind direction to model the spatial dispersion of air pollution emissions. In this paper, wind direction does not simply affect air pollution dispersion but also represents a key component in sugarcane burning regulations in Florida. The wind direction data during the sugarcane harvest season and the non-harvest season enable me to provide a more convincing causal estimate of the policy effect.

The rest of the paper is laid out as follows. Section 2 presents the institutional features of Florida's sugar industry and burning regulations in Florida. Section 3 describes the data sources. Section 4 quantifies the effect of policy changes on burnings. Section 5 further demonstrates the impact of upwind restrictions on downwind air pollution. Section 6 examines whether the changes in pollution disproportionately affect highly vulnerable communities. Section 7 concludes and discusses the policy implications of the paper.

2 Background and Study Area

2.1 The big sugar companies

Florida ranks first nationally in the value of sugar produced from sugarcane, which is approximately 50% of the total U.S. value of sugar in 2021. The Florida sugar industry employs over 14,000 people, has an annual income of over 800 million, and a total economic value (from direct and indirect effects) of over $\$2$ billion (Palm Beach County Cooperative Extension, 2021). The primary sugar producers in Florida and their corporate owner sugar mills are the U.S. Sugar Corporation, Florida Crystals Corporation, and Sugarcane Growers Cooperative of Florida. The first two companies grow 65% of sugarcane, 25% sugarcane is grown by farmers belonging to the Sugarcane Growers Cooperative of Florida, and the remaining 10% is grown by independent farmers and sold to sugar mills.

Residents in the sugarcane growing region have attempted to challenge the burning, and some even launched lawsuits to stop it, but it has not been easy.[1] For starters, many feel a sense of conflict as the sugarcane company is one of the major employers in the area. Worse, the sugarcane industry insists the burning practice is safe, closely monitored, and highly regulated, and it complies with Clean Air Act standards. However, an investigation by ProPublica and The Palm Beach Post in 2021 found only one air quality monitor around the sugarcane fields, and it has been broken for eight years.[2]

2.2 Why do they burn sugarcane

Before harvest, farmers burn sugarcane crops to remove the leaves and tops of the sugarcane plant, leaving only the sugar-bearing stalk to be harvested. Every year from October through April, about 10,000 sugarcane fields of over 440,000 acres are burned around the Everglades Agricultural Area (EAA) to minimize the biomass transported to mills and

[1] See the recent report on sugarcane burning lawsuit dropped by Florida residents https://www.winknews.com/2022/02/26/sugarcane-burning-lawsuit-dropped-by-florida-residents

[2] See the investigation here https://projects.propublica.org/black-snow/

streamline the sugar extraction process (Baucum and Rice, 2009). The leaves contain virtually no sugar and are treated as trash. Burning sugarcane fields reduces the energy expenditure of the farmers, eliminates unnecessary wear of field and factory machinery, decreases the amount of material that factories process, and shortens the harvest season by 10% (Carney et al., 2000). Until an equally economically efficient way to eliminate the trash is discovered, sugarcane burning will remain a necessary harvesting method (Hiscox et al., 2015). In contrast, green harvest is accomplished using mechanical harvesters to separate the sugarcane leaves and tops from the sugar-bearing stalk without burning.

2.3 Existing burning policy in Florida

The Florida Forest Service has pioneered conservation through controlled, prescribed fires. Every pre-harvest burn requires a burn permit for each field where the burn will occur, and permits are granted only on the day of harvest. On the day that farmers want to burn, they have to contact the local Florida Forest Service office and request a burn authorization. Its approval depends on a comprehensive review of weather conditions. The Florida Forest Service (FFS) allows pre-harvest open burning between 9:00 am and one hour before sunset. During harvest season, sugarcane fields are burned in small areas - 40 acres at a time with fires lasting 15 to 20 minutes on average. The sugarcane harvest fires are tightly clustered around the south shore of Lake Okeechobee surrounding the small cities of Belle Glade, Clewiston, and Pahokee, and 10-40 km from the densely populated coastal cities of South Florida, which are home to more than 6 million people (Nowell et al., 2022).

On Oct 1, 2019, Agriculture Commissioner Nikki Fried announced the following statewide changes to the prescribed burning. First, the burn authorizations now factor in the Air Quality Index, a measure of environmental quality. Second, a state-of-the-art software system is implemented to provide better real-time information for wildfire emergency responders and more user-friendly fire maps for the public. Thirdly, the smoke plume prediction tool is updated to include the latest weather models. The new statewide safety rules about prescribed burns also have more restrictions on sugarcane burning. Firstly, a minimum 80-acre buffer is required between wildlands and burns in sugarcane fields on dry, windy days to reduce the wildfire threat. Secondly, no nighttime burns will be permitted without special approval. Thirdly, burning with fog advisories will be banned before 11:00 am on days to enhance public safety and smoke dispersion. Lastly, landowners will now have 72 hours, reduced from 96 hours, to suppress all muck fires. Overall, the burning regulations for sugarcane have become tighter, but wind-based law still exists. The 2019 rule changes do not change the geographical locations of the four burn zones but bring in the Air Quality Index and Dispersion Indices. These changes are intended to reduce the potential smoke impact on all communities (The Florida Department of Agriculture and Consumer Services, 2021).

2.4 Sugarcane burning zones

Since 1991, sugarcane burning has not been permitted when the wind blows in certain directions. The rules are written to emphasize protection for the more populated communities of eastern Palm Beach but fail to offer the same protection for western communities. Figure 1[3] shows the detailed geographic maps and rules of the burning zones in places from 1992 to 2020. Zone 1 in the east has the most restrictions, and there will be no sugarcane burning if the wind is from NNW, NW, W, SW, and SSW, while Zone 4 in the west doesn't have equal protection when the wind is projected to blow towards it. Worse, when the wind comes from NW, W, or SW and wind speed exceeds 15 miles per hour, sugarcane burning requires backing fire in Zone 4.[4]

3 Data

The central analysis links the remote sensing data and administrative data with what I know about fire types and air pollution at the census tract level from 10/2012 to 09/2021.

3.1 Fires data

I download the daily fire data from the Active Fire Product based on NASA's Visible Infrared Imaging Radiometer Suit (VIIRS) 375 m. This product records all fires starting Oct 1, 2012, detects fires in a 375m x 375m grid, and provides the centroid of the pixel with a fire event. It has hotspot detection and improved spatial resolution, showing a greater response to fires in relatively small areas. The pre-harvest burns are controlled and generally burn approximately 40 acres at a time so that one VIIRS pixel can cover around one burn. I restrict the fires from October to April to cover the entire sugarcane burning season.

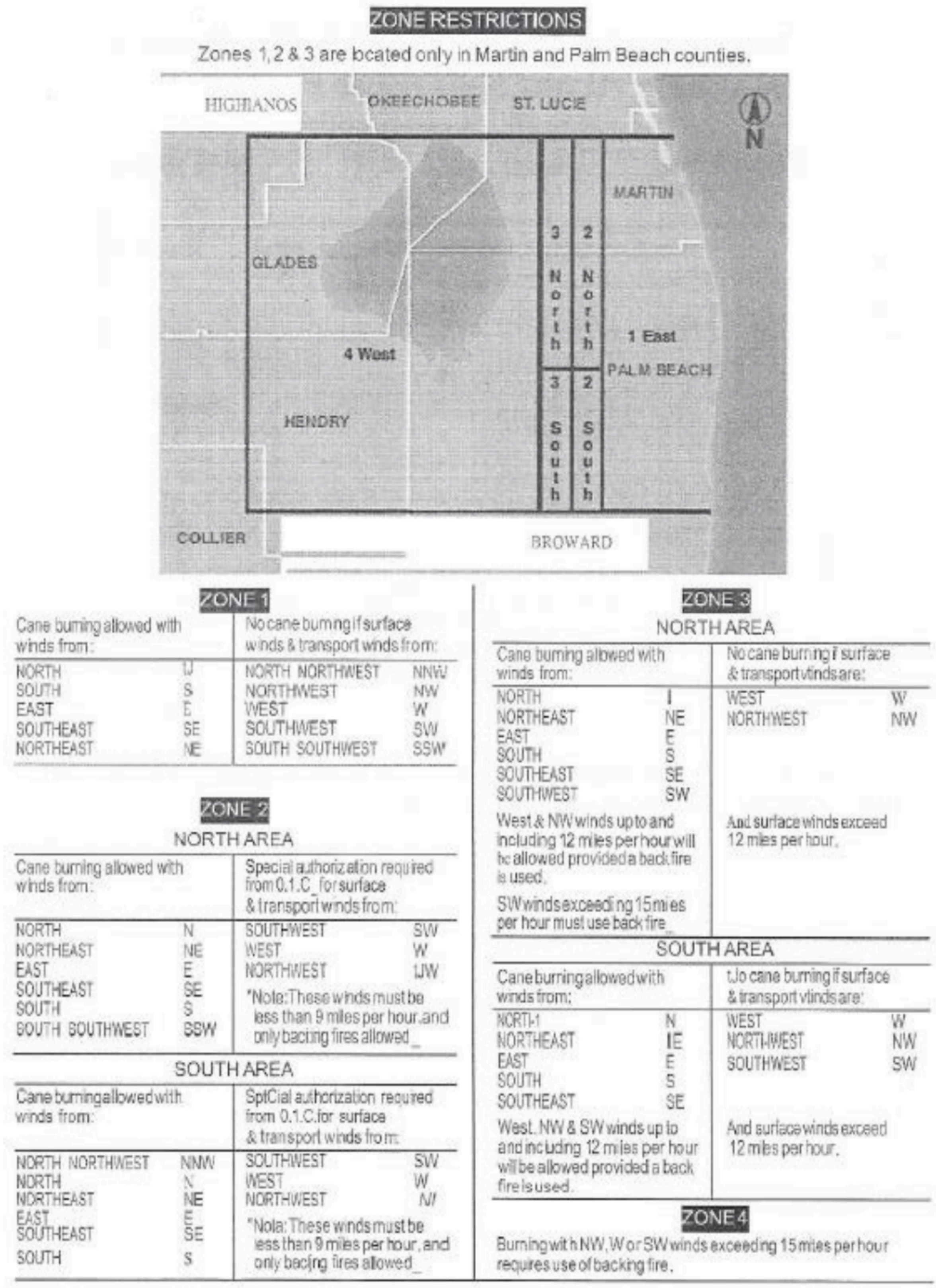
3.2 Burning authorizations summary

I scrap the daily burning authorizations summary from the Florida Forest Service Reporting System, which includes the number and total acres of authorized open burns broken down by burn type for each county in Florida starting from Jan 20, 2012. On the day people want to burn, they contact the local Florida Forest Service office and request a burn authorization. The Duty Officer will check for the location of the burn, plot the burn on a map and generate a smoke plume for the burn to ensure there are no potential problems with the smoke. Do the newly implemented stringent regulations lead to fewer authorized fires? Figure A3 shows the raw levels of the authorized fires over time before and after the first day of the policy changes. For the authorized fire data, each observation is at the county-date level (7 counties, 1910 days). There are seven counties in total, 4 are sugarcane-growing

[3]This map is from the Stop the Burn Campaign website obtained from a U.S. Sugar Handout Circa. https://drive.google.com/file/d/0B50HBF5vaoScdHJIWmtUejVOYzVjNEtoSXg4MlJudkRuV1Qw/view?resourcekey=0-CsxLYbavq4eyBh6IY1lfTQ

[4]Backing fire is a fire spreading against the wind. The flames tilt away from the fire's direction of spread.

