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Cap-and-Trade and Air Quality: Which Communities Benefit the Most?

Nicole Bobbs
nab139@uakron.edu

Senior Project

Department of Economics

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Advisor: *Dr. Ali Enami*

Abstract

Air Quality significantly impacts public health, particularly for individuals with respiratory issues. Cap-and-trade (CAT) programs aim to mitigate emissions, focusing on greenhouse gases to improve air quality. This paper evaluated the long-run effectiveness of CAT programs, comparing multi-sector and single-sector initiatives, and their impact on air quality across counties with varying economic statuses. Using a difference-in-difference approach, comprehensive data spanning recent years up to 2023 is analyzed. The dataset includes air quality measures, population, personal income, average temperature, precipitation, and vehicle registrations enabling a thorough examination of the programs' effects. Results reveal a complex relationship. Both programs' initiatives create a decrease in good air quality days for poor counties. The multi-sector programs demonstrate a more significant reduction in negative air quality days, such as moderate and very unhealthy, particularly benefiting poor counties. Conversely, poor counties with single-sector programs experience an increase in negative air quality. The results from this work conclude that multi-sector programs are more beneficial for poor counties, yet all program types need to make changes for maximum impact.

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I. Introduction

Air quality is an important factor for many people when considering their overall health. For those with respiratory issues, poor air quality could be a serious threat to their lives. Even people without respiratory issues can be deeply affected if they are consistently breathing in contaminated air. The EPA (2023) finds that air pollution has been, and continues to be, a critical function of all air quality issues. In 2022 alone, the United States has around 66 million tons of pollution emitted into the atmosphere.

Cap-and-trade (CAT) programs are designed to reduce emissions by providing an incentive for firms to reduce their total emissions. These programs specifically focus on greenhouse gas (GHG) emissions which play a significant role in climate change. A limit or "cap" is placed on all total emissions for a given entity, while allowing them to trade with other corporations. The trading of emissions establishes a new market with a supply and demand for emission allowances. Companies with a high demand for the allowance will buy, or 'trade', from others, creating an incentive for companies to transition towards cleaner production. The companies with clean production, and a surplus of emission allowances, will be able to sell to other companies that need more.

This research aims to assess the long-term effectiveness of Cap-and-Trade programs in improving air quality. Specifically, the work will compare the use of multi-sector and single-sector programs[1]. Each program is evaluated by the percentage of days with either good or hazardous air quality days. This approach to the analysis is more applicable to the average citizen

[1] The multi-sector programs include the state-level Cap-and-trade programs in California, Oregon, and Washington. Single-sector programs are states in the Regional Greenhouse Gas Initiative.

since it can be easier to grasp as opposed to evaluating particles in the air like many other papers do.

Additionally, the paper evaluates the impact of the programs at a county level, focusing on counties with different economic levels. The significance of evaluating counties with different economic statuses is to see how the programs impact poor counties versus more prosperous ones.

The work in the paper addresses the impact these programs have on different demographics and whether the emission goals are being met in the long term. The data in this paper is also more comprehensive than what others have done. From what I have seen, there aren't any papers that include data for three Cap-and-trade programs, in their treatment[2]. Washington and Oregon are relatively new programs and as a result, there is minimal research done on them. Incorporating those states into the research helps examine the impact on air quality for an entire region, rather than focusing solely on a specific state.

The data includes the air quality for the most recent years up to 2023. With the most up-to-date data, my analysis can effectively look at the impact of these programs throughout their entire implementation. Only looking at data for a couple of years before and after the compliance periods, as some papers do, only gives a small view of the effects of these programs on air quality. The comprehensive data will allow for a complete analysis of the effect on air quality.

Other data in the work include the population and personal income. Those variables span from 2000 to 2022 and are the only variables besides air quality that is measured at the county level. There is also the average temperature and precipitation for each state. There is also data for the vehicle registrations in each state, categorized by vehicle type. This includes automobiles,

[2] This research includes data for California, Oregon, and Washington into the treatment.

buses, trucks, and motorcycles. The registration data is used as a proxy for the emissions produced by vehicles.

By employing a difference-in-difference model, this paper analyses the impact CAT programs have on air quality compared to what it would be without the programs. Multiple models are run to determine the true results and all the models followed a similar trend. For both programs, there was a decrease in good air quality days for poor counties. Both the single and multi-sector programs experience negative effects on poor counties, but there is a difference between the overall effects. In decreasing the negative air quality days, like moderate and very unhealthy, the multi-sector programs prove to be more effective. Within these programs, the counties that are poor experience a decrease in the percentage of days. On the other hand, poor counties with a single-sector program have an increase in negative air quality. Ultimately, both programs need changes to be influential on all groups of people regarding air quality, but multi-sector programs are shown to be better for poor counties.

The remainder of this paper is organized as follows: Section 3 provides background on previous literature; Section 4 describes the data and provides descriptive statistics; Section 5 discusses the theory and the empirical strategy; Section 6 presents the results; Section 7 presents potential conclusions and concludes.

II. Literature Review

States aiming to reduce emissions within their borders are increasingly choosing to implement their programs regulated by the state governments. One successful program is California's cap-and-trade system, which covers approximately 400 facilities in the power, industrial, transport, and building sectors. Hernandez-Cortes and Meng (2022) find that California's Cap-and-Trade program successfully reduces greenhouse gas emissions. Between

2012 and 2017, GHG emissions decreased at an average rate at a rate of 9%. Before the program's implementation, GHG emissions from all facilities were rising annually by 19%. However, after the implementation of the program, the annual rate of GHG emissions declined to 11%. These positive findings demonstrate the effectiveness of state-level Cap-and-trade programs in reducing emissions.

Other research suggests that California's Cap-and-trade has both environmental and economic implications. Baioni (2023) conducts an interrupted time series analysis and finds an annual increase in real GDP compared to states without a CAT program. Initially, the data indicates a decline in real GDP for a few years after implementation, but eventually, it begins to rise gradually. The paper doesn't suggest any reasons for the initial decline, but it could be a result of increased costs for the firms. To comply with the new regulations, the firms might have chosen to switch to cleaner modes of production. This is just one possibility, but it provides some context for the decreased GDP. California is not the only state with a CAT program run by the state government.

Oregon's program mirrors California's as it also targets emissions reduction, focusing on the power and industry sectors. Given that the program only took effect in 2022, there is limited available data and research on its impact. However, projections indicate promising outcomes. According to Graves et al. (2020), the program is expected to decrease annual GHG emissions by 2.7 to 8.3 million metric tons by 2035. Additionally, emissions are projected to decrease by 2.9 to 9.8 million metric tons by 2050. Based on these estimates, it could be inferred that Oregon will experience similar benefits to California, such as a potential increase in real GDP. Nonetheless, as of the latest research, it is hard to say for certain what the outcomes will be.

Cap-and-trade programs in general also provide positive impacts for the firms they cover. Firms can increase their optimal production when there are emissions caps, (Wang et al., 2018). As firms continuously decrease their emissions by producing cleaner products, their profits rise since they can produce more. Furthermore, Chen et al. (2020) find that CAT programs could reduce marginal costs for firms with efficient production. If emission caps are set high enough, some firms may have a surplus of allowances, which they could sell to firms with higher emissions. This not only generates additional profit but also encourages investments in cleaner forms of production methods. Of course, it is crucial to ensure that emission caps do not become too lenient to the extent that overall emissions in the state fail to decrease. However, finding the right balance proves to be beneficial for everyone.

While the assumption is that every firm will adhere to these emission caps, some research suggests that not all will do so, (Aakre and Hovi, 2010; Yang et al., 2021). Behavior proves challenging to predict, and some firms might find it more profitable to continue doing business as they always have been. In California, there is a monetary penalty for surpassing emission allowances. Firms that do not comply, find that even with the fine, their high production levels allow them to still turn a profit. When the compliance fee is low, Yang et al. (2021) find that firms are inclined to continue to produce beyond their emission caps. The key is to have a high fine, forcing firms to comply. With small fees for noncompliance firms opt to produce more, knowing they won't face significant penalties for exceeding limits. For firms, compliance with the emission caps proves more effective at maximizing their profits than noncompliance.

While these CAT programs are demonstrating positive effects on emissions, they still carry negative consequences. One consequence is the disproportion effect on disadvantaged communities. In California, for instance, a large majority of facilities covered by CAT are in disadvantaged neighborhoods (Cushing et al., 2018). These neighborhoods have 34% more residents of color compared to facilities located elsewhere. Additionally, data indicates that 62% of California's residents live within six miles of a facility covered by CAT (Pastor et al., 2013). Among this population, 46% are people of color. Furthermore, 57.4% of California's residents who are people of color are living less than 0.5 miles from a facility. Even though the emissions in the entire state are decreasing, studies that look at the emissions at a neighborhood level tell a different story. Grainger and Ruangmas (2017) find that in areas with high poverty rates, there are smaller reduction of emissions than in other areas. Furthermore, Cushings et al. (2018) report that most areas with a high percentage of persons of color see an increase in emissions after the CAT is implemented. So, while the overall emissions in California are decreasing, there needs to be more of a focus on how minority areas are being affected.

The Regional Green House Initiative (RGGI) is another CAT program operating similarly to the other programs but specifically covers the power sector. Since its inception with the first compliance period in 2009, there have been multiple states that have joined this program[3]. In these states, coal consumption in the electric power industry decreases by around 73% from 2009 to 2018 (Yan, 2021). Furthermore, natural gas consumption in the same industry decreases by 30% for the same time frame. As a result of the reductions in natural gas consumption, carbon dioxide emissions are reduced by approximately 3.4 million tons per year. In RGGI states, there is also a 40% decrease in overall emissions between 2009-2012, (Murray and Maniloff, 2015). Without the program, these states would have experienced 50% higher emissions in 2012 than they did. This program consistently yields positive results within the participating states.

[3] As of 2024, Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island, Vermont, and Virginia are involved with RGGI.

Some states, like Pennsylvania, are attempting to enter RGGI because they see the benefits it is bringing to the participating states. Yang et al. (2021) estimate that if Pennsylvania can join RGGI, by 2030 they will reduce their carbon dioxide levels by 39.1 million tons and sulfur dioxide levels by about 49,000 tons. Most sulfur dioxide emissions result from power plant productions and contribute to various health problems as they convert into secondary partials in the air. By reducing sulfur dioxide and other emissions, it is expected that health problems caused by emissions from power plants will decrease.

Even with the proven benefits, this program has its faults, as every program does. A main concern with RGGI is leakage. Leakage occurs when the states that participate in RGGI experience a decrease in production or emissions, but neighboring states increase their emissions as a result. RGGI states have a reduction in electricity generation from power plants that use coal. For example, Pennsylvania and Ohio increase their electricity generation as a result (Chan and Marrow, 2018). Even though the RGGI states can reduce their electricity generation, Pennsylvania and Ohio's increased production is solely due to RGGI's implementation.