Figure 1: The geographic map of the sugarcane burning zones during 1992-2020



Note: There're 358 census tracts in Zone 1, 2 census tracts are in Zone 2, 1 census tract is in Zone 3, and 33 census tracts are in Zone 4. The empirical analysis includes all the census tracts in Zone 1 and Zone 4.

counties, and the remaining 3 are adjacent counties in the sugarcane-burning regulation zones, as shown in Figure 1. There is no striking discontinuity in authorized fires before and after Oct 1, 2019, in Figure A3.

3.3 Sugarcane coverage data

Except for focusing on the harvest period, to identify the sugarcane fires, I use the Cropland Data Layer, which is a crop-specific land cover data layer created annually for continental States by the U.S. Department of Agriculture. It provides annual crop acreage at every 30-by-30 meter pixel in the U.S. So, I can classify sugarcane fires by identifying whether a fire event happens inside a sugarcane field.

3.4 Weather data

The permits for sugarcane burning depend on the weather conditions on the burning day, including wind direction, wind speed, and atmospheric conditions. So I obtain the daily temperature, precipitation, wind direction/speed, humidity, and visibility data from Visual Crossing Weather Data.

Visual Crossing combines multiple nearby weather reports into a single hourly report. This is done through interpolation, a powerful feature of the Visual Crossing system for locations that are not near a major reporting station or where the geography is such that it can create temperature changes in a short distance. This feature is necessary for all locations where the requested location is better served by multiple weather stations. By interpolating nearby weather station values, the resulting weather observation ensures that the Visual Crossing data will be as accurate as possible.[5] I provide the Query Builder with the TIGER census tract boundary files. Then Visual Crossing uses multiple nearby stations to interpolate more exact weather for each census tract. Finally, I have daily weather data at the census tract level from 10/2012 to 09/2021.

3.5 Pollution data

Using pollution monitor data to get a good spatial and temporal measure of pollution would be ideal. However, the monitor network could be very sparse, especially in south Florida, where there is only one air quality monitor near the sugarcane field, as shown in Figure A1. As a result, I turn to the remote sensing literature that has dealt with this problem (Gendron-Carrier et al., 2022; Gupta et al., 2006; Hernandez-Cortes, 2022; Kumar et al., 2011; Suri, 2022; Van Donkelaar et al., 2010) in which they use aerosol optical depth data (AOD) to measure air quality. And I collect information on AOD from Google Earth Engine at the 1 km grid[6] level since 2012. AOD is a quantitative estimate of the amount of aerosol present in the atmosphere and a proxy for surface PM2.5. The daily AOD data is then aggregated from the grid to the census tract. The limitation of AOD data is that the aerosols released into the atmosphere may be from anthropogenic activities and natural

[5] See more description here: https://www.visualcrossing.com/resources/documentation/weather-data/how-historical-weather-data-is-updated/

[6] This data product is a MODIS Terra, and Aqua combined Multi-angle Implementation of Atmospheric Correction (MAIAC) Land Aerosol Optical Depth (AOD) gridded Level 2 product produced daily at 1 km resolution.

events, not just sugarcane burning. So Nowell et al. (2022) simulate PM2.5 concentrations attributable to sugarcane fires using HYSPLIT atmospheric dispersion model.

3.6 Socioeconomic characteristics

To see whether highly vulnerable communities experience higher pollution levels, I use data from the Social Vulnerability Index created by the Centers for Disease Control and Prevention. Social vulnerability is a factor that affects a communitys ability to prevent human suffering and financial loss in a disaster. The index ranks the census tracts on 15 social factors, including poverty, employment, minority status, and disability, and further groups them into four related themes: Socioeconomic, Household Composition & Disability, Minority Status & Language, and Housing Type & Transportation. Then, each census tract receives a separate ranking for each of the four themes and an overall ranking. And the tract rankings are based on percentiles, and percentile ranking values range from 0 to 1, with higher values indicating greater vulnerability (Centers for Disease Control and Prevention, 2018).

Table 1 provides the summary statistics for the characteristics across sugarcane burning zones for 2012-2018, before the implementation of stringent burning regulations in 2019. The data in Table 1 show that the population size in Zone 1 is much larger than in Zone 4 based on the number of census tracts. Moreover, the data show that the sugarcane scale is larger in Zone 4 than in Zone 1. And the data further suggest that the census tracts in Zone 4 experience much more fires and sugarcane fires than Zone 1. However, there is no significant difference in the daily AOD level.[7] Based on Figure A2, most cities in the US have mean AOD < 200. In my sample, the average AOD during sugarcane harvesting season is > 200. Table 1 also shows that communities in Zone 4 are more likely to be highly vulnerable regarding all social vulnerability measures. The west wind restrictions reflect Florida's special protection towards Zone 1 rather than the communities near the sugarcane field, Zone 4. Taken together, the pollution exposure from sugarcane fires is disproportionately experienced by vulnerable communities before 2019.

4 Effects of the policy changes on burnings

The previous wind-based regulations still exist even with the newly changed burning rules. This raises the question: to what extent would the current burning rules change the burning behaviors of people in the sugarcane-growing regions? Due to the lack of the reported fire data at smaller spatial units,[8] it is crucial to see how farmers respond

[7] High AOD values indicate a relatively hazy atmosphere, while low values of AOD indicate a relatively clear atmosphere.

[8] I requested the burning authorizations from the Florida Department of Agriculture and Consumer Services on Feb 25, 2022. These administrative data include the day of the burn, the longitude and latitude of the location, and the total acres of authorized open burns for sugarcane. The request was forwarded to the Directors Office for final review and approval.

Table 1: Summary statistics

	(1) Zone4	(2) Zone1	(3) Difference
Number of census tracts	33	358	
Acreage of sugarcane	205,077	3613	201,464***
	(18837)	(2852)	(0.000)
Share of sugarcane area in	0.302	0.064	0.238***
total area of agriculture	(0.031)	(0.053)	(0.000)
Daily total fires	0.181	0.001	0.190***
	(1.208)	(0.127)	(0.000)
Daily sugarcane fires	0.067	0.00003	0.067***
	(0.584)	(0.007)	(0.000)
Daily AOD level	205.067	206.183	-1.116
	(122.171)	(114.312)	(0.091)
SV overall ranking	0.747	0.409	0.338***
	(0.275)	(0.304)	(0.000)
SV Socioeconomic ranking	0.802	0.395	0.407***
	(0.191)	(0.297)	(0.000)
SV Household Composition &	0.663	0.422	0.241***
Disability ranking	(0.228)	(0.243)	(0.000)
SV Minority Status &	0.627	0.489	0.138***
Language ranking	(0.305)	(0.279)	(0.000)
SV Housing Type &	0.684	0.433	0.251***
Transportation ranking	(0.315)	(0.296)	(0.000)

Notes: This table reports the mean of variables in pretreatment periods (2012-2018). For columns 1 and 2, standard deviations are in brackets. For column 3, the p-value for the t-test of equal means of two groups is in parentheses. Gendron-Carrier et al. (2022) report the nominal scale of AOD reported by MODIS is 0-5,000, and they rescale to 0-5 for legibility, as is common in the literature. In the table, AOD is not rescaled. The last five rows are the mean of the CDC Social Vulnerability Index for the four themes and its overall position in 2018. The rankings are based on percentiles and range from 0 to 1, with higher values indicating greater vulnerability. *** p<0.01; ** p<0.05; * p<0.10

to the stringent regulations by looking at the number of observed fires based on satellite data. To answer this question, I use both difference-in-differences (DD) and differences-in-differences-in-differences (DDD) estimations.

Before breaking out by sugarcane burning zones, I use a DD estimation to analyze the average effect of policy changes at the aggregate level. The estimation equation is:

$$\begin{aligned} Y_{idmt} = \alpha_0 + \alpha_1 \times WindRestrict_{id} + \alpha_2 \times Post_{id} + \alpha_3 \times Post_{id} \times WindRestrict_{id} \\ + \lambda W_{id} + \gamma_i + \rho_{im} + \mu_t + \epsilon_{idm} \end{aligned} \tag{1}$$

Here, i references census tract, d denotes date, m indicates month, and t represents year. The sugarcane harvest season lasts from October to April each year. The variable Y_{idmt} is the number of daily observed total fires in census tract i on date d during the harvest season. $WindRestrict_{id}$ is a dummy equal to 1 if the daily wind direction in census tract i is in the following range: NNW, NW, W, SW, or SSW. In my data, wind direction indicates the direction from where the wind is blowing and is in degrees from the North. The value ranges from 0 degrees (from the North) to 90 degrees (from the East), 180 degrees (from the South), and 270 degrees (from the West) back to 360 degrees. I define $WindRestrict_{id} = 1$ if the wind direction is in the range of [202.5, 337.5] so that it covers the entire range of wind direction restrictions.[9] $Post_{id}$ is a dummy equal to 1, indicating the days after Oct 1, 2019. In the main results, the standard errors are clustered at the census tract level to account for serial correlation. I also try alternative levels of clustering: census by month and census by month by year, with similar conclusions.

Since the permits for sugarcane burning and the measured pollution are also affected by weather conditions, it is essential to include weather controls. The matrix of weather controls, W_{id}, includes daily temperature, precipitation, wind speed, humidity, and visibility in the census tract. The vector γ_i contains census tract fixed effects to control for any time-invariant characteristics in a census tract. The vector ρ_m are month-of-year fixed effects, and μ_t are year-fixed effects to control for seasonality in harvesting activities. α_3 shows the difference-in-difference estimate of the average impact of policy changes on the number of observed fires before breaking out by sugarcane burning zones.

Table 2 reports the results. Columns (1)-(3) imply an approximate 29%-35% decrease in the daily observed total fires on average after the policy and when the wind restrictions occur. Furthermore, I try to classify sugarcane fires by identifying whether a fire event inside a sugarcane field as defined by linking Cropland Data Layer with fire data. However, a scientific study shows that satellites have a hard time detecting sugarcane fires in the Southeast U.S. region due to their small size (40 acres at a time) and short duration (30-60 minutes usually) (Nowell et al., 2018). There are many measurement errors in sugarcane fires, so it is not surprising to see the effect of policy effect is attenuating and not significant for sugarcane fires in Table A1.[10] Recall that more than 50% of the authorized fires are sugarcane fires in my sample from October to April, as shown in Figure A3. Moreover, the wind-based burning regulations target sugarcane burning only. Hence, the policy effects on the number of total fires can provide signals for sugarcane fires. At the same time, the sign of the Wind Restriction dummy suggests that the current wind-based regulations reduce the number of fires and corresponding AOD levels. Columns (4)-(6) imply a slightly 3.3% to 6.4% decrease in AOD levels on average associated with the 2019 policy changes. The improvement in air quality reconciles with the result that the number of fires decreases. In summary, before breaking out into sugarcane burning zones, the finding is consistent with the goal of the policy changes in 2019, which is to add restrictions on burning and improve the air quality overall. One might worry about the spillovers across certain types of days within zones or the spillovers within certain types of days across zones, driving the results above. So the following steps address this concern from the two aspects.

The first attempt is to analyze whether they are pre-trends in the number of observed fires specific to wind restriction days relative to non-restricted days within Zone 1 or Zone 4. So I estimate the following equation for each Zone separately.

[9] The WindRestrict dummy is defined in a way that represents the full restriction but is not intended to model the placebo effects because the wind directions are highly correlated across nearby regions.

[10] The results for sugarcane fires are available upon request.

Table 2: Policy effect on fires and AOD levels (DD) at the aggregate level

	(1) TF	(2) TF	(3) TF	(4) logAOD	(5) logAOD	(6) logAOD
Wind Restriction	-0.002	-0.001	-0.001	-0.087***	-0.087***	-0.079***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Post	0.002	0.002	-0.006*	-0.045***	0.044***	0.223***
	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)	(0.007)
Wind Restriction x Post	-0.006**	-0.006**	-0.005**	-0.064***	-0.033***	-0.045***
	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
Adj. R^2	0.094	0.094	0.094	0.322	0.364	0.371
Pre dep mean	0.017	0.017	0.017	5.152	5.152	5.152
Census FE	✓	✓	✓	✓	✓	✓
Month FE		✓	✓		✓	✓
Year FE			✓			✓

Notes: TF denotes the number of daily observed total fires. The entries in columns (1) to (3) in Table 2 are coefficient estimates from the DD estimator in equation (1), where the dependent variable is the number of daily observed total fires in each census tract x day x year. The number of observed fires is reconstructed by combining Satellite remote sensing data (VIIRS 375m and Cropland Data Layer) and census tract boundaries. Columns (4) to (6) are coefficient estimates from the DD estimator in equation (1), where the dependent variables are daily AOD levels, measured in log. The regression includes detailed weather controls: daily temperature, precipitation, wind speed, wind gust, humidity, and visibility. Additional controls are listed at the bottom of Table 2. The number of observations is 599, 697 in columns (1)-(3) and 345,058 in columns (4)-(6). Standard errors, clustered at the census tract level, are in parentheses. *** p<0.01; ** p<0.05; * p<0.10

$$\begin{aligned} Y_{idmt} = \tau_0 + \tau_1 \times WindRestrict_{id} + \sum_{t=2012}^{2020} \tau_{2t} Year_t \\ + \sum_{t=2012}^{2020} \tau_{3t} \times Year_t \times WindRestrict_{id} \\ + \lambda W_{id} + \gamma_i + \rho_m + \epsilon_{idm} \end{aligned} \tag{2}$$

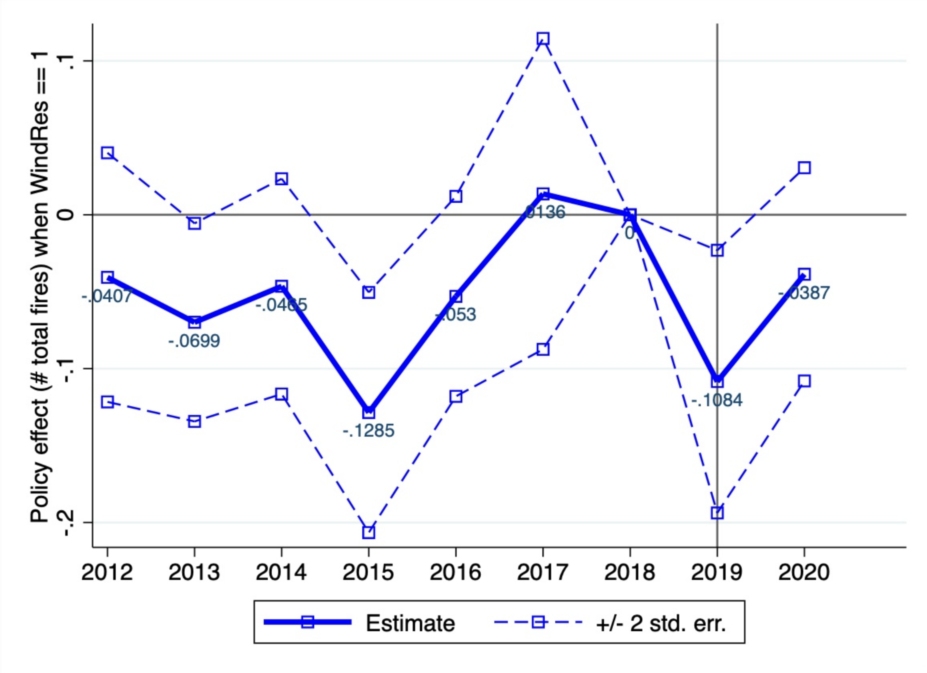
Where $Year_t$ include a set of year dummies for the years 2012-2020, the coefficients $\tau_{3t}s$ are plotted in event study style figures to assess whether there are pre-policy trends in fire count that are specific to Zone 4 or Zone 1 after adjustment for census tract unobservable characteristics and seasonality in monthly harvesting activities.

Figure A4 suggests no pre-trend in the daily observed total fires in Zone 4/Zone 1 on days with wind restrictions relative to days without wind restrictions. At the same time, it shows the heterogenous treatment effects across Zones. The results for static DD estimations are in Table A2.

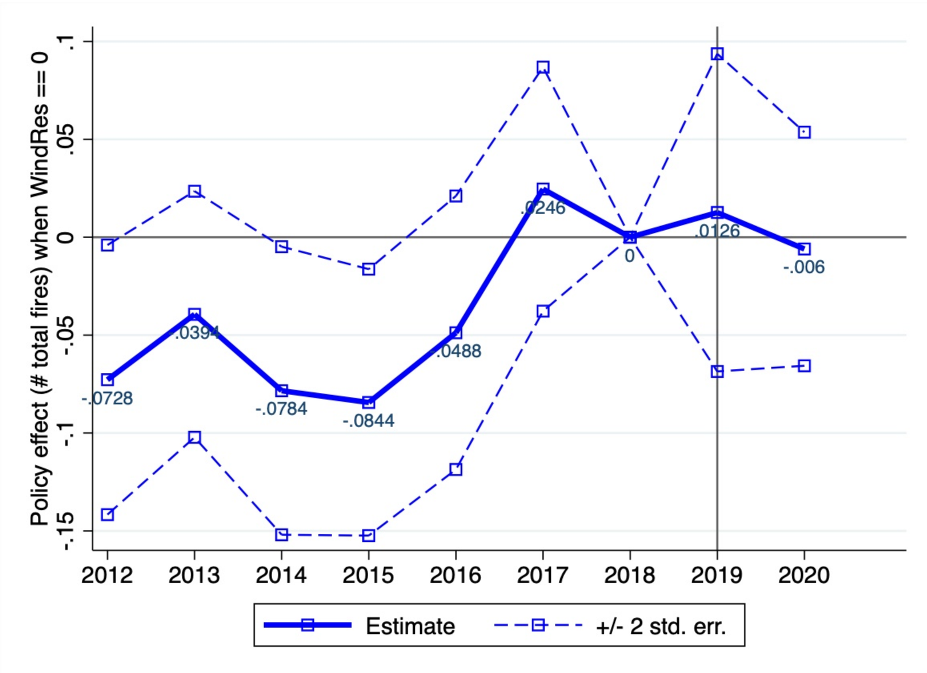
The second attempt is to see the trend of fire on days with wind restrictions or days without wind restrictions across Zones by specifying the DD regression for each wind restriction status separately:

$$\begin{aligned} Y_{idmt} = \eta_0 + \sum_{t=2012}^{2020} \eta_{1t} \times Year_t + \sum_{t=2012}^{2020} \eta_{2t} \times Zone4 \times Year_t \\ + \lambda W_{id} + \gamma_i + \rho_m + \epsilon_{idm} \end{aligned} \tag{3}$$

Where $Year_t$ includes a set of year dummies for 2012-2020, again, $\eta_{2t}s$ are plotted in the event study plot for days with wind restrictions and days without wind restrictions, respectively.