Leakage of carbon dioxide also occurs because of RGGI. Fell and Maniloff (2019) find that RGGI states decrease carbon dioxide emissions by 8.8 million tons annually. However, in the surrounding states of Pennsylvania and Ohio, carbon dioxide emissions increased by 4.5 million tons annually due to the program. The increase of carbon dioxide in these states could cause harm to the environment by having a direct hand in climate change. The emission increase could also create more smog and air pollution that will eventually contribute to worsened air for the state's citizens. So, while there are proven positive benefits resulting from RGGI, the surrounding states experience negative consequences.

This research aims to address some of the shortcomings of other papers. Many other papers overlook discussing air quality in terms that specifically address different air quality types. To the best of my knowledge almost all the previous research utilized data on specific pollutants, such as carbon monoxide and sulfur dioxide. While this is important, it fails to analyze air quality based on the average day. Through this analysis, I can use different air quality types to observe how CAT programs affect air quality on an average day. This analytical approach proves more applicable to the average person, as it’s easier to understand the distinction between a good day versus a hazardous day.

III. Data

For this paper, the data reflects the years 2000-2023 and only encompasses the states with programs and their neighbors[4].The data for the research is extracted from four main resources and includes two handmade variables. The main variables are all described at a county and state level. The main variables at the county level include air quality days, population, and average personal income. The rest of the data, average temperature, precipitation, and vehicle registration are valued at the state level. Table 1 presents the summary statistics for each key variable in this study, which includes the number of observations, mean, median, standard deviation, and minimum and maximum values. The statistics alone do not accurately portray every aspect of these variables, so further figures break them down.

A. Air Quality Data

The air quality data was extracted from the Environmental Protection Agency’s (EPA) website, providing yearly county-level information on air quality. This dataset spans from 2000

[4] The states include Arizona, California, Connecticut, Delaware, Idaho, Kentucky, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Nevada, North Caroline, Ohio, Oregon, Pennsylvania, Rhode Island, Tennessee, Vermont, Virginia, Washington, and West Virginia.

to 2023, encompassing air quality measurements for each county. While not every county in the United States is represented, the EPA explains that this omission is due to malfunctions in their data recovery process, which occurs randomly.

It is crucial to note all the statistics for variables on days with a specific air quality type, such as “Good Day”, are expressed as a percentage. Many counties have missing data within a year and do not report data for all 365 days. To maintain consistency, the number of days for each air quality type is divided by the total days reported. This ensures a comparable ratio for each county and air quality type.

Seeing the data for the air quality days is better served over time. Figure 1 demonstrates how the average percentage of each air quality type changed from 2000 to 2023, segmented into two panels. Panel A displays the average percentage of good days and moderate days over the years. There are significantly more good days and moderate days reported throughout the years, so the percentage changes are larger compared to the rest. Over time, there are slight fluctuations for both types, that seem to oppose each other. Since these air quality types change into each other, it makes sense that if one increases the other would decrease. Overall, good days seem to increase over the year, whereas moderate days decrease.

Panel B shows the remaining air quality types, unhealthy for sensitive groups (UFSG), unhealthy, very unhealthy, and hazardous days. These changes are very minimal, only occurring in a fraction of a percentage point, if at all. On the graph, all four groups seem to be decreasing over time. Very unhealthy and hazardous days are difficult to see, but it’s important to note that since their averages are so minimal, there are very few days with bad air quality. It would be more noteworthy if there were large changes in these days.

B. Population and Personal Income Data

The second data source is the Bureau of Economic Analysis, a government agency of the United States that provides economic statistics. This source provides data on population and average personal income for each county from the years 2000-2022. The missing year of data for personal income and population is what causes the number of observations for each variable to be different. All these databases have undergone manual cleaning to ensure proper analysis between variables. This process involved formatting adjustments of the data to ensure all the databases had a uniform layout. There was no manipulation of the data itself; rather, the focus was on aligning the columns representing years into rows in the income and population data.

C. Temperature and Precipitation Data

The data for temperature and precipitation is from the National Center for Environmental Information (NOAA), a scientific agency overseen by the United States government. The temperature data reflects the average temperature in Fahrenheit for a county. On the other hand, the data for precipitation is the summation of all the precipitation in a state for a given year. Precipitation is defined as anything that falls from the sky, which includes rain, hail, snow, etc. Both databases required cleaning up by hand, like what was done for the population and income data.

D. Vehicle Registration Data

The final data source is the U.S. Department of Transportation (DOT) which aggregates all the vehicle registrations for each state from 2000 to 2018. The data breaks down into different types of vehicles including, automobiles, busses, trucks, and motorcycles. This data works as a proxy for the emissions produced by cars in each state. The number of registrations can be used as a substitute since the more vehicles the more emissions are being produced. It can be assumed that the states with higher vehicle registrations will have more emissions from their vehicles.

E. Treatment and Poor

The variable “Treatment” defined the different counties based on their participation in a CAT program or lack thereof. There are two different treatments, each for the different types of programs. For both treatment types, 1 is recorded in a county that has a CAT program and 0 otherwise. Figure 2 offers a more detailed breakdown for which states, and their counties, have a CAT program. Each program type is compared to its neighboring states. In Figure 2, how each state is being used in the data is described. The information used to define each county in their respective treatment group was found on each state’s website.

The final variable, poor, defines whether a county is poor or not. 1 defining the county as poor and 0 as not poor. This variable is created using the data for personal income. If a county's income in 2012 is below the median for the data set, $37,245, then the county is defined as poor. This variable will be utilized to measure the effects of CAT programs on counties with different economic statuses.

Figure 3 looks at the counties that are described as poor or rich in the data set. The map shows different colors for rich and poor based on the CAT program type, however both were defined by the median described above. What’s interesting about the graph is how the multi-sector programs have poor counties that cover a lot of land. If the results prove that the CAT programs hurt the poor counties, then a larger area will be experiencing worse air quality.

IV. Theory and Methodology

What’s unique about a CAT program is its perfectly inelastic supply curve, which arises from the government’s creation of emission allowances and its ability to dictate market quantity. If the government decides to decrease emission allowances, trading prices rise as a result, leading to a leftward shift in the supply curve. This benefits firms with cleaner production methods the most. The overarching advantage is that regardless of price changes or shifts in the demand curve, the quantity remains constant.

In Cap-and-trade programs, the supply and demand play a central role. The demand curve reflects the firms' willingness to buy emissions at varying prices, considering their production needs and emission regulations. As emission allowance prices drop, firms become willing to pollute more. If demand for emissions rises, the demand curve will shift to the right, resulting in higher trading prices. Panel A in Figure 4 demonstrated these fundamentals for supply and demand through CAT programs. The prices increase and decrease with the movement of the demand curve; however, the quantity remains constant.

The cap-and-trade program contrasts with a carbon tax. With the tax system, the government fixes the price as opposed to the quantity. When the quantity is not fixed it is difficult to reach a desired level of pollution because the firms who are willing to pay more to pollute will do so. Figure 4 panel B shows the tax system’s supply and demand curves. With the price fixed, the quantity changes with the movement of the demand curve. CAT programs fix the quantity, which allows them to say what the optimal level of pollution is. They can also decrease the quantity over time if needed. Allowing the government to set the emissions quantity enables them to influence the firms to produce at a level that aligns with their air quality goals.

The Coase Theorem offers another perspective on understanding Cap-and-trade programs. Both the theorem and CAT programs emphasize the importance of clearly defined property rights. While setting rights for the environment poses challenges, in the case of negative externalities like air pollution, everyone’s right to produce emissions can be determined. The ‘cap’ represents the quantity of emissions set by the government, effectively defining property rights by permitting firms to pollute the air. Once property rights are established, firms are incentivized to participate by exploiting any gains from trade, (Hahn and Stavins, 2010).

The ‘trade’ aspect of the program enables the firms to establish a price for environmental rights. Firms capable of lowering emissions can trade with those in need, creating efficient pricing and production levels. Through this process of trading and negotiation, the program facilitates the most efficient price and levels of production, (Hahn and Stavins, 2010). The same ideas described above with the Coase theorem can be seen in the supply and demand graphs.

In some instances, CAT programs may violate the principles of the Coase Theorem. High transaction costs can impede the achievement of efficient outcomes. These costs can rise from activities such as search and research, bargaining and decision-making, and monitoring and enforcement, (Hahn and Stavins, 2010). While some actions, like finding new trading partners and researching market conditions, are assumed to be costless they could increase costs. Consequently, these costs prevent the efficient outcome from being produced and simultaneously limit emission reduction efforts.

While the theoretical framework regarding the effectiveness of Cap-and-trade programs could reduce emissions, there are unintended consequences. As mentioned earlier, some research suggests some counties experience an increase in emissions following the implementation of the programs. Even though there is a lot of research proving the effectiveness of CAT programs, there are spillover effects that are proving to impact lower economic areas.

This paper tests the assumptions made through the theoretical framework regarding the effectiveness of Cap-and-Trade programs in reducing emissions through trading on the overall quality of air. By aiming to create an efficient outcome for emission trading, the program predicts a decrease in pollution each year of implementation. An analysis of data throughout the United States provides evidence on whether the elements of the CAT programs that align with economic frameworks genuinely lead to emission reduction.

The effect of CAT programs on air quality is measured using a two-way fixed effect difference-in-difference model. This analyzes the air quality in a state with a CAT program compared to the air quality if there wasn't a program. Equation 1 reflects what is being used in the model to estimate the effects.

$$AirQualType_{ct} = \beta_0 + \beta_1 MultiCATProg_{ct} + \beta_2 SingleCATProg_{ct} + \beta_3 MultiCAT * Poor_{ct} + \beta_4 SingleCAT * Poor_{ct} + X_{ct} + County_c + Year_t + \varepsilon_{ct} \quad \textbf{(1)}$$

AirQualType measures the percentage of days for a specific air quality type in county c and year t. MultiCATProg is an indicator variable equal to 1 if a county has a multi-sector program and zero otherwise. SingleCATProg is another indicator variable equal to 1 if a county has a single-sector program and zero otherwise. MultiCAT*Poor is an interaction term that multiplies the variables MultiCATProg and Poor. Poor is an indicator variable denoting 1 if a county is labeled as poor and 0 otherwise. SingleCAT*Poor is another interaction term that multiplies the variables SingleCATProg and Poor. X represents all the control variables including average personal income, population, average temperature, total precipitation, automobiles, busses, trucks, and motorcycle registrations. County and Year are county and year fixed effects, respectively. Lastly, ε is the white noise.

The inclusion of county of fixed effects captures unobserved factors in each county that could impact air quality. For example, the county fixed effects could capture the geographical features within each county that do not change. Similarly, the year-fixed effects encompass any factor that could make an impact on air quality for all counties each year. These variables are constant among the counties but differ over the years.

Table 2 presents a comparison of means for the control variables between groups with and without a CAT program, before the enactment of these programs. Panel A focuses on multi-sector programs before 2013, while Panel B examines single-sector programs before 2008. Contrary to expectations, all control variables across both groups exhibit significant differences from each other, as shown by the presence of stars within both panels. Having the least number of stars would be preferable for indicating minimal differences between groups. However, our findings do not align with these expectations, as there are significant differences across all control variables for both sectors.

The parallel trend test examines the trend in the average values for Good Days to assess whether the treatment and control groups would have followed similar patterns in the absence of CAT programs. Figure 5 displays graphs illustrating the trend for the control and treatment groups before the enactment of CAT programs. The vertical dashed lines mark the enactment points for each treatment group.

In Panel A, the trends for multi-sector groups are compared to the trends of their neighboring states. Since the first multi-sector program began in 2013, we are concerned with how the trends looked before that year. Deciding on a parallel trend based on visuals is a little difficult. Panel B focuses on the average good days for single-sector programs compared to their neighboring states. Similarly to the multi-sector programs, the lines seem to be following a parallel trend based on visuals alone. While both types of programs seem to be following a parallel trend with their control groups, it is better determined through a statistical test to have a definitive answer.

Table 3 provides a more robust method for assessing parallel trends compared to visual inspection alone. Equation 2 represents the regression model employed to determine the parallel trend through a statistical test. With this approach, reliance on visual assessment with line graphs is minimized.

$AirQualType_{ct} = \beta_0 + B_1 Year_t + \beta_2 Year^2{}_t + \gamma Treatment_{ct} + \alpha_1 TY_{ct} + \alpha_2 TY^2{}_{ct}$ **(2)**

AirQualType measures the percentage of days for a specific air quality type in county c and year t. The year represents the year being measured. Treatment is an indicator variable equal to 1 if a county has a multi-sector program, equal to 2 if a county has a single-sector program, and zero otherwise. TY and TY^2 are interaction variables that represent *Treatment*Year* and *Treatment*Year*Year*, respectively.

Both Models represent the average Good Days for the multi-sector and single-sector programs. Focusing on the variables TY and TY^2, we can determine if the treatment and controls pass the parallel trend test. In both Models, the coefficients for TY and TY^2 are statistically insignificant. This indicates the presence of a parallel trend between the treatment and control groups. While the variable TY for single-sector programs is statistically significant at a 10% level, this is so low that it would be hard to argue against a parallel trend. So, both the visual and statistical parallel trend tests reflect that both treatments and their respective controls are comparable.

V. Results

To determine the effects of CAT programs on air quality, several models are run based on each air quality type. Table 4 includes models for both CAT programs representing the six air quality types. Specifically, Panel 1 represents the good air quality days for the multi-sector programs, while Panel 2 focuses on the good days for the single sector. Individually examining air quality types can help determine if certain days are impacted differently than others. The models in Table 4 are all simple, excluding the control variables, while including the county and year-fixed effects. Multiple other models are run to check the result, including models with the control variables and models taking the logarithmic form of air quality, which are in the appendix. All the models follow a similar pattern with the results.

With CAT programs the expectation is the percentage of good days would increase. On the other hand, the number of hazardous days should be decreasing. However, the results contradict the expectations. The coefficient for good days for counties with a multisector program is positive. More specifically, poor counties with a multi-sector program are associated with a 1.7 percentage point decrease in good days. For comparison, the rich counties experience a 1.4 percentage points increase in good days. This result is statistically significant at a 10% level, but it is still important to see how the counties are being affected differently.

For the single-sector counties, they experience even more of a decrease in good days. Holding everything else constant, when a county has a single sector program and is poor, it is associated with 8.2 percentage points fewer good air quality days than a county without a program. This means poor counties under the single-sector program experience almost 5 times fewer good days than the poor multi-sector programs. What is different between the two program types is how the rich counties compare to the poor regarding good gays. The rich counties under the single sector program, experience 5.6 less percentage points. While this is still less than the poor counties, the silver lining is they are not seeing an increase in good days. The other more extreme air quality types for hazardous days show no change in hazardous days for both programs.

While good and hazardous days are not being impacted as expected, middle-ground air quality days, like moderate and very unhealthy days, show more promising results. Compared to rich counties, poor counties with multi-sector programs show a 5.9-percentage point increase in moderate days. Furthermore, the rich counties only experience a 1.9-percentage point increase. The single-sector programs also experience a 4.9-percentage points increase in moderate days. Rich counties also experience similar results with a 4.8-percentage point increase.

The very unhealthy days allow for a further comparison between the different programs. The poor counties subjected to the multi-sectoral regulations are related to a .4 percentage point decrease compared to other counties. The poor counties with a single sectoral program have no change in their very unhealthy days. This is important because even though it is small, the multi-sector programs can decrease very unhealthy air quality, while the single-sector programs cannot enact any change. To further analyze the difference, rich counties within both programs have a .1 percentage point decrease. So, the multi-sector program was the only one that was able to enact a positive change for the poor communities.

The impact these programs are having on their poor communities is very important. Multi-sector programs prove to be more beneficial for underprivileged areas with their increase in moderate and decrease in very unhealthy air quality. Poor counties with a single-sector program are being negatively impacted because of these programs. Even though there isn't a beneficial change in good and hazardous air quality, if the other air quality types are changing for the better it is still beneficial for the public.

One reason for these results could be that the single-sector programs do not cover enough firms to make a positive change. Since the multi-sector programs can regulate more firms, it would make sense that they can reduce more emissions. This would cause the air quality in these areas to be better. Another explanation is that more firms are in poor communities in the single-sector states. If firms feel they can save money by locating their production in poor areas, they will do so and harm the air. Regardless of the reasoning, the multi-sector programs prove to be more beneficial for poor communities than the single-sector programs.

VI. Conclusion

While Cap-and-trade programs aim to reduce emissions and create a positive impact on air quality, the results show complicated outcomes. The expectation of increased good air quality days is not reflected in the results. The most impact the CAT programs have is on air quality days that are in the middle of the spectrum, like moderate and very unhealthy. Seeing positive results in the poor communities with multi-sector programs shows promising results for the overall health of the citizens. However, these programs still need to be amended in a way that can create a greater change in the air, specifically to improve good days and decrease hazardous ones. This can be done by changing the emission caps to be stricter and charging higher fines to companies that do not comply.

States also need to be more aware of how the less economically affluent counties are being impacted. Poor counties are suffering because of the implementation of CAT programs, specifically with single-sector programs. For one reason or another, the air quality is not improving in these areas. For CAT programs to be successful, they need to have a positive impact on all citizens, not just ones who happen to live in rich counties. Overall, Cap-and-trade programs have the potential to create real change in the overall air quality, but significant changes need to be made so that we see greater impacts.

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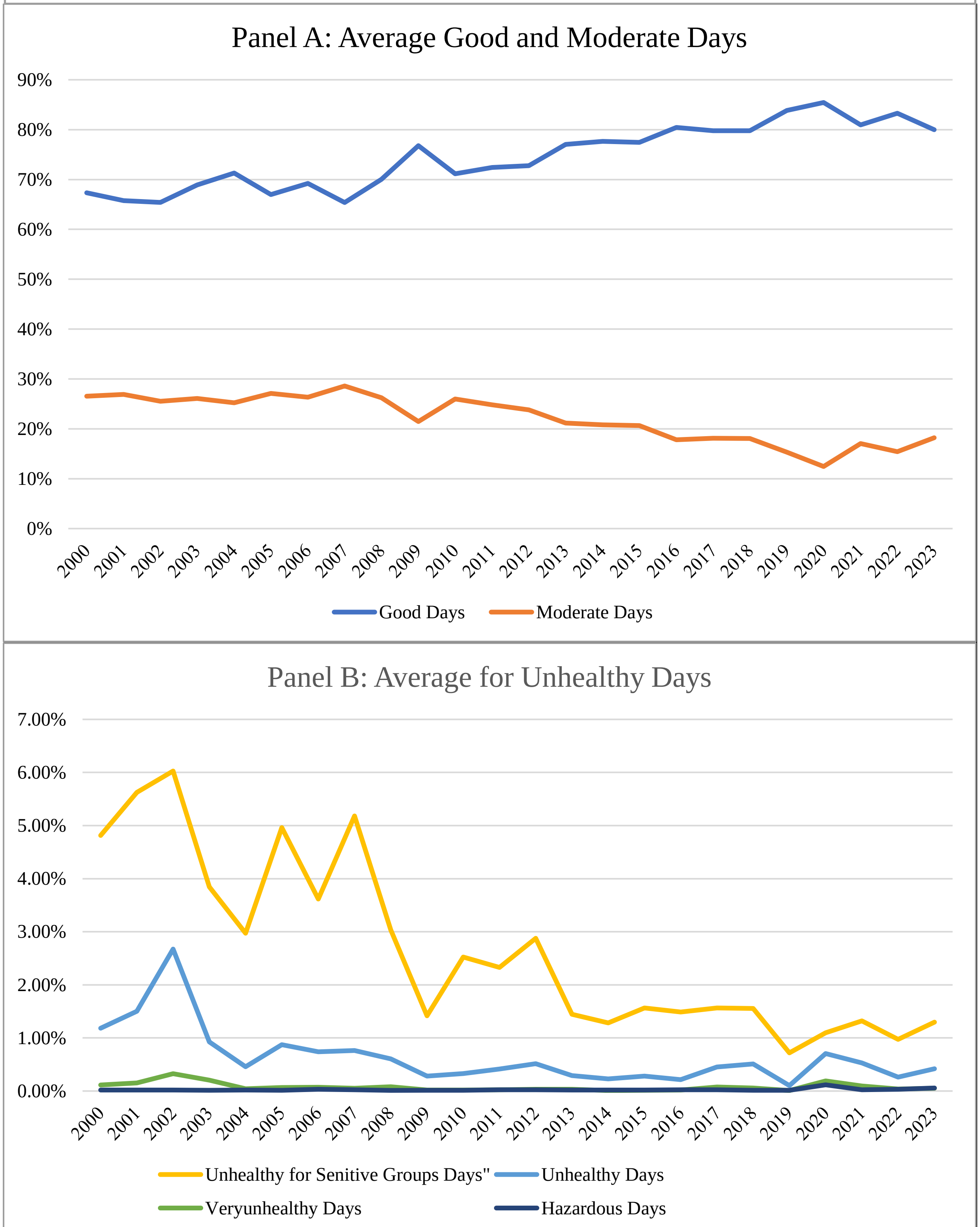
VIII. Tables and Figures

Table 1: Summary Statistics						
Variable	**Observations**	**Mean**	**Median**	**Std Dev**	**Minimum**	**Maximum**
Good Days	11,115	74.33%	77.74%	18.50%	3.23%	100.00%
Moderate Days	11,115	22.22%	20.05%	14.83%	0.00%	76.43%
Unhealthy for Sensitive Groups Days	11,115	2.70%	.98%	4.30%	0.00%	41.94%
Unhealthy Days	11,115	0.02%	0.00%	.31%	0.00%	17.12%
Very Unhealthy Days	11,115	0.65%	0.00%	1.94%	0.00%	31.23%
Hazardous Days	11,115	0.07%	0.00%	.50%	0.00%	20.21%
Population	10,685	297,589	111,790	633,377	1,098	10,123,521
Personal Income	10,685	$40,390	$37,245	$15,491	$14,495	$193,617
Temperature	11,115	53°F	53°F	5°F	37°F	76°F
Precipitation	11,115	40.69”	43.54”	13.48”	5.86”	68.35”
Auto Registration	8,906	4,820,902	3,299,259	4,869,831	218,302	20,037,727
Bus Registration	8,906	28,692	22,848	23,343	1070	99
Truck Registration	8,906	3,816,483	2,531,239	3,641,286	217,239	15,033,965
Motorcycle Registration	8,906	232,507	157,821	210,410	10,980	842,543