(a) Event study for the number of total fires with wind restrictions, 2012-2020



(b) Event study for the number of total fires without wind restrictions, 2012-2020

Figure 2: DD dynamic policy effect on # observed fires by wind restriction status

Notes: The estimates in Figure 2 are from the event study regressions for daily reconstructed fire counts (measured in the count and observed at census tract x day x year) in equation (3) where the estimates for the year 2018 are restricted to have a value of 0. The regression includes detailed weather controls, census tract fixed effects, and month-of-year fixed effects. The standard errors underlying the confidence intervals (dashed lines) are clustered at the census tract level. The p-value of the F-test for testing the joint significance of the pre-trend coefficients is 0.0191 in panel (a) and 0.2581 in panel (b).

At first glance, there is a pre-trend in the number of observed total fires regardless of the wind restriction status. However, the number of observed total fires on days with wind restrictions and days without wind restrictions trend similarly upward before introducing policy changes based on Figure 2.

In summary, the parallel trend may hold in the DD specification in equation (2) but not hold in the DD specification in equation (3). Thus, a DD that compares the outcomes on days with wind restrictions or days without wind restrictions across Zone 4 and Zone 1 may be compromised. But a similar uptrend in the number of observed fires motivates the DDD design. DDD controls the potential time-varying confounders that develop differently across Zone 1 and Zone 4. The DDD estimator exploits three sources of variation. First, it compares the outcome before and after October 1, 2019. Florida Forest Service initiated these changes statewide in Oct 2019. Second, 358 census tracts are in Zone 1, which has the most protection when the wind is projected to blow toward them, and 33 are in Zone 4, which has the least protection. Third, the wind-based burning regulation will take effect when the wind blows from specific west-related directions. So the DDD specification can address the previous concerns about spillovers within a certain type of day across Zones.

I next specify the DDD regression as follows.

$$\begin{aligned} Y_{idmt} = &\beta_0 + \beta_1 WindResdtrict_{id} + \beta_2 \times Post_{id} \\ &+ \beta_3 WindRestrict_{id} \times Post_{id} + \beta_4 WindRestrict_{id} \times Zone4_i \\ &+ \beta_5 Zone4_i \times Post_{id} + \beta_6 WindRestrict_{id} \times Zone4_i \times Post_{id} \\ &+ \lambda W_{id} + \gamma_i + \rho_m + \mu_t + \epsilon_{idm} \end{aligned} \tag{4}$$

The notations are the same as before. The variable Y_{idmt} is the number of observed total fires in census tract i on date d. $Post_{id}$ is a dummy equal to 1, indicating the days after the policy change on Oct 1, 2019. $WindRestrict_{id} = 1$ if the wind direction is in [202.5, 337.5], covering the entire range from SSW to NNW. W_{id} are weather controls. The vector γ_i contains census tract fixed effects to control for any time-invariant characteristics in a census tract. μ_t are year fixed effects and ρ_m are month-of-year fixed effects controlling for seasonality in harvesting activities. All regressions use a balanced panel of census tract-day-year. In the main results, the standard errors are clustered at the census tract level to account for serial correlation.

The parameter of interest is β_6 associated with the triple interaction term, which captures the variation in outcomes specific to Zone 4, relative to Zone 1, on days when the wind restrictions take place, relative to no wind restrictions, on days after policy changes, relative to before its initiation and represents the average effect of policy changes on daily observed fires.

To have a causal interpretation, the triple difference estimator requires the assumption that Zone 1 and Zone 4 exhibit similar outcome trends in the absence of the 2019 policy changes. To test the validity of the common trend assumption, the separate measures of the policy's effects in each year provide additional information. Hence, I also report the parameters $\gamma_{6t}s$ from the following model in the event study style graph in Figure 3:

$$
\begin{aligned}
Y_{idmt} &= \gamma_0 + \gamma_1 WindRestrict_{id} + \sum_{t=2012}^{2020} \gamma_{2t} \times Year_t \\
&+ \sum_{t=2012}^{2020} \gamma_{3t} WindRestrict_{id} \times Year_t + \gamma_4 WindRestrict_{id} \times Zone4_i \\
&+ \sum_{t=2012}^{2020} \gamma_{5t} Zone4_i \times Year_t + \sum_{t=2012}^{2020} \gamma_{6t} WindRestrict_{id} \times Zone4_i \times Year_t \\
&+ \lambda W_{id} + \gamma_i + \rho_m + \epsilon_{idm}
\end{aligned} \tag{5}
$$

Where $Year_t$ includes a set of year dummies for 2012-2020. To be consistent with the definition of $Post_{id}$, $Year$ is redefined as the following: if the month is from Oct to Dec, Year is just the actual year associated with date d; if the month is between Jan to April, Year is the exact year related to the date d minus 1.

Figure 3 shows an event study graph measuring the difference between the daily number of observed total fires in Zone 4 and Zone 1 on days with wind restrictions and without wind restrictions separately by year, with the year 2018 normalized to take the value zero. Based on Figure 3, the coefficients for the interaction term between $Year_t$, $WindRestrict$, and $Zone4$ before the year 2019 are not statistically significant, which indicates a lack of pre-trends, and may suggest parallel trends hold. So, Figure 3 supports the validity of DDD estimation.

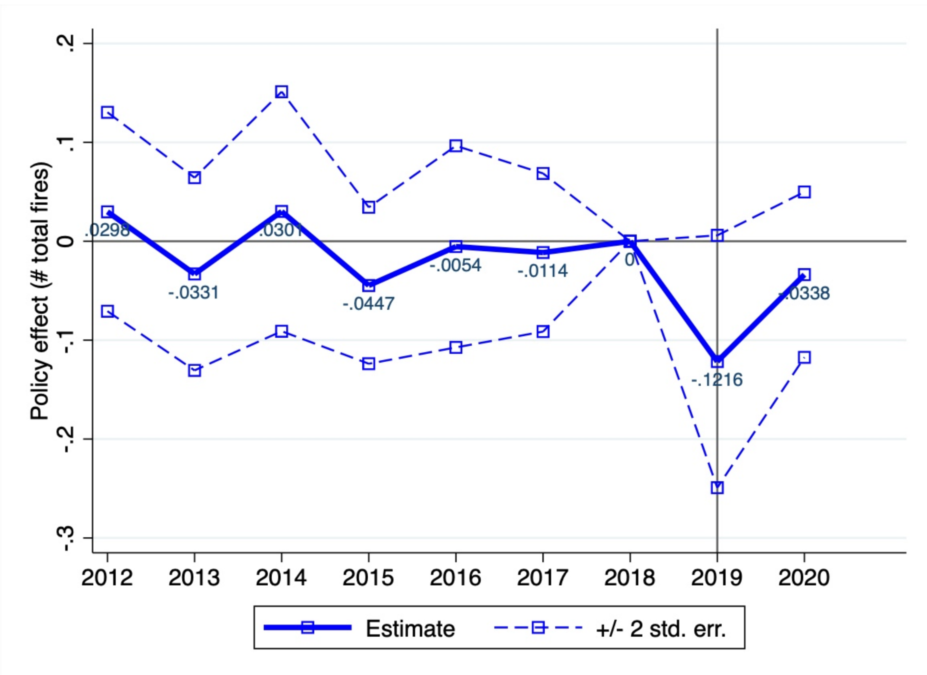


Figure 3: DDD dynamic policy effect on # total fires

Notes: The estimates in Figure 3 are from the event study regressions for the daily total number of fires (measured in the count and observed at census tract x day x year) in equation (5) where the estimates for the year 2018 are restricted to have a value of 0. The regression includes detailed weather controls, census tract fixed effects, and month-of-year fixed effects. The standard errors underlying the confidence intervals (dashed lines) are clustered at the census tract level. The p-value of the F-test for testing the joint significance of the pre-trend coefficients is 0.3475, which indicates a lack of pre-trend.

Table 3 reports the results from estimating Equation (4). In Columns (1)-(3), I find the policy decreases the number of daily observed total fires by around 0.075 in Zone 4 on

Table 3: Impact of policy change on daily observed fires and AOD levels (DDD)

	(1) TF	(2) TF	(3) TF	(4) logAOD	(5) logAOD	(6) logAOD
Wind Restriction	-5.4**	-4.3**	-4.1*	-70.5***	-68.2***	-60.4***
	(2.4)	(2.2)	(2.1)	(4.2)	(4.4)	(4.3)
Post	-3.9***	-3.6**	-13.1***	-57.6***	56.7***	246.0***
	(1.3)	(1.4)	(4.2)	(6.6)	(4.1)	(7.7)
Wind Restriction x Post	0.01	0.05	0.26	-65.1***	-36.6***	-49.6***
	(0.57)	(0.63)	(0.71)	(4.4)	(4.4)	(4.5)
Wind Restriction x Zone4	39.6***	39.3***	39.2***	-166.0***	-175.0***	-175.0***
	(12.0)	(12.0)	(12.0)	(12.1)	(12.0)	(12.1)
Zone4 x Post	44.6**	43.7**	44.9**	56.4***	-66.7***	-90.8***
	(21.4)	(21.5)	(21.6)	(9.8)	(7.9)	(8.6)
Wind Restriction x Zone4 x Post	-75.0**	-75.1**	-75.1**	38.2**	23.9	24.2
	(31.6)	(31.6)	(31.6)	(17.3)	(16.3)	(16.6)
Adj. R^2	0.094	0.094	0.095	0.324	0.365	0.372
Pre dep mean (Zone4)	0.181	0.181	0.181	5.109	5.109	5.109
Census FE	✓	✓	✓	✓	✓	✓
Month FE		✓	✓		✓	✓
Year FE			✓			✓

Notes: TF denotes the number of daily observed total fires. The coefficient estimates in all entries are multiplied by 1000 for readability. The entries in Table 3 are coefficient estimates from the DDD estimator in equation (4), where the dependent variables are the number of daily observed total fires and daily AOD levels in each census tract x day x year. The regression includes detailed weather controls: daily temperature, precipitation, wind speed, wind gust, humidity, and visibility. Additional controls are listed at the bottom of Table 3. The number of observations is 599, 697 in columns (1)-(3) and 345,058 in columns (4)-(6). Standard errors, clustered at the census tract level, are in parentheses. *** p<0.01; ** p<0.05; * p<0.10

average on days with wind restrictions relative to Zone 1, which translates into a decrease of 41% decrease in daily observed total fires in Zone 4. Furthermore, Figure 4 points out that the effect of the policy is more prominent in 2019. Given that there are only two years after the policy changes and the COVID-19 pandemic started in 2020, it is hard to justify why the policy effect was more negligible in 2020. Interestingly, the number of fires in Zone 4 decreases on restricted days but increases on non-restricted days. This may imply that farmers strategically shift burnings to non-restricted days in response to the daily regulation. In contrast, the number of fires in Zone 1 decreases regardless of the wind restrictions status. Taken together, the findings suggest that the newly changed regulations add further restrictions to the historically wind-based regulations and do not give additional protection to Zone 4 when the wind is projected to blow toward it. Moreover, the results are consistent with the findings that sugarcane smoke was preferentially directed toward smaller and less affluent inland communities due to the wind-based burning regulations (Nowell et al., 2022). Fires do not move, but pollution is the consequence of fires. In Columns (4)-(6) of Table 3, I do not see a significant additional effect of policy on air quality in Zone 4. However, the negative sign of Wind Restriction x Post indicates the policy changes further reduce AOD levels on top of wind restrictions in Zone 1, which translate into a 3.66% - 6.51% decrease in AOD levels. Table A3 shows the results of the falsification test where I restrict the sample of fires to the months outside of the sugarcane harvest season (May-September) from 2013 to 2021. There is no significant difference in the number of total fires/AOD levels outside the sugarcane harvest season for Zone 4 relative to Zone 1 after the policy changes.