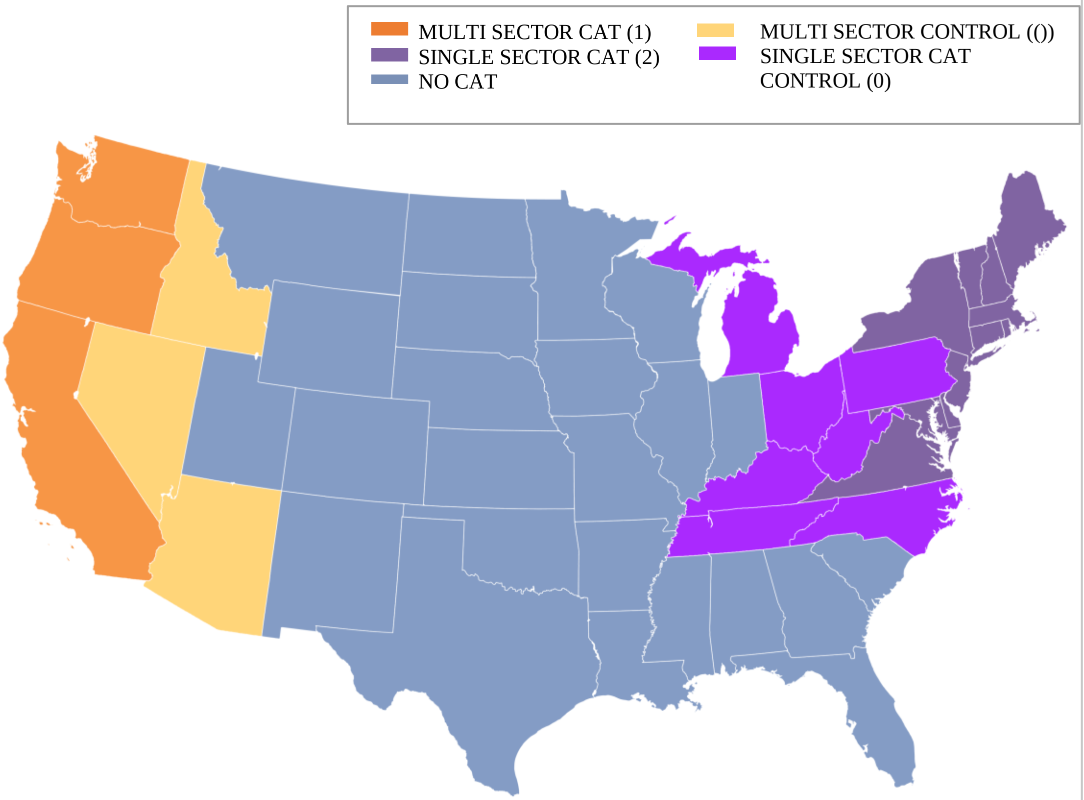
Source: NOAA National Centers for Environmental information, n.d., U.S. Bureau of Economic Analysis, 2022; US Environmental Protection Agency, 2023; Winter, D.,2022 and own calculations.

Figure 1: Average Air Quality Days
2000-2023



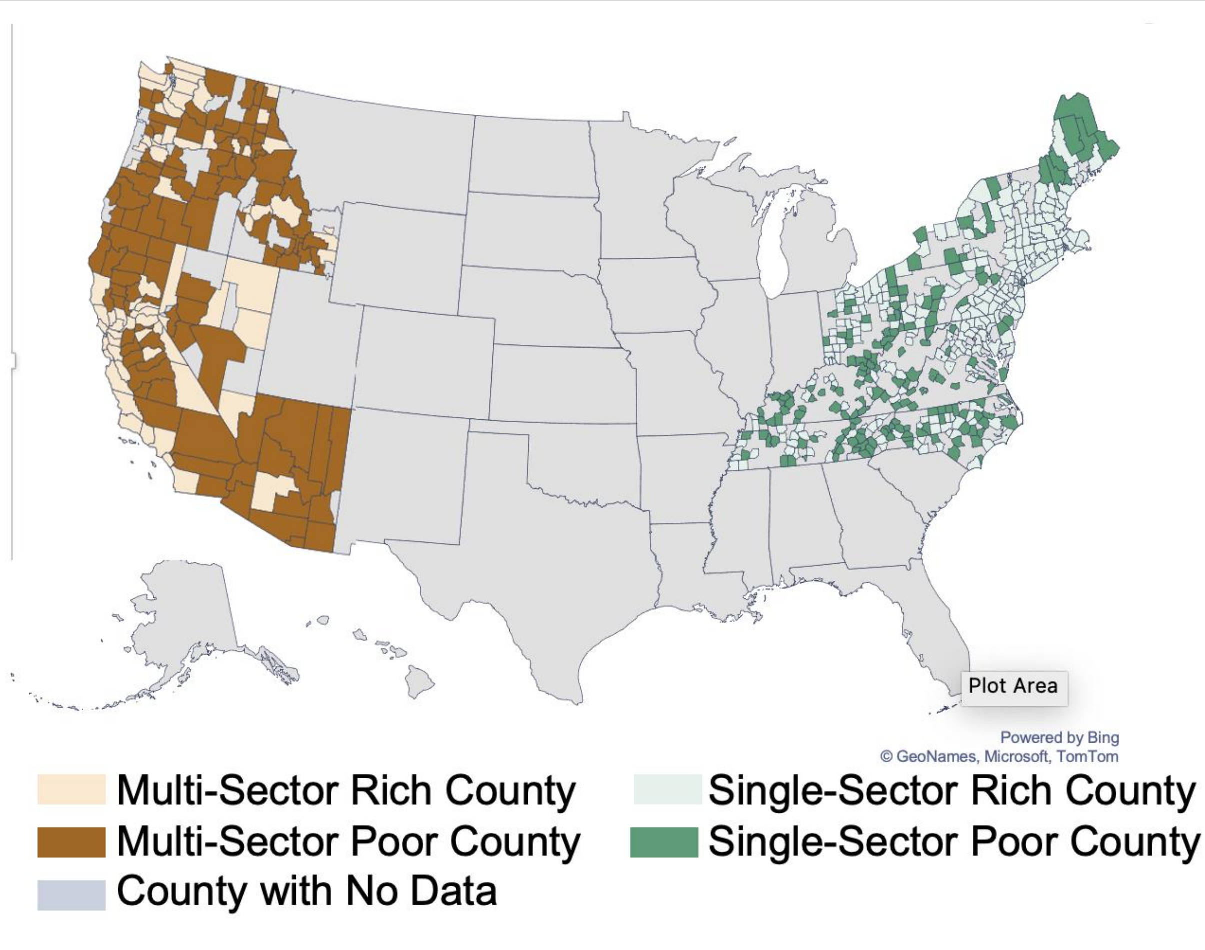
Source: Environmental Protection Agency, 2023 and own calculations
Notes: Each chart is measured by the average percentage of days in each year.

Figure 2: CAP-AND-TRADE PROGRAMS IN THE USA



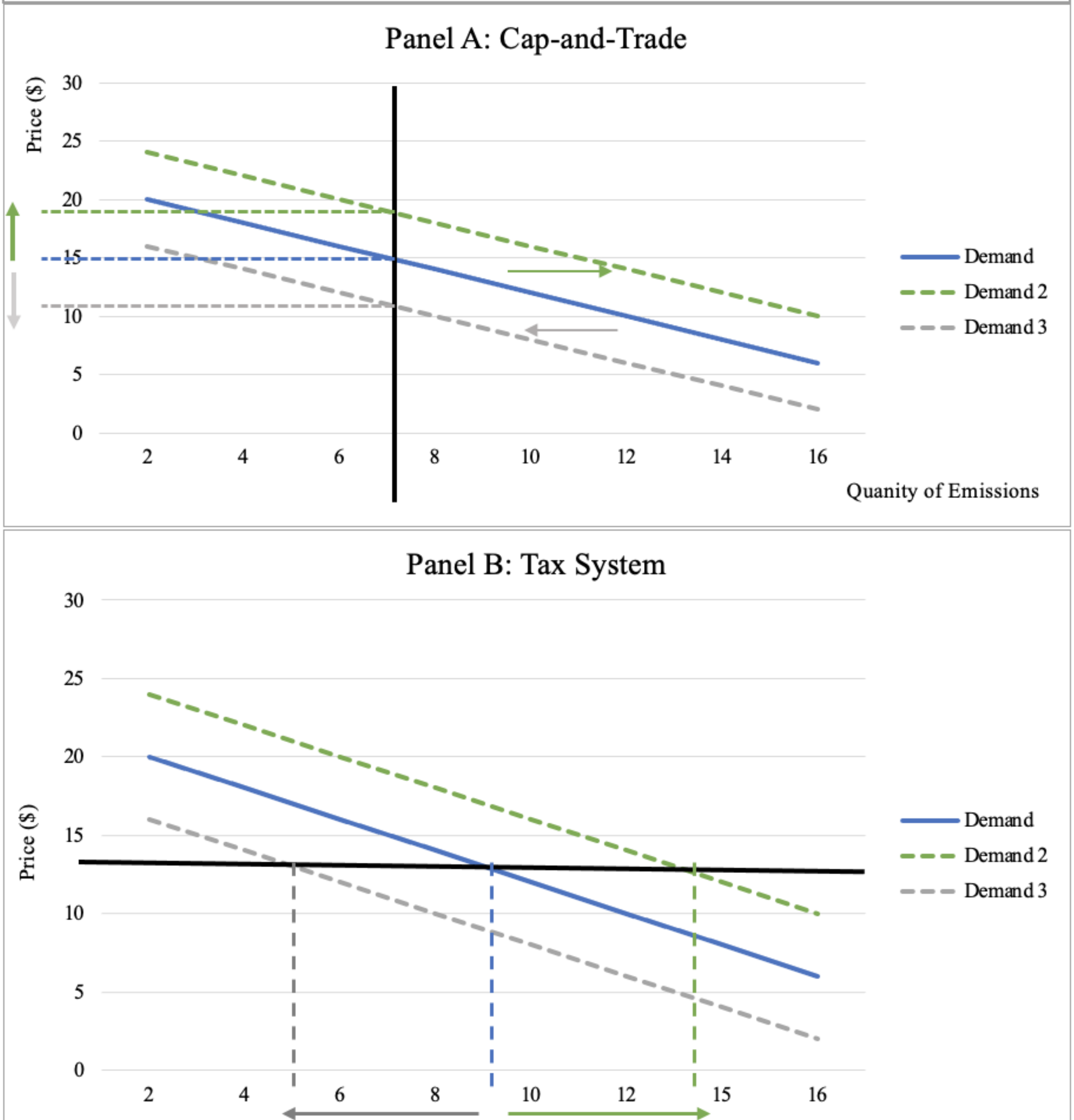
Source: *Program Design Archive | RGGI, Inc.*, n.d
Note: CAT denotes Cap-and-Trade

Figure 3: Poor vs Rich Counties



Source: Bureau of Economic Analysis, 2022 and own calculations.

Figure 4: Supply and Demand Example



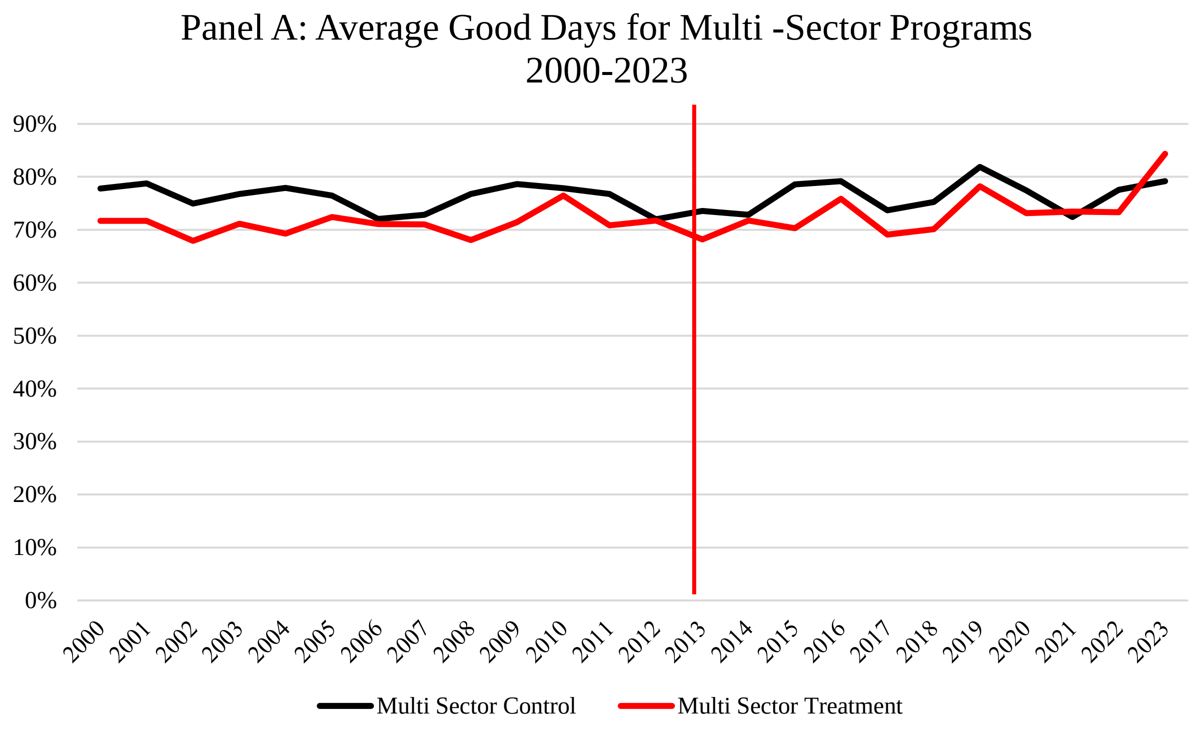
Source: Own calculations
Notes: This is a hypothetical model. Demand 2 shows if the demand were to increase in each scenario. Demand 3 shows if the demand were to decrease in each scenario. All arrows represent movement and correspond to their respective line based on color.

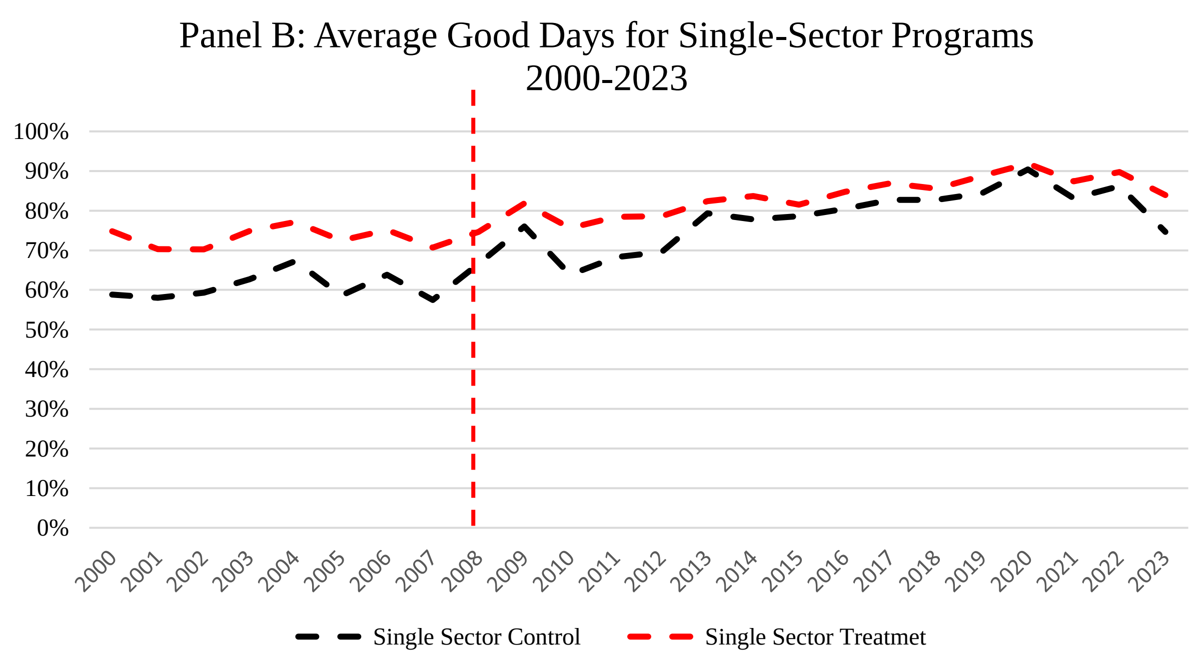
Table 2: Balance of Regressors			
Regressors	Treatment	Control	Difference
Panel A: Multi-Sector 2000-2012			
Personal Income	$33,799.50	$28,655	$5,144.5***
Population	438,396	230,007	208,389***
Temperature	53.23	51.89	-1.34***
Precipitation	28.86	16.39	12.47***
Auto Registrations	10,589,628	1,125,934	9,463,694***
Bus Registrations	35,021.80	4,433.70	30,588.20***
Truck Registrations	7,564,394	1,272,615	6,391,779***
Motorcycle Registrations	417,713	86,804.4	330,909***
Panel B: Single-Sector 2000-2007			
Personal Income	$36,129.6	$29,157.9	$6,971.8***
Population	336,100	173,401	162,699***
Temperature	50.01	54.81	4.80***
Precipitation	45.77	46.67	0.89***
Auto Registrations	4,242,405	3,891,282	351,123***
Bus Registrations	26,615.30	26,621.90	-6.64
Truck Registrations	1,807,059	2,547,680	740,621***
Motorcycle Registrations	109,413	151,904	42,490***

Source: NOAA National Centers for Environmental information, n.d., U.S. Bureau of Economic Analysis, 2022; US Environmental Protection Agency, 2023; Winter, D.,2022 and own calculations.

Notes: All values are the averages for their regressors. Difference is calculated by subtracting the value for control from the value for treatment. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Figure 5: Visual Parallel Trend Test





Source: Environmental Protection Agency, 2023 and own calculations
Notes: Solid lines reflect multi-sector programs and dashed lines represent single-sector programs.

Table 3: Parallel Trend Test		
Regressors	**Multi-Sector**	**Single-Sector**
CAT Program	-0.065***	0.071***
	(0.023)	(0.005)
Year	-0.004	0.022***
	(0.019)	(0.005)
$Year^2$	0.000	-0.004***
	(0.001)	(0.001)
Treatment*Year	0.002	-0.007*
	(0.010)	(0.004)
Treatment*$Year^2$	0.000	0.001
	(0.001)	(0.001)
Intercept	0.772***	0.598***
	(0.019)	(0.006)
Overall Significance	4.05***	97.01***

Source: Environmental Protection Agency, 2023 and own calculations.

Notes: Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Table 4: Regressions for Each Air Quality Type

Panel A: Multi-Sector						
Regressors	**Good Days**	**Moderate Days**	**Sensitive Groups Days**	**Unhealthy Days**	**Very Unhealthy Days**	**Hazardous Days**
Multi-Sector CAT	0.014*	0.019***	-0.023***	-0.007***	-0.001***	-0.001*
	(0.008)	(0.007)	(0.002)	(0.001)	(0.001)	(0.000)
Multi*Poor	-0.031***	0.040***	0.007*	-0.013***	-0.003***	0.001*
	(0.010)	(0.009)	(0.003)	(0.003)	(0.001)	(0.000)
Intercept	0.716***	0.242***	0.033***	0.009***	0.000	-0.000
	(0.022)	(0.020)	(0.004)	(0.002)	(0.001)	(0.000)
County Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	3,463	3,463	3,463	3,463	3,463	3,463
Adjusted R-Square	0.8544	0.7815	0.8412	0.6964	0.3146	0.3370
Overall Significance	456.45***	288.86***	72.72***	18.57***	2.94***	2.00***

Panel B: Single Sector						
Regressors	**Good Days**	**Moderate Days**	**Sensitive Groups Days**	**Unhealthy Days**	**Very Unhealthy Days**	**Hazardous Days**
Single-Sector CAT	-0.056***	0.048***	0.011***	-0.002***	-0.001***	-0.000
	(0.004)	(0.004)	(0.001)	(0.000)	(0.000)	(0.000)
Single*Poor	-0.027***	0.010	0.009***	0.006***	0.001***	-0.000
	(0.008)	(0.007)	(0.002)	(0.001)	(0.000)	(0.000)
Intercept	0.676***	0.265***	0.049***	0.009***	0.001***	-0.000
	(0.033)	(0.034)	(0.003)	(0.001)	(0.000)	(0.000)
County Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	7,652	7,652	7,652	7,652	7,652	7,652
Adjusted R-Square	0.7886	0.7525	0.6686	0.5229	0.2439	-0.00988
Overall Significance	138.79***	157.81***	40.16***	14.51***	1.94***	0.21

Source: NOAA National Centers for Environmental information, n.d., U.S. Bureau of Economic Analysis, 2022; US Environmental Protection Agency, 2023; Winter, D., 2022 and own calculations.

Notes: Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

IX. Appendix A: Air Quality Results with Controls

Table 5: Good Days with Controls						
Regressors	**Model 13**	**Model 14**	**Model 15**	**Model 16**	**Model 17**	**Model 18**
Multi-Sector CAT	0.020** (0.008)	0.000 (0.009)	-0.006 (0.013)			
Multi*Poor	-0.031*** (0.010)	-0.024** (0.011)	-0.033** (0.013)			
Single-Sector CAT				-0.044*** (0.004)	-0.043*** (0.004)	-0.027*** (0.004)
Single*Poor				-0.029*** (.008)	-0.036*** (.009)	-0.035*** (.009)
Controls for Precipitation?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Temperature?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Population?	No	Yes	Yes	No	Yes	Yes
Controls for Personal Income?	No	Yes	Yes	No	Yes	Yes
Controls for Auto Registrations?	No	No	Yes	No	No	Yes
Controls for Bus registrations?	No	No	Yes	No	No	Yes
County Fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	3,463	3,324	2,734	7,652	7,361	6,172
Adjusted R-Square	0.8559	0.8640	0.8631	0.7963	0.8022	0.7959
Overall Significance	455.11***	488.77***	456.36***	144.79***	151.22***	168.74***

Source: NOAA National Centers for Environmental information, n.d., U.S. Bureau of Economic Analysis, 2022; US Environmental Protection Agency, 2023; Winter, D., 2022 and own calculations.