One thing to keep in mind when interpreting the results is that I am slightly simplifying the policy by coding restriction days when wind direction comes from SSW to NNW. The wind restriction is just one of the criteria of the permit to burn, and it is easier to measure. However, the newly implemented burning rules factor in Air Quality Index (AQI), publicly available maps, and smoke plume prediction tools before authorizing the burnings. There are two concerns here. It can be the case that when I code the wind restriction as 1, the modeling or AQI shows the air quality is fine, so that day is not restricted. Or it can be the case when I code the wind restriction as 0 while other factors prohibit the burning. And I am not able to capture those considerations in the regression. So the results here only speak to one mechanism - wind restriction, which may understate the effect of the policy.

5 Effects of the policy changes on the downwind pollution

The wind-based sugarcane burning regulations aim to minimize pollution exposure for the populated communities in the east rather than reducing the air pollution where the fires occur. So another question comes: how do the wind restrictions in Zone 4 affect the air quality in Zone 1 after the policy changes since air pollution is the downwind consequence of the fires? To answer this question, I first calculate the proportion of census tracts in Zone 4 that have wind restrictions on each day, that is, $\frac{\sum_{i \in Zone4} WindRestrict_{id}}{33}$ where 33 is the number of census tracts in Zone 4. Then I estimate the following equation:

$$
\begin{aligned}
Y_{idmt}^{Zone1} = {} & \delta_0 + \delta_1 \times \overline{WR_d^{Zone4}} + \delta_2 \times Post_{id} + \delta_3 \times Post_{id} \times \overline{WR_d^{Zone4}} \\
& + \lambda W_{id} + \gamma_i + \rho_m + \mu_t + \epsilon_{idm}
\end{aligned} \tag{6}
$$

where Y_{idm}^{Zone1} is the daily AOD level in census tract i in Zone1 on date d in month m. $\overline{WR_d^{Zone4}}$ is the proportion of census tract in Zone4 that have wind restrictions on date d.[11] $Post_{id}$ is a dummy equal to 1, indicating the days after the policy change on Oct 1, 2019. W_{id} are weather controls. The vector γ_i contains census tract fixed effects to control for any time-invariant characteristics in a census tract. μ_t are year fixed effects and ρ_m are month-of-year fixed effects controlling for seasonality in harvesting activities.

The parameter of interest is δ_3, which describes the marginal effect of policy changes on the daily AOD levels in Zone 1. Table 4 shows the results. The results show that the daily AOD level decreases by 1.9% to 4.8% in Zone 1 after Oct 2019 relative to the baseline. Interestingly, the coefficients for $\overline{WR_d^{Zone4}}$ are negative and significant, which indicates that when there are wind restrictions in Zone 4, the average AOD level in Zone 1 is lower than the baseline. However, the new policy could also be causing an increase in pollution levels on no-restricted days due to farmers' potential strategic shifting of the burning in Zone 4, which would be a negative SUTVA violation.

[11] The equation doesn't include the wind direction in census tract i because it's highly correlated with the $\overline{WR_d^{Zone4}}$.

Table 4: DD policy effect on downwind pollution

	(1)	(2)	(3)
	logAOD	logAOD	logAOD
Post	-0.062***	0.043***	0.235***
	[0.007]	[0.004]	[0.007]
$\overline{WR_d^{Zone4}}$	-0.085***	-0.097***	-0.083***
	[0.003]	[0.003]	[0.003]
$\overline{WR_d^{Zone4}} \times Post$	-0.048***	-0.019***	-0.042***
	[0.006]	[0.006]	[0.006]
N	311,718	311,718	311,718
Adj. R^2	0.309	0.349	0.357
Census FE	✓	✓	✓
Month FE		✓	✓
Year FE			✓

Notes: The entries in Table 4 are coefficient estimates from the DD estimator in equation (6), where the dependent variable is the number of daily AOD levels in each census tract x day x year measured in log in Zone 1. The regression includes detailed weather controls: daily temperature, precipitation, wind speed, wind gust, humidity, and visibility. Standard errors, clustered at the census tract level, are in parentheses. *** p<0.01; ** p<0.05; * p<0.10

To address the concern about negative SUTVA, I need to refer to some institutional knowledge. Sugarcane deteriorates at a quick rate, just like other perishable crops. The sugarcane must be processed into sugar in mills before trading and storing it. And the unreasonable delays in cane transportation from the fields to the mill are frequently linked to several problems related to sucrose losses (Misra et al., 2022). Given the present milling capacity in south Florida, a full five months (October to March) are required to process approximately 400,000 acres planted to sugarcane. Some sugarcane must be harvested before achieving maximum sucrose levels to sustain early-season (OctoberNovember) milling operations (Sandhu et al., 2019). So each cane field is tied into an integrated harvesting schedule. If a sugarcane field does not get a burn permit approved on the day it is scheduled to be harvested, it is green-harvested so that the overall harvesting schedule is not interrupted (Ferguson, 2022).[12] The informal institutional knowledge may lessen the concerns of strategic shifting. Even if farmers can time shift the burning based on the wind direction, the complex rules of the new regulations, the capacity of mills, and the integrated harvesting schedule make strategic time shifting less possible. At the same time, Table A4 shows the results of the falsification test where I restrict the sample to the months outside the sugarcane harvest season (May-September). The signs of the coefficients for Post in Table A4 and Table 4 may indicate that the air quality in Zone 1 is trending downward.

If there is no wind restriction on sugarcane burning, the air pollution from upwind sugarcane burning will concentrate in the downwind of Zone 4, which is Zone 1. Table A4 shows a slight reduction in the downwind AOD level after the policy. And the coefficients for $\overline{WR_d^{Zone4}}$ are positive and significant, which reflects the physical relationship between wind and downwind air pollution concentrations. The findings in this section provide ev-

[12] Patrick Ferguson is leading Stop Sugar Field Burning Campaign for the Sierra Club. He learned this from conversations with farmers and former employees of the sugarcane industry. Moreover, he mentioned that the sugar industry does not share such internal documents publicly.

idence that the 2019 stringent burning policy further reduces pollution downwind during the sugarcane harvesting season. Moreover, the results here complement the recent findings that $PM_{2.5}$ from sugarcane fires dropped abruptly to the east and more slowly to the west and south because Forest Forest Service denies burning permit requests under brisk westerly winds (Nowell et al., 2022).

6 Distributional effects of the stringent regulations

Analyzing the distributional effects of the uniform tighter regulations in the context of the discriminatory wind-based regulations is important because the residents near the sugarcane fields are more likely to be people of low income and color. I classify vulnerable communities by using the CDC vulnerability index. Specifically, a community is highly vulnerable if its overall ranking is higher than the 90 percentile. In Zone 4, 19 out of 33 (58%) census tracts are highly vulnerable. In contrast, 35 out of 358 (10%) census tracts are highly vulnerable in Zone 1.

Section 5 shows that the air quality in Zone 1 further increases due to the stringent burning regulations. To see whether the highly vulnerable communities in Zone 1 have lower pollution after the policy change, I estimate equation (6) again for highly vulnerable communities and non-highly vulnerable communities separately. Table 5 shows the results and implies that all communities in Zone 1 experience a 1.7% to 6.9% decrease in daily AOD level after the policy changes, given that there are wind restrictions in Zone 4. By comparing the coefficients of $\overline{WR_d^{Zone4}} \times Post$ from columns (1)-(3) to columns (4)-(6), it seems that the highly vulnerable communities confront a larger improvement in air quality compared to the non-highly vulnerable communities in Zone 1.

Table 5: Distributional effects in Zone 1

	Highly vulnerable			Non-highly vulnerable		
	(1)	(2)	(3)	(4)	(5)	(6)
	logAOD	logAOD	logAOD	logAOD	logAOD	logAOD
Post	-0.062***	0.051***	0.207***	-0.062***	0.042***	0.239***
	(0.021)	(0.013)	(0.023)	(0.007)	(0.004)	(0.007)
$\overline{WR_d^{Zone4}}$	0.072***	-0.084***	-0.066***	-0.087***	-0.099***	-0.085***
	(0.013)	(0.013)	(0.013)	(0.003)	(0.003)	(0.003)
$\overline{WR_d^{Zone4}} \times Post$	-0.069***	-0.040**	-0.066***	-0.046***	-0.017***	-0.039***
	(0.017)	(0.017)	(0.017)	(0.006)	(0.006)	(0.006)
N	30,944	30,944	30,944	280,744	280,744	280,744
Adj. R^2	0.316	0.348	0.356	0.308	0.349	0.358
Census FE	✓	✓	✓	✓	✓	✓
Month FE		✓	✓		✓	✓
Year FE			✓			✓

Notes: The entries in Table 5 are coefficient estimates from the DD estimator in equation (6). For columns (1)-(3), the dependent variable is the daily AOD levels measured in log in the highly vulnerable census tracts in Zone 1. In columns (4)-(6), the outcome is the daily AOD measured in log in the non-highly vulnerable census tracts in Zone 1. The regression includes detailed weather controls: daily temperature, precipitation, wind speed, wind gust, humidity, and visibility. Standard errors, clustered at the census tract level, are in parentheses. *** p<0.01; ** p<0.05; * p<0.10

What's the policy effect on air quality in Zone 4 on non-restricted days? Section 4 shows the unintended consequence of the new policy is that the policy increased the number of fires in Zone 4 on no-restricted days. Firstly, I estimate the following equation (7) to see whether the communities in Zone 4 experience worse air quality on non-restricted days.

$$
\begin{aligned}
Y_{idmt}^{Zone4} = {} & \varphi_0 + \varphi_1 \times \overline{NWR_d^{Zone4}} + \varphi_2 \times Post_{id} + \varphi_3 \times Post_{id} \times \overline{NWR_d^{Zone4}} \\
& + \lambda W_{id} + \gamma_i + \rho_m + \mu_t + \epsilon_{idm}
\end{aligned}
\tag{7}
$$

where Y_{idmt}^{Zone4} is the daily AOD level in the census tract i in Zone 4 on date d in month m. $\overline{NWR_d^{Zone4}} = 1 - \frac{\sum_{i \in Zone4} WindRestrict_{id}}{33}$, so $\overline{NWR_d^{Zone4}}$ is the proportion of census tract in Zone 4 that do not have wind restrictions on date d. $Post_d$ is a dummy variable equal to 1, indicating the days after the policy change on Oct 1, 2019. The coefficient of interest is φ_3, which indicates whether Zone 4 has experienced higher pollution on non-restricted days due to the tighter burning regulations.

Table 6 shows the results and suggests that when the wind is projected to blow towards Zone 4, there is a 4% to 7% increase in the daily AOD levels in Zone 4. Table A5 shows the results of the falsification test where I restrict the sample to the months outside the sugarcane harvest season (May-September). Table A5 shows that the air quality improves on non-restricted days.

Table 6: DD policy effect on pollution in Zone 4

	(1) logAOD	(2) logAOD	(3) logAOD
Post	-0.025*	-0.114***	0.129***
	(0.013)	(0.024)	(0.030)
$\overline{NWR_d^{Zone4}}$	0.205***	0.205***	0.189***
	(0.014)	(0.015)	(0.014)
$\overline{NWR_d^{Zone4}} \times Post$	0.040**	0.056***	0.070***
	(0.017)	(0.018)	(0.018)
N	33,340	33,340	33,340
Adj. R^2	0.442	0.524	0.536
Census FE	✓	✓	✓
Month FE		✓	✓
Year FE			✓

Notes: The entries in Table 6 are coefficient estimates from the DD estimator in equation (7), where the dependent variable is the daily AOD levels in each census tract x day x year measured in log in Zone 4. The regression includes detailed weather controls: daily temperature, precipitation, wind speed, wind gust, humidity, and visibility. Standard errors, clustered at the census tract level, are in parentheses. *** p<0.01; ** p<0.05; * p<0.10

To see whether the highly vulnerable communities in Zone 4 experience higher pollution, I estimate equation (7) again for highly vulnerable and non-highly communities separately. Table 7 shows the results and suggests that when the wind is projected to blow towards Zone 4, there is a 4.4% to 7.4% increase in the daily AOD levels in highly vulnerable communities in Zone 4. At the same time, there is a 3.5% to 6.0% increase in the daily AOD levels in non-highly vulnerable communities in Zone 4, and the effects are smaller. Comparing the results in columns (1)-(3) in Table 6 and columns (1)-(3) in Table 7, it seems that the effect of policy on air quality in Zone 4 is slightly smaller than the effect in the highly vulnerable communities in Zone 4. More than 50% of communities in Zone 4 are highly vulnerable and concentrated around the sugarcane field. At the same time, more than 75% of the days during harvest season have no wind restrictions. The results here imply that the uniform tighter regulations in 2019 may further increase the environmental inequality in Zone 4.

Table 7: Distributional effects in Zone 4

	Highly vulnerable			Non-highly vulnerable		
	(1)	(2)	(3)	(4)	(5)	(6)
	logAOD	logAOD	logAOD	logAOD	logAOD	logAOD
Post	-0.034*	-0.133***	0.117***	-0.007	-0.081**	0.144**
	(0.019)	(0.031)	(0.038)	(0.016)	(0.036)	(0.049)
$\overline{NWR_d^{Zone4}}$	0.197***	0.194***	0.181***	0.216***	0.218***	0.199***
	(0.018)	(0.019)	(0.019)	(0.022)	(0.023)	(0.021)
$\overline{NWR_d^{Zone4}} \times Post$	0.044*	0.064**	0.074**	0.035	0.043	0.060**
	(0.024)	(0.026)	(0.027)	(0.022)	(0.024)	(0.024)
N	19,164	19,164	19,164	14,176	14,176	14,176
Adj. R^2	0.439	0.518	0.531	0.450	0.537	0.547
Census FE	✓	✓	✓	✓	✓	✓
Month FE		✓	✓		✓	✓
Year FE			✓			✓

Notes: The entries in Table 7 are coefficient estimates from the DD estimator in equation (7). For columns (1)-(3), the dependent variable is the daily AOD levels in the non-highly vulnerable census tracts in Zone 4. In columns (4)-(6), the outcome is the daily AOD in the non-highly vulnerable census tracts in Zone 4. The outcome is measured in log and observed at the census tract x day x year. The regression includes detailed weather controls: daily temperature, precipitation, wind speed, wind gust, humidity, and visibility. Standard errors, clustered at the census tract level, are in parentheses. *** p<0.01; ** p<0.05; * p<0.10

7 Discussion

What are the impacts of the stringent burning regulations in Florida's sugarcane harvesting season? First, although there is no evidence that the number of authorized fires in the sugarcane growing regions decreases, there is a 41% decrease in the number of observed fires on average in Zone 4 relative to Zone 1 on restricted days. On the no-restricted day, the policy increases the number of fires in Zone 4 but reduces the number of fires in Zone 1 again. As a result, the air quality in Zone 1 improves due to limiting the burning in Zone 4. Finally, the paper points out the unintended consequence of the policy, that is, on the non-restricted day, the highly vulnerable communities in Zone 4 experience worse air quality. The results may be helpful for the ongoing policy debates about the newly-changed burning regulations to reduce pollution from sugarcane burning in South Florida.

The key concern in the paper is the strategic shifting of fires from restriction days to non-restriction days. Based on the informal interview, complex rules of authorizing burning, and the capacity of the sugar mills, it is reasonable to assume there is no strategic time shifting of fires. The results imply that tighter uniform regulations can help improve air quality, given that discriminatory wind-based regulations have existed for decades. However, they are not free. Policymakers wishing to reduce air pollution in populated regions face two challenges: the demographic characteristics of people living around the sugarcane field and the economic efficiency of burning sugarcane. Where does the pollution from sugarcane burning go? Either west or east. The newly changed burning regulations seem to be endogenous. To improve the air quality in downwind regions, they limit the burning in the upwind areas to protect people downwind. At the same time, they burden people who live near the sugarcane when the downwind people do not expose to pollution from fires. Reducing the number of fires improves the air quality in sugarcane-growing regions. Who bears the cost? East side or west side? The ability of farmers to burn sugarcane is a significant economic factor for the survival of the individual farmer and the sugarcane industry. Although the paper points out specific positive effects of stringent burning regulations, the sugarcane growing region bears the cost of the improvements in air quality.

The welfare impacts of the policy are unclear. In sum, the policy changes are at least a good start and raise people's attention toward pollution from sugarcane burning. These regulations reduce pollution in rich places by limiting the behaviors in low-income areas. However, to deal with equity, environmental regulations should incorporate the environmental justice component and consider the winners and losers.

Appendix A: Supplementary figures and tables

Table A1: Impact of policy change on daily sugarcane fires (DD)

	(1)	(2)	(3)
	SF	SF	SF
Wind Restriction	0.001**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)
Post	0.0004	-0.0004	-0.0016
	(0.0016)	(0.0010)	(0.0012)
Wind Restriction x Post	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)
Adj. R^2	0.195	0.195	0.195
Pre dep mean	0.006	0.006	0.006
Census FE	✓	✓	✓
Month FE		✓	✓
Year FE			✓

Notes: SF represents the number of daily observed sugarcane fires. The entries in columns (1) to (3) in Table A1 are coefficient estimates from the DD estimator in equation (1), where the dependent variable is the number of daily observed sugarcane fires in each census tract x day x year. The number of observed sugarcane fires is reconstructed by combining remote sensing data (VIIRS 375m and Cropland Data Layer) and census tract boundaries. The regression includes detailed weather controls: daily temperature, precipitation, wind speed, wind gust, humidity, and visibility. The number of observations is 599,697. Standard errors, clustered at the census tract level, are in parentheses. *** $p<0.01$; ** $p<0.05$; * $p<0.10$

Table A2: Impact of policy changes on daily observed fires separate by Zones (DD)

	Zone 1			Zone 4		
	(1)	(2)	(3)	(4)	(5)	(6)
	TF	TF	TF	TF	TF	TF
Wind Restriction	-0.519	-0.411	-0.476	1.880	10.400	5.860
	(0.358)	(0.341)	(0.358)	(16.2)	(14.8)	(16.2)
Post	-0.882	-0.580	-0.422	61.7**	54.4**	-49.5*
	(0.660)	(0.598)	(1.13)	(26.7)	(25.3)	(27.5)
Wind Restriction x Post	-0.331	-0.535	-0.567	-53.8*	-50.0*	-44.4
	(0.512)	(0.492)	(0.512)	(27.6)	(26.6)	(26.6)
N	553,678	553,678	553,678	46,019	46,019	46,019
Adj. R^2	0.005	0.005	0.005	0.094	0.094	0.095
Pre dep mean	0.001	0.001	0.001	0.017	0.017	0.017
Census FE	✓	✓	✓	✓	✓	✓
Month FE		✓	✓		✓	✓
Year FE			✓			✓

Notes: TF denotes the number of daily observed total fires. The entries in columns (1) to (6) in Table A2 are coefficient estimates from the static DD estimator in equation (2), where the dependent variable is the number of daily observed total fires in each census tract x day x year in Zone 1/Zone 4. The coefficient estimates are multiplied by 1000 for readability. The regression includes detailed weather controls: daily temperature, precipitation, wind speed, wind gust, humidity, and visibility. Standard errors, clustered at the census tract level, are in parentheses. *** $p<0.01$; ** $p<0.05$; * $p<0.10$

There's only one air quality monitor near the sugarcane field.