Notes: Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Table 6: Moderate Days with Controls						
Regressors	**Model 19**	**Model 20**	**Model 21**	**Model 22**	**Model 23**	**Model 24**
Multi-Sector CAT	0.014** (0.007)	0.034*** (0.008)	0.010 (0.011)			
Multi*Poor	0.039*** (0.009)	0.030*** (0.010)	0.033*** (0.012)			
Single-Sector CAT				0.039*** (0.004)	0.037*** (0.004)	0.022*** (0.004)
Single*Poor				0.012* (0.007)	0.018** (0.007)	0.017** (0.008)
Controls for Precipitation?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Temperature?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Population?	No	Yes	Yes	No	Yes	Yes
Controls for Personal Income?	No	Yes	Yes	No	Yes	Yes
Controls for Auto Registrations?	No	No	Yes	No	No	Yes
Controls for Bus registrations?	No	No	Yes	No	No	Yes
County Fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Precipitation?	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	3,463	3,324	2,734	7,652	7,361	6,172
Adjusted R-Square	0.7832	0.7913	0.7923	0.7596	0.7651	0.7597
Overall Significance	287.11***	301.92***	294.27***	225.35***	270.78***	176.77***

Source: NOAA National Centers for Environmental information, n.d., U.S. Bureau of Economic Analysis, 2022; US Environmental Protection Agency, 2023; Winter, D.,2022 and own calculations.

Notes: Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Table 7: Unhealthy for Sensitive Groups Days with Controls						
Regressors	**Model 25**	**Model 26**	**Model 27**	**Model 28**	**Model 29**	**Model 30**
Multi-Sector CAT	-0.024*** (0.003)	-0.024*** (0.003)	-0.007 (0.005)			
Multi*Poor	0.006* (0.003)	0.009** (0.004)	0.013*** (0.005)			
Single-Sector CAT				0.009*** (0.001)	0.009*** (0.001)	0.008*** (0.001)
Single*Poor				0.010*** (0.002)	0.011*** (0.002)	0.010*** (0.002)
Controls for Precipitation?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Temperature?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Population?	No	Yes	Yes	No	Yes	Yes
Controls for Personal Income?	No	Yes	Yes	No	Yes	Yes
Controls for Auto Registrations?	No	No	Yes	No	No	Yes
Controls for Bus registrations?	No	No	Yes	No	No	Yes
County Fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	3,463	3,324	2,734	7,652	7,361	6,172
Adjusted R-Square	0.8416	0.8553	0.8626	0.6735	0.6806	0.6790
Overall Significance	71.89***	75.71***	73.08***	36.69***	37.51***	53.43***

Source: NOAA National Centers for Environmental information, n.d., U.S. Bureau of Economic Analysis, 2022; US Environmental Protection Agency, 2023; Winter, D.,2022 and own calculations.

Notes: Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Table 8: Unhealthy Days with Controls						
Regressors	**Model 31**	**Model 32**	**Model 33**	**Model 34**	**Model 35**	**Model 36**
Multi-Sector CAT	-0.008*** (0.001)	-0.009*** (0.001)	0.002 (0.002)			
Multi*Poor	-0.013*** (0.003)	-0.012*** (0.003)	-0.011*** (0.003)			
Single-Sector CAT				-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
Single*Poor				0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)
Controls for Precipitation?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Temperature?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Population?	No	Yes	Yes	No	Yes	Yes
Controls for Personal Income?	No	Yes	Yes	No	Yes	Yes
Controls for Auto Registrations?	No	No	Yes	No	No	Yes
Controls for Bus registrations?	No	No	Yes	No	No	Yes
County Fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	3,463	3,324	2,734	7,652	7,361	6,172
Adjusted R-Square	0.6973	0.7230	0.7904	0.5242	0.5379	0.5431
Overall Significance	18.47***	23.06***	25.77***	14.32***	14.38***	14.90***

Source: NOAA National Centers for Environmental information, n.d., U.S. Bureau of Economic Analysis, 2022; US Environmental Protection Agency, 2023; Winter, D., 2022 and own calculations.

Notes: Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Table 9: Very Unhealthy Days with Controls						
Regressors	**Model 37**	**Model 38**	**Model 39**	**Model 40**	**Model 41**	**Model 42**
Multi-Sector CAT	-0.001*** (0.001)	-0.002** (0.001)	0.001* (0.001)			
Multi*Poor	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)			
Single-Sector CAT				-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Single*Poor				0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Controls for Precipitation?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Temperature?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Population?	No	Yes	Yes	No	Yes	Yes
Controls for Personal Income?	No	Yes	Yes	No	Yes	Yes
Controls for Auto Registrations?	No	No	Yes	No	No	Yes
Controls for Bus registrations?	No	No	Yes	No	No	Yes
County Fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	3,463	3,324	2,734	7,652	7,361	6,172
Adjusted R-Square	0.3149	0.3252	0.5266	0.2449	0.2606	0.2678
Overall Significance	2.93***	2.96***	2.72***	1.94***	1.92***	1.98***

Source: NOAA National Centers for Environmental information, n.d., U.S. Bureau of Economic Analysis, 2022; US Environmental Protection Agency, 2023; Winter, D., 2022 and own calculations.

Notes: Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Table 10: Hazardous Days with Controls						
Regressors	**Model 43**	**Model 44**	**Model 45**	**Model 46**	**Model 47**	**Model 48**
Multi-Sector CAT	-0.001* (0.000)	-0.001 (0.001)	0.000 (0.001)			
Multi*Poor	0.001* (0.000)	0.001 (0.001)	0.001 (0.001)			
Single-Sector CAT				-0.000 (0.000)	0.000*** (0.000)	0.000*** (0.000)
Single*Poor				-0.000 (0.000)	0.000*** (0.000)	0.000*** (0.000)
Controls for Precipitation?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Temperature?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Population?	No	Yes	Yes	No	Yes	Yes
Controls for Personal Income?	No	Yes	Yes	No	Yes	Yes
Controls for Auto Registrations?	No	No	Yes	No	No	Yes
Controls for Bus registrations?	No	No	Yes	No	No	Yes
County Fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	3,463	3,324	2,734	7,652	7,361	6,172
Adjusted R-Square	0.3370	0.4649	0.5034	-0.01012	.	.
Overall Significance	2.10***	2.48***	1.62***	0.15	.***	.***

Source: NOAA National Centers for Environmental information, n.d., U.S. Bureau of Economic Analysis, 2022; US Environmental Protection Agency, 2023; Winter, D., 2022 and own calculations.

Notes: Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

X. Appendix B: Logarithmic Models with Controls Results

Table 11: Logarithmic Good Days with Controls						
Regressors	**Model 49**	**Model 50**	**Model 51**	**Model 52**	**Model 53**	**Model 54**
Multi-Sector CAT	0.050*** (0.018)	0.022 (0.020)	-0.008 (0.033)			
Multi*Poor	-0.046* (0.025)	-0.044 (0.028)	-0.074** (0.034)			
Single-Sector CAT				-0.080*** (0.006)	-0.080*** (0.007)	-0.051*** (0.008)
Single*Poor				-0.046*** (0.012)	-0.055*** (0.012)	-0.055*** (0.013)
Controls for Precipitation?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Temperature?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Population?	No	Yes	Yes	No	Yes	Yes
Controls for Personal Income?	No	Yes	Yes	No	Yes	Yes
Controls for Auto Registrations?	No	No	Yes	No	No	Yes
Controls for Bus registrations?	No	No	Yes	No	No	Yes
County Fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	3,463	3,324	2,734	7,652	7,361	6,172
Adjusted R-Square	0.8613	0.8728	0.8736	0.7543	0.7635	0.7599
Overall Significance	160.94***	168.03***	156.04***	94.41***	97.02***	108.33***

Source: NOAA National Centers for Environmental information, n.d., U.S. Bureau of Economic Analysis, 2022; US Environmental Protection Agency, 2023; Winter, D., 2022 and own calculations.

Notes: Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Table 12: Logarithmic Moderate Days with Controls						
Regressors	**Model 55**	**Model 56**	**Model 57**	**Model 58**	**Model 59**	**Model 60**
Multi-Sector CAT	0.050*** (0.018)	0.022 (0.020)	-0.008 (0.033)			
Multi*Poor	-0.046* (0.025)	-0.044 (0.028)	-0.074** (0.034)			
Single-Sector CAT				-0.080*** (0.006)	-0.080*** (0.007)	-0.051*** (0.008)
Single*Poor				-0.046*** (0.012)	-0.055*** (0.012)	-0.055*** (0.013)
Controls for Precipitation?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Temperature?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Population?	No	Yes	Yes	No	Yes	Yes
Controls for Personal Income?	No	Yes	Yes	No	Yes	Yes
Controls for Auto Registrations?	No	No	Yes	No	No	Yes
Controls for Bus registrations?	No	No	Yes	No	No	Yes
County Fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	3,463	3,324	2,734	7,652	7,361	6,172
Adjusted R-Square	0.8613	0.8728	0.8736	0.7543	0.7635	0.7599
Overall Significance	160.94***	168.03***	156.04***	94.41***	97.02***	108.33***

Source: NOAA National Centers for Environmental information, n.d., U.S. Bureau of Economic Analysis, 2022; US Environmental Protection Agency, 2023; Winter, D., 2022 and own calculations.

Notes: Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Table 13: Logarithmic Unhealthy for Sensitive Groups Days with Controls						
Regressors	**Model 61**	**Model 62**	**Model 63**	**Model 64**	**Model 65**	**Model 66**
Multi-Sector CAT	-0.327*** (0.074)	-0.306*** (0.082)	-0.101 (0.127)			
Multi*Poor	0.207** (0.083)	0.192** (0.090)	0.274*** (0.104)			
Single-Sector CAT				0.270*** (0.036)	0.247*** (0.038)	0.224*** (0.041)
Single*Poor				-0.090 (0.091)	-0.046 (0.094)	-0.107 (0.104)
Controls for Precipitation?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Temperature?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Population?	No	Yes	Yes	No	Yes	Yes
Controls for Personal Income?	No	Yes	Yes	No	Yes	Yes
Controls for Auto Registrations?	No	No	Yes	No	No	Yes
Controls for Bus registrations?	No	No	Yes	No	No	Yes
County Fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2,404	2,354	1,914	5,414	5,187	4,735
Adjusted R-Square	0.7272	0.7349	0.7453	0.7363	0.7483	0.7360
Overall Significance	115.62***	128.07***	126.67***	1,575,725,253.77	1,099,515,457.69	12910412541.62**

Source: NOAA National Centers for Environmental information, n.d., U.S. Bureau of Economic Analysis, 2022; US Environmental Protection Agency, 2023; Winter, D., 2022 and own calculations.