Table A3: Falsification tests(DDD) during non-harvest season

	(1) TF	(2) TF	(3) logAOD	(4) logAOD
Wind Restriction	-0.861	-0.341	4.48	11.0***
	(0.658)	(0.918)	(4.11)	(4.12)
Post	-1.06	-1.38*	5.75*	0.512
	(0.715)	(0.787)	(3.22)	(3.27)
Wind Restriction x Post	2.02***	1.54***	52.9***	59.2***
	(0.755)	(0.516)	(7.86)	(8.01)
Wind Restriction x Zone4	3.34	2.85	-54.1***	-59.3***
	(9.25)	(9.43)	(15.7)	(15.8)
Zone4 x Post	36.7	36.8	-68.5***	-64.7***
	(28.2)	(28.2)	(10.5)	(10.4)
Wind Restriction x Zone4 x Post	-41.0	-41.2	24.5	5.80
	(47.4)	(47.5)	(21.3)	(21.6)
N	438,724	438,724	229,680	229,680
Adj. R^2	0.017	0.017	0.187	0.198
Pre dep mean	0.005	0.005	5.561	5.561
Pre dep mean (Zone4)	0.044	0.044	5.589	5.589
Census FE	✓	✓	✓	✓
Month FE		✓		✓

Notes: TF denotes the number of daily observed total fires. The coefficient estimates in all entries are multiplied by 1000 for readability. The entries in Table A3 are coefficient estimates from the DDD estimator in equation (4), restricting the sample to the months outside of the harvesting season. The regression includes detailed weather controls: daily temperature, precipitation, wind speed, wind gust, humidity, and visibility. Standard errors, clustered at the census tract level, are in parentheses. *** p<0.01; ** p<0.05; * p<0.10

Table A4: Falsification tests(DD) during non-harvest season in Zone 1

	(1) logAOD	(2) logAOD
Post	0.014***	0.010***
	(0.003)	(0.003)
$\overline{WR_d^{Zone4}}$	0.056***	0.063***
	(0.004)	(0.004)
$\overline{WR_d^{Zone4}} \times Post$	-0.010	-0.019**
	(0.008)	(0.008)
N	207,071	207,071
Adj. R^2	0.176	0.186
Census FE	✓	✓
Month FE		✓

Notes: The coefficient estimates are multiplied by 1000 for readability. The entries in Table A4 are coefficient estimates from the DD estimator in equation (6), where the dependent variable is daily AOD levels in each census tract x day x year in Zone 1, restricting the sample to the months outside of the harvesting season. The regression includes detailed weather controls: daily temperature, precipitation, wind speed, wind gust, humidity, and visibility. Standard errors, clustered at the census tract level, are in parentheses. *** p<0.01; ** p<0.05; * p<0.10

Table A5: Falsification tests(DD) during non-harvest season in Zone 4

	(1)	(2)
	logAOD	logAOD
Post	0.068***	0.039**
	(0.017)	(0.019)
$\overline{NWR_d^{Zone4}}$	0.024	0.015
	(0.019)	(0.020)
$\overline{NWR_d^{Zone4}} \times Post$	-0.128***	-0.096***
	(0.022)	(0.022)
N	22,609	22,609
Adj. R^2	0.299	0.320
Census FE	✓	✓
Month FE		✓

Notes: The entries in Table A5 are coefficient estimates from the DD estimator in equation (7), where the dependent variable is daily AOD levels in each census tract x day x year in Zone 4 restricting the sample to be the months outside of the harvesting season. The regression includes detailed weather controls: daily temperature, precipitation, wind speed, wind gust, humidity, and visibility. Standard errors, clustered at the census tract level, are in parentheses. *** p<0.01; ** p<0.05; * p<0.10

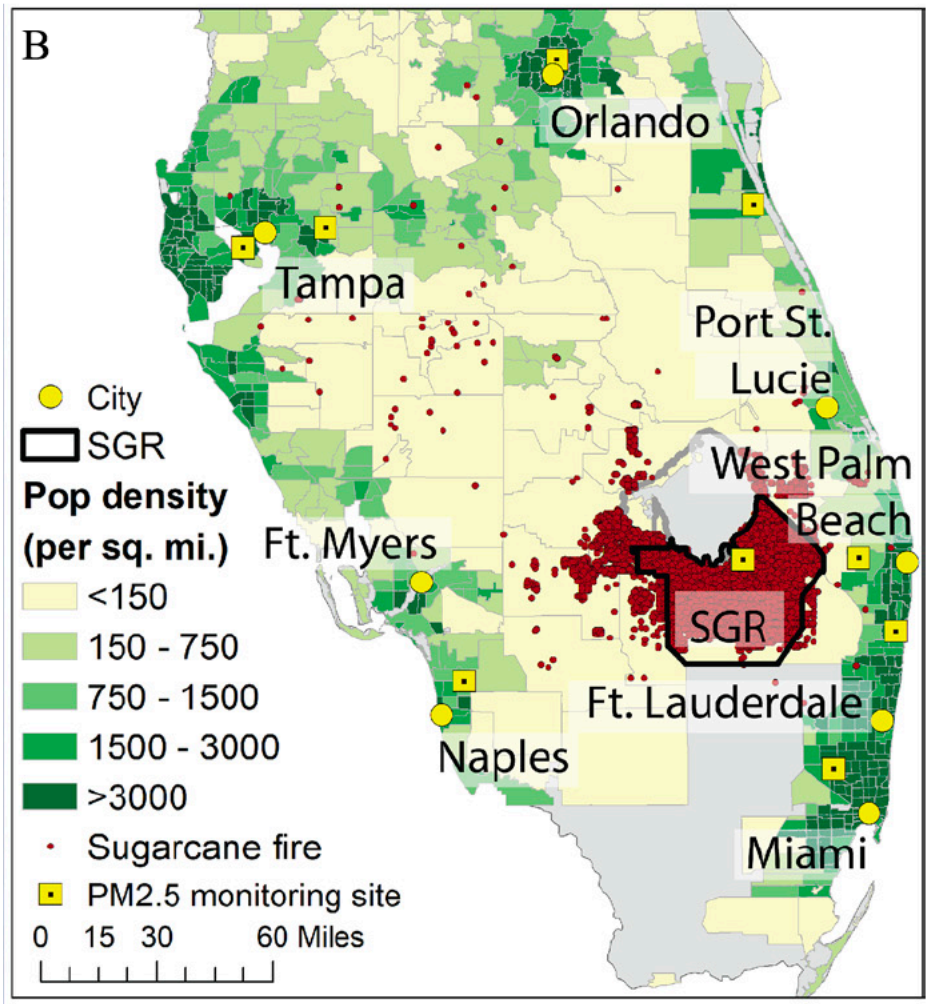


Figure A1: Locations of sugarcane fires and major cities

Notes: Locations of sugarcane fires and major cities (yellow circles). The sugarcane-growing region (SGR) is shown in black, and colors show population density by Zip code. The U.S. EPA monitoring sites are indicated by yellow boxes with dots in the center (Nowell et al., 2022).

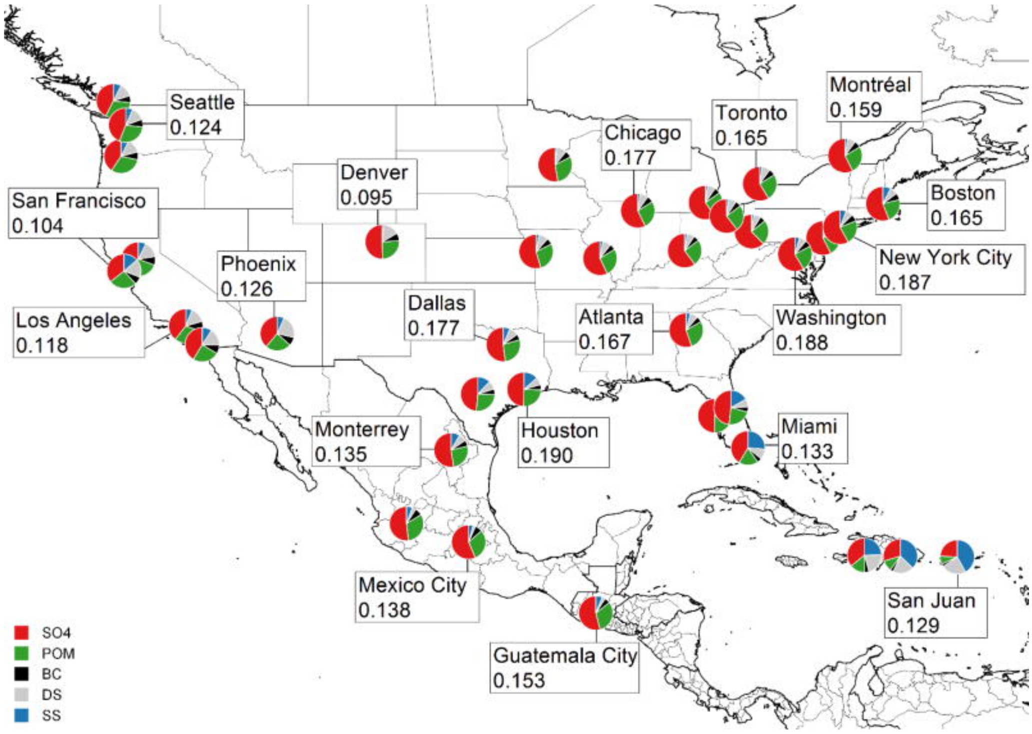
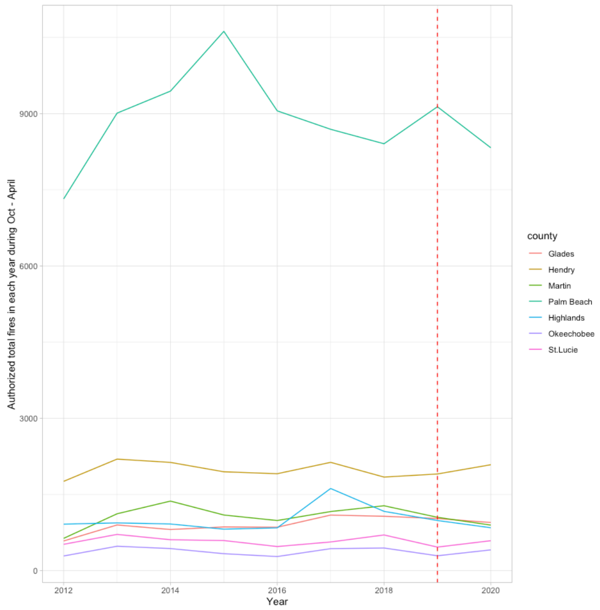


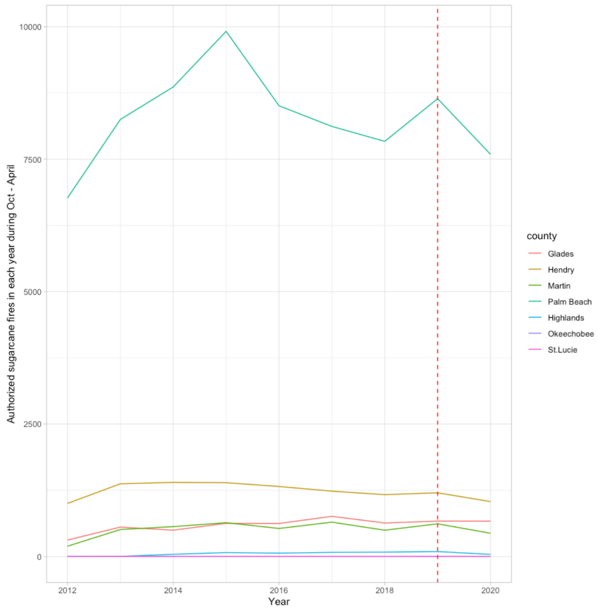
Figure A2: Mean AOD is provided for a few cities

Notes: The proportions of aerosol species to total AOD for a selection of major cities in North and Central America are shown in this figure Provençal et al. (2017).

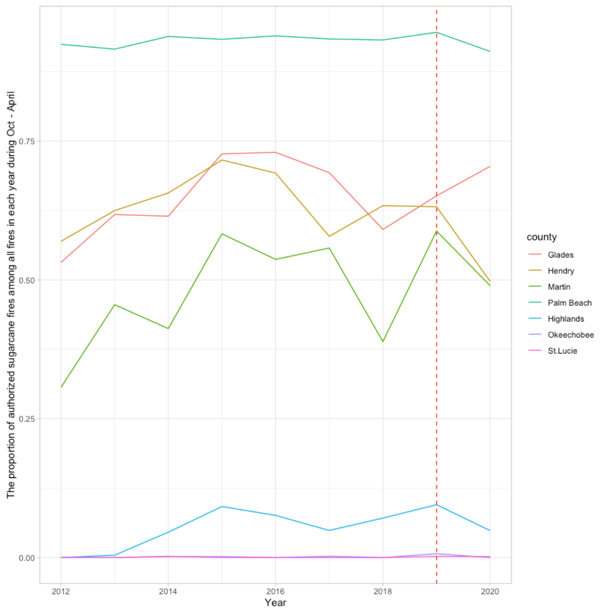
Provençal et al. (2017) point out the highest urban AOD values are observed in Central and Eastern United States and Canada, ranging from 0.133 in Miami to 0.190 in Houston. The Northeastern United States is highly populated and industrialized, which explains the higher AOD values in Philadelphia (0.190), Cincinnati (0.189), Washington (0.188), New York City (0.187), Pittsburgh (0.184), Cleveland (0.181) and St. Louis (0.180).



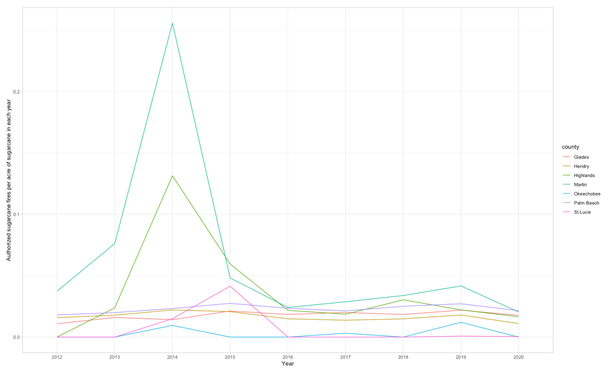
(a) total authorized fires by year



(b) total authorized sugar fires by year



(c) proportion of sugar fires to all fires

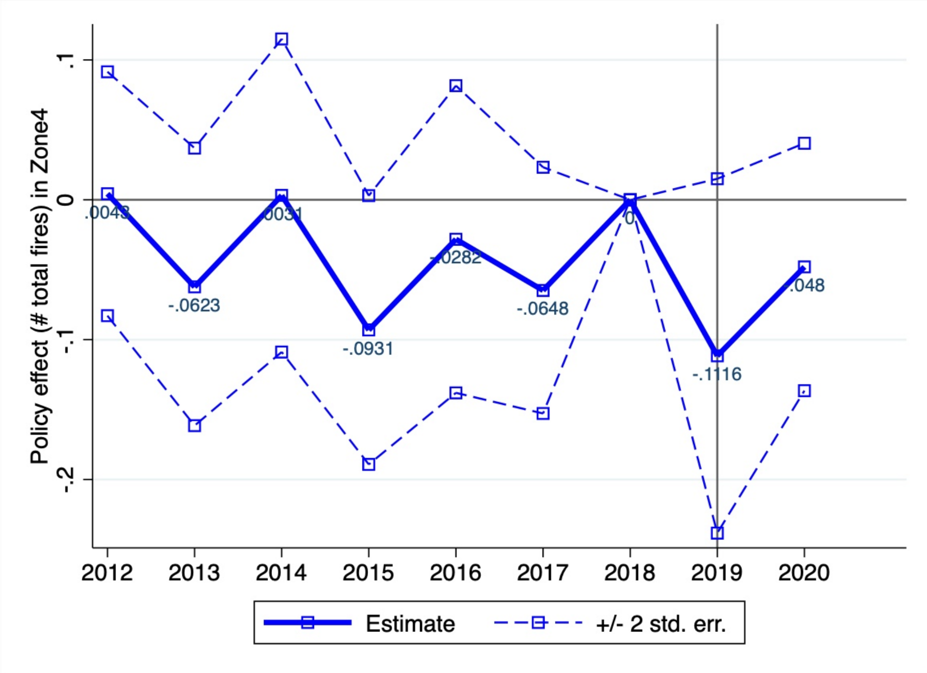


(d) sugar fires per acre of sugarcane

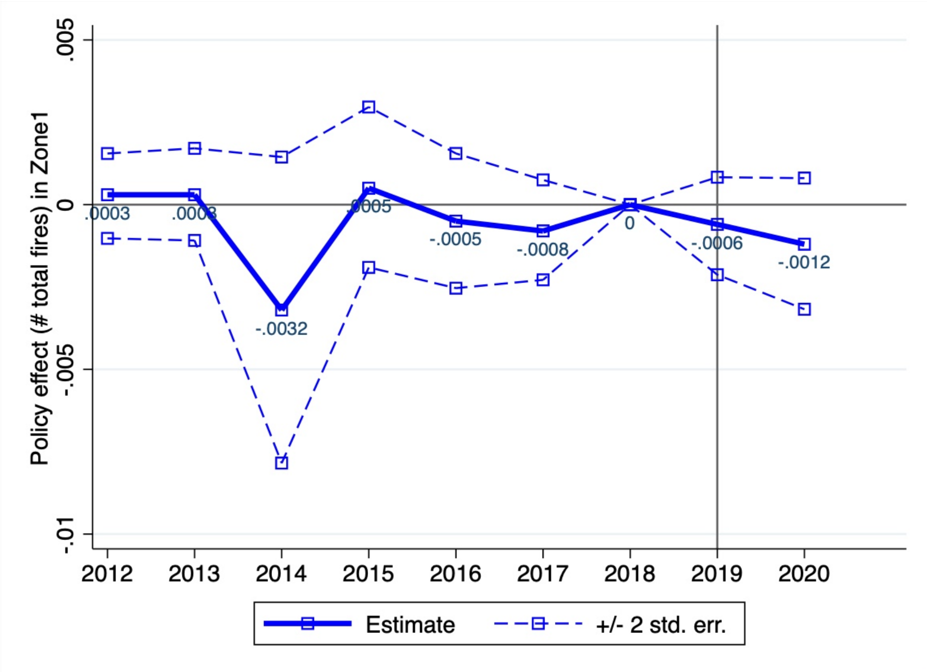
Figure A3: Trend of the annual authorized fires by county

Notes: The counts in Figure A3 are from the burning authorization summary in Florida Forest Service Reporting System. The original authorized fire data is measured in the count and observed at county x day x year). The number in Figure A3 is the sum of the daily authorized fires/sugarcane fires in each county from October to April next year.

Figure A3 does not provide evidence that the policy changes reduce the number of authorized total fires and sugarcane fires across the sugarcane-growing counties. There are some potential explanations for this finding. First, the air quality monitors are not evenly distributed around the sugarcane growing zones, and only one monitor exists, as shown in Figure A1. So incorporating AQI into burn authorizations may not show the air quality in those seven counties. Second, the quality of the reported fire data may be low. The authorized fire data are spatially aggregated at the county level, making it problematic to model how the permit for burning is approved precisely. Third, it may also be that when farmers cannot burn, they will burn on a different day, which is internally consistent.



(a) Event study for the number of total fires in Zone 4, 2012-2020



(b) Event study for the number of total fires in Zone 1, 2012-2020

Figure A4: DD dynamic policy effect on # observed total fires by Zone

Notes: The estimates in Figure A4 are from the event study regressions for daily reconstructed fire counts (measured in the count and observed at census tract x day x year) in equation (2) where the estimates for the year 2018 are restricted to have a value of 0. The regression includes detailed weather controls, census tract fixed effects, and month-of-year fixed effects. The standard errors underlying the confidence intervals (dashed lines) are clustered at the census tract level. The p-value of the F-test for testing the joint significance of the pre-trend coefficients is 0.1334 in panel (a) and 0.3552 in panel (b).

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