Notes: Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Table 14: Logarithmic Unhealthy Days with Controls						
Regressors	**Model 67**	**Model 68**	**Model 69**	**Model 70**	**Model 71**	**Model 72**
Multi-Sector CAT	-0.276** (0.123)	-0.396*** (0.131)	0.034 (0.213)			
Multi*Poor	-0.250** (0.126)	-0.093 (0.137)	0.015 (0.165)			
Single-Sector CAT				-0.091 (0.061)	-0.124* (0.067)	-0.126* (0.070)
Single*Poor				0.365* (0.209)	0.340 (0.239)	0.217 (0.213)
Controls for Precipitation?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Temperature?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Population?	No	Yes	Yes	No	Yes	Yes
Controls for Personal Income?	No	Yes	Yes	No	Yes	Yes
Controls for Auto Registrations?	No	No	Yes	No	No	Yes
Controls for Bus registrations?	No	No	Yes	No	No	Yes
County Fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1,420	1,401	1,090	2,437	2,309	2,259
Adjusted R-Square	0.5822	0.5932	0.6434	0.5800	0.5995	0.6023
Overall Significance	82.35***	85.65***	878.62***	61.28***	21.91***	24.45***

Source: NOAA National Centers for Environmental information, n.d., U.S. Bureau of Economic Analysis, 2022; US Environmental Protection Agency, 2023; Winter, D., 2022 and own calculations.

Notes: Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Table 15: Logarithmic Very Unhealthy Days with Controls						
Regressors	**Model 73**	**Model 74**	**Model 75**	**Model 76**	**Model 77**	**Model 78**
Multi-Sector CAT	0.450 (0.317)	0.501* (0.290)	0.671* (0.404)			
Multi*Poor	-0.808*** (0.218)	-0.842*** (0.260)	-0.547* (0.323)			
Single-Sector CAT				-0.455** (0.180)	-0.401 (0.315)	-0.551 (0.367)
Single*Poor				1.090* (0.612)	0.000*** (0.000)	0.000*** (0.000)
Controls for Precipitation?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Temperature?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Population?	No	Yes	Yes	No	Yes	Yes
Controls for Personal Income?	No	Yes	Yes	No	Yes	Yes
Controls for Auto Registrations?	No	No	Yes	No	No	Yes
Controls for Bus registrations?	No	No	Yes	No	No	Yes
County Fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	451	447	317	492	459	459
Adjusted R-Square	0.3806	0.3928	0.5588	0.3606	0.3796	0.3792
Overall Significance	173.97***	10.13***	27.90***	827,009,359.54**	2,344,527,971.26	1,124,396,782.96

Source: NOAA National Centers for Environmental information, n.d., U.S. Bureau of Economic Analysis, 2022; US Environmental Protection Agency, 2023; Winter, D.,2022 and own calculations.

Notes: Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Table 16: Logarithmic Hazardous Days with Controls				
Regressors	**Model 79**	**Model 80**	**Model 81**	**Model 82**
Multi-Sector CAT	-0.312 (0.392)	-0.000 (0.413)	-0.165 (0.535)	
Multi*Poor	0.993** (0.500)	0.520 (0.490)	0.683 (0.593)	
Single-Sector CAT				-0.401 (0.315)
Single*Poor				0.000*** (0.000)
Controls for Precipitation?	Yes	Yes	Yes	Yes
Controls for Temperature?	Yes	Yes	Yes	Yes
Controls for Population?	No	Yes	Yes	Yes
Controls for Personal Income?	No	Yes	Yes	Yes
Controls for Auto Registrations?	No	No	Yes	No
Controls for Bus registrations?	No	No	Yes	No
County Fixed effects?	Yes	Yes	Yes	Yes
Year fixed Effects?	Yes	Yes	Yes	Yes
Number of Observations	199	192	112	459
Adjusted R-Square	0.4638	0.4442	0.4880	0.3796
Overall Significance	1,182,098,490.42	1,824,966,932.87	115,241,402.29**	2,344,527,971.26

Source: NOAA National Centers for Environmental information, n.d., U.S. Bureau of Economic Analysis, 2022; US Environmental Protection Agency, 2023; Winter, D., 2022 and own calculations.

Notes: Robust standard errors are in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

XI. Appendix C: SAS Codes

```
/*Import Temp DAta*/
PROC IMPORT DATAFILE="/home/u62973430/MySAS/Hon Project/Temp.xlsx"
			OUT=WORK.Temp2
				dbms=xlsx
				replace;
				getnames=yes;
run;

Proc Sort data=temp2;
	by County Year;
run;

/*Import AQ Data for multi sector programs*/
PROC IMPORT DATAFILE="/home/u62973430/MySAS/Hon Project/HonData.xlsx"
			OUT=WORK.AQ2
				dbms=xlsx
				replace;
				sheet="AQ2";
				getnames=yes;
run;

proc sort  data=AQ2;
	by County year;
run;

/*Import Treatment Data for multi sector programs*/
PROC IMPORT DATAFILE="/home/u62973430/MySAS/Hon Project/HonData.xlsx"
			OUT=WORK.Treatment2
				dbms=xlsx
				replace;
				sheet="Treatment2";
				getnames=yes;
run;

proc sort  data=Treatment2;
	by County;
run;

/*Combine Treamtent and AQ for multi sector*/
Data CombinedMulti;
	merge AQ2 Treatment2;
	by County;
	if Firsteffectiveyear="" then DID=0;
	else if  Year>FirstEffectiveYear then DID=1;
	else DID=0;

	/*if Secondeffectiveyear="" then DID2=0;
	else if  Year>SecondEffectiveYear then DID2=1;
	else DID2=0;*/

	keep County Year Goodperct moderateperct
		SensitivePerct
		HazardousPerct
		UnhealthyPerct
```

```
                    VeryUnhealthyPerct
                    HazardousPerct State precip auto bus truck motorcycle DID poor;
Run;

/* Combine all 3 datasets for multi*/
Data MultiAQTreatTemp;
          merge CombinedMulti Temp2;
          by county year;
          if State="" then Delete;
run;

/* Income data for multi*/
proc import datafile="/home/u62973430/MySAS/Hon Project/PersonalIncomeDataFix.xlsx"
          out=work.Income2
          DBMS=XLSX
          REPLACE;
RUN;

proc sort data=income2;
          by county year;
run;

/*Multi sector data*/
data Multi;
          merge MultiAQTreatTemp income2;
          by county year;
          if year ne 2023 and pop='' then delete;
          if State='' then Delete;
          if State="California" then Treatment=1;
          else if State="Oregon" then Treatment=1;
          else if State="Washington" then Treatment=1;
          else if State="Vermont" then Treatment =2;
          else if State="New York" then Treatment =2;
          else if State="Virginia" then Treatment=2;
          else if State="Maryland" then Treatment=2;
          else if State="New Jersey" then Treatment=2;
          else if State="New Hampshire" then Treatment=2;
          else if State="Maine" then Treatment=2;
          else if State="Conneticut" then Treatment=2;
          else if State="Deleware" then Treatment=2;
          else if State="Massachusetts" then Treatment=2;
          else if State="Rhode Island" then Treatment=2;
          else Treatment=0;


          if Year=1990 then YearADJ=-11;
          else if Year=1991 then YearADJ=-10;
          else if Year=1992 then YearADJ=-9;
          else if Year=1993 then YearADJ=-8;
          else if Year=1994 then YearADJ=-7;
          else if Year=1995 then YearADJ=-6;
          else if Year=1996 then YearADJ=-5;
          else if Year=1997 then YearADJ=-4;
          else if Year=1998 then YearADJ=-3;
          else if Year=1999 then YearADJ=-2;
          else if Year=2000 then YearADJ=-1;
```

```
	else if Year=2001 then YearADJ=0;
	else if Year=2002 then YearADJ=1;
	else if Year=2003 then YearADJ=2;
	else if Year=2004 then YearADJ=3;
	else if Year=2005 then YearADJ=4;
	else if Year=2006 then YearADJ=5;
	else if Year=2007 then YearADJ=6;
	else if Year=2008 then YearADJ=7;
	else if Year=2009 then YearADJ=8;
	else if Year=2010 then YearADJ=9;
	else if Year=2011 then YearADJ=10;
	else if Year=2012 then YearADJ=11;
	else YearADJ="";

	Y2=YearADJ*YearADJ;
	Y3=Y2*YearADJ;
	Y4=Y3*YearADJ;
	Y5=Y4*YearADJ;
	TY=Treatment*YearADJ;
	TY2=Treatment*Y2;
	TY3=Treatment*Y3;
	TY4=Treatment*Y4;
	TY5=Treatment*Y5;

	LogGoodperct=Log(Goodperct);

	if year=2012 and persinc<37254 then poor=1;
	else if year=2012 and persinc>=37254 then poor=0;
run;

/************************************************************

/*Import Temp DAta*/
PROC IMPORT DATAFILE="/home/u62973430/MySAS/Hon Project/Temp.xlsx"
			OUT=WORK.Temp3
				dbms=xlsx
				replace;
				getnames=yes;
run;

Proc Sort data=temp3;
	by County Year;
run;

/*Import AQ Data for single sector programs*/
PROC IMPORT DATAFILE="/home/u62973430/MySAS/Hon Project/HonData.xlsx"
			OUT=WORK.AQ3
				dbms=xlsx
				replace;
				sheet="AQ3";
				getnames=yes;
run;

proc sort  data=AQ3;
	by County year;
run;
```

```
/*Import Treatment Data for single sector programs*/
PROC IMPORT DATAFILE="/home/u62973430/MySAS/Hon Project/HonData.xlsx"
                OUT=WORK.Treatment3
                     dbms=xlsx
                     replace;
                     sheet="Treatment2";
                     getnames=yes;
run;

proc sort  data=Treatment3;
       by County;
run;

/*Combine Treamtent and AQ for single sector*/
Data CombinedSingle;
       merge AQ3 Treatment3;
       by County;
       /*if Firsteffectiveyear="" then DID=0;
       else if  Year>FirstEffectiveYear then DID=1;
       else DID=0;*/

       if Secondeffectiveyear="" then DID2=0;
       else if  Year>SecondEffectiveYear then DID2=1;
       else DID2=0;

       keep County Year Goodperct moderateperct
              SensitivePerct
              HazardousPerct
              UnhealthyPerct
              VeryUnhealthyPerct
              HazardousPerct State precip auto bus truck motorcycle DID2 poor;
Run;

/* Combine all 3 datasets for single*/
Data SingleAQTreatTemp;
       merge CombinedSingle Temp3;
       by county year;
       if State="" then Delete;
run;

/* Income data for single*/
proc import datafile="/home/u62973430/MySAS/Hon Project/PersonalIncomeDataFix.xlsx"
       out=work.Income3
       DBMS=XLSX
       REPLACE;
RUN;

proc sort data=income3;
       by county year;
run;

/*Multi sector data*/
data Single;
       merge SingleAQTreatTemp income3;
       by county year;
```

```
if year ne 2023 and pop='' then delete;
if State='' then Delete;
if State="California" then Treatment=1;
else if State="Oregon" then Treatment=1;
else if State="Washington" then Treatment=1;
else if State="Vermont" then Treatment =2;
else if State="New York" then Treatment =2;
else if State="Virginia" then Treatment=2;
else if State="Maryland" then Treatment=2;
else if State="New Jersey" then Treatment=2;
else if State="New Hampshire" then Treatment=2;
else if State="Maine" then Treatment=2;
else if State="Conneticut" then Treatment=2;
else if State="Deleware" then Treatment=2;
else if State="Massachusetts" then Treatment=2;
else if State="Rhode Island" then Treatment=2;
else Treatment=0;


if Year=1990 then YearADJ=-11;
else if Year=1991 then YearADJ=-10;
else if Year=1992 then YearADJ=-9;
else if Year=1993 then YearADJ=-8;
else if Year=1994 then YearADJ=-7;
else if Year=1995 then YearADJ=-6;
else if Year=1996 then YearADJ=-5;
else if Year=1997 then YearADJ=-4;
else if Year=1998 then YearADJ=-3;
else if Year=1999 then YearADJ=-2;
else if Year=2000 then YearADJ=-1;
else if Year=2001 then YearADJ=0;
else if Year=2002 then YearADJ=1;
else if Year=2003 then YearADJ=2;
else if Year=2004 then YearADJ=3;
else if Year=2005 then YearADJ=4;
else if Year=2006 then YearADJ=5;
else if Year=2007 then YearADJ=6;
else if Year=2008 then YearADJ=7;
else if Year=2009 then YearADJ=8;
else if Year=2010 then YearADJ=9;
else if Year=2011 then YearADJ=10;
else if Year=2012 then YearADJ=11;
else YearADJ="";

Y2=YearADJ*YearADJ;
Y3=Y2*YearADJ;
Y4=Y3*YearADJ;
Y5=Y4*YearADJ;
TY=Treatment*YearADJ;
TY2=Treatment*Y2;
TY3=Treatment*Y3;
TY4=Treatment*Y4;
TY5=Treatment*Y5;

LogGoodperct=Log(Goodperct);
```

```
	if year=2012 and persinc<37254 then poor=1;
	else if year=2012 and persinc>=37254 then poor=0;

	if year=2023 then pop=100;
run;

/**********************************************************/
/*Combine single and multi for summary stat*/
data summarystat;
	set single multi;
run;


/************************************************************/
/*Summary statistics*/
Proc means data=summarystat N Mean Median Std Min Max;
	where year>1999;
	var Goodperct
		moderateperct
		SensitivePerct
		HazardousPerct
		UnhealthyPerct
		VeryUnhealthyPerct
		Pop
		PersInc
		Avgtemp
		precip auto bus truck motorcycle;
run;

/*********************************************************************/
/*Export Summary stat data*/
proc export data=single
  outfile='/home/u62973430/MySAS/Hon Project/single.xlsx'
  dbms=xlsx
  replace;
  sheet="My Sheet";
run;
/***********************************************************************/
/*TTests*/
Proc TTest Data =multi plots=none;
	Where Year<2013 and Year>1999 and Treatment<=1;
	Var
		PersInc
		Pop
		AvgTemp precip auto bus truck motorcycle;
	Class Treatment;
run;


Proc TTest Data =single plots=none;
Where Year<2008 and Year>1999 and Treatment ne 1;
	Var
		PersInc
		Pop
		AvgTemp
		precip auto bus truck motorcycle;
```

```
	Class Treatment;
run;
/*************************************************************************/
/*Parallel Trend*/
ods output ParameterEstimates=PEforModel1 Effects=OverallSigModel1;
proc surveyreg data=Multi;
	where Treatment<=1 and year<2013 and year>1999;
	class County;
	Model1: Model Goodperct= YearADJ Treatment Y2 /*Y3 Y4 Y5*/ TY TY2 /*TY3 TY4 TY5 PersInc Pop
AvgTemp County*/ /Solution AdjRsq;
run;

ods output ParameterEstimates=PEforModel2 Effects=OverallSigModel2;
proc surveyreg data=single;
	where Treatment ne 1 and year<2008 and year>1999;
	class County ;
	Model2: Model Goodperct= YearADJ Treatment Y2 /*Y3 Y4 Y5*/ TY TY2 /*TY3 TY4 TY5 PersInc Pop
AvgTemp County*/ /Solution AdjRsq;
run;

Data Table_Long;
	length Model $10; /* Makes sure the variable Model has the right length and its values are not truncated */
	length Parameter $30; /* Makes sure the variable Parameter has the right length and its values are not
truncated */
	set PEforModel1 PEforModel2  indsname=M; /*"indsname" creates an indicator variable (here I call it
"M") that tracks the name of databases use in the "set" statement */
	where Substr(Parameter,1,6) ne "County" /*and Substr(Parameter,1,4) ne "Year"*/ ;
	*THisISM=M;

	if	M="WORK.PEFORMODEL1" then Model="Model1";
		else Model="Model2";

		if Probt le 0.01 then Star="***";
		else if probt le 0.05 then Star="**";
	   else if probt le 0.1 then Star="*";
	   else Star="";

	EditedResults=cats(Put(Estimate,comma16.3),star);
	output;

	EditedResults=cats("(",put(StdErr,comma16.3),")");
	output;

run;

proc sort data=Table_Long out=Table_Long_Sorted;
	by Model Parameter;
run;

data Model1Results(rename=(EditedResults=Model1))
		Model2Results(rename=(EditedResults=Model2));
	set Table_Long_Sorted;
	if Model="Model1" then output Model1Results;
		else output Model2Results;

	drop Model;
```

```
	keep Parameter EditedResults;
run;

data Table_Wide;
	merge Model1Results Model2Results;
	by Parameter;

	if parameter="Treatment" then order=1;
	else if parameter="YearAdj" then order=2;
	else if Parameter="Y2" then Order=3;
	else if Parameter="TY" then Order=4;
	else if Parameter="TY2" then Order=5;
	else order=6;

	if mod(_n_,2)=1 then Regressors=Parameter;

run;

proc sort data=Table_Wide out=Table_Wide_Sorted(drop=Order Parameter);
	by Order;
run;

Data OSM1(rename=(EditedValue=Model1)) OSM2(rename=(EditedValue=Model2));
	set OverallSigModel1 OverallSigModel2 indsname=M;
	where Effect="Model";
	if ProbF le 0.01 then Star="***";
		else if probf le 0.05 then Star="**";
	   else if probf le 0.1 then Star="*";
	   else Star="";
	ThisISM=M;

	Label1="OverallSignificance";
	EditedValue=cats(put(FValue,comma16.2),Star);

	if M="WORK.OVERALLSIGMODEL1" then output OSM1;
	else output OSM2;

	keep Label1 EditedValue;
run;

Data OverallSig;
	merge OSM1 OSM2;
	by Label1;
run;


data OtherStat;
	set OverallSig;
	rename Label1=Regressors;
run;

data Table_Wide_Sorted_withStat;
	set Table_Wide_Sorted OtherStat;
run;

proc format;
```

```
	value $VariableName(default=50)
				"Treatment"="CAT Program";

Run;

ods excel file="/home/u62973430/MySAS/Hon Project/ParallelTrend.xlsx" options(Embedded_Titles="ON"
Embedded_Footnotes="ON"); /*Use the path to your MySAS folder */
Title " Parallel Trend Test ";
footnote justify=left"Source: .
Notes: robust standard errors are in parentheses. *, **, and *** indicate
10%, 5%, and 1% significance levels, respectively. Model 1 good air quality. Model 2 represents moderate air
quality.
Model 3 represents unhealthy for sensitive groups air quality. Model 4 represents unhealthy air quality.
Model 5 represents very unhealthy air quality. Model 6 represnets hazardous air quality,";

proc print data=Table_Wide_Sorted_withStat noobs;
	var regressors;
	var Model1-Model2 / style(header)={Just=Center} style(data)={Just=Center tagattr="type:string"};
	format Regressors $VariableName.;
run;
ods excel close;
/****************************************************************************/
/* Graphing*/
proc means data=all mean n;
	where year<2013;
	var Goodperct;
	class treatment year;
	output out=Test;
run;

data Test2;
	set test;
	where (Treatment is not missing) and (year is not missing) and _stat_="MEAN";
run;

proc sgplot data=Test2;
	series x=year y=Goodperct /group=treatment;
run;
/****************************************************************************/

/*Results*/
ods output ParameterEstimates=PEforModel3 DataSummary=ObsModel3 FitStatistics=AdjrsqModel3
Effects=OverallSigModel3;
proc surveyreg data=multi;
	where year>1999;
	class County year/ref=first;
	Model3: Model Goodperct= DID poor*did County year/Solution AdjRsq;
run;

ods output ParameterEstimates=PEforModel4 DataSummary=ObsModel4 FitStatistics=AdjrsqModel4
Effects=OverallSigModel4;
proc surveyreg data=single;
	where year>1999;
	class County year /ref=first;
	Model4: Model Goodperct=DID2 poor*DID2 County Year /Solution AdjRsq;
run;
```

```
ods output ParameterEstimates=PEforModel5 DataSummary=ObsModel5 FitStatistics=AdjrsqModel5
Effects=OverallSigModel5;
proc surveyreg data=multi;
	where year>1999;
	class County year /ref=first;
	Model5: Model Moderateperct= DID DID*poor County Year /Solution AdjRsq;
run;

ods output ParameterEstimates=PEforModel6 DataSummary=ObsModel6 FitStatistics=AdjrsqModel6
Effects=OverallSigModel6;
proc surveyreg data=single;
	where year>1999;
	class County year /ref=first;
	Model6: Model Moderateperct= DID2 DID2*poor County Year  /Solution AdjRsq;
run;

ods output ParameterEstimates=PEforModel7 DataSummary=ObsModel7 FitStatistics=AdjrsqModel7
Effects=OverallSigModel7;
proc surveyreg data=multi;
	where year>1999;
	class County year /ref=first;
	Model7: Model Sensitiveperct= DID DID*poor County Year /Solution AdjRsq;
run;

ods output ParameterEstimates=PEforModel8 DataSummary=ObsModel8 FitStatistics=AdjrsqModel8
Effects=OverallSigModel8;
proc surveyreg data=single;
	where year>1999;
	class County year /ref=first;
	Model8: Model Sensitiveperct= DID2 DID2*poor County Year /Solution AdjRsq;
run;

ods output ParameterEstimates=PEforModel9 DataSummary=ObsModel9 FitStatistics=AdjrsqModel9
Effects=OverallSigModel9;
proc surveyreg data=multi;
	where year>1999;
	class County year /ref=first;
	Model9: Model Unhealthyperct= DID DID*poor County Year /Solution AdjRsq;
run;

ods output ParameterEstimates=PEforModel10 DataSummary=ObsModel10 FitStatistics=AdjrsqModel10
Effects=OverallSigModel10;
proc surveyreg data=single;
	where year>1999;
	class County year /ref=first;
	Model10: Model Unhealthyperct= DID2 DID2*poor County Year /Solution AdjRsq;
run;

ods output ParameterEstimates=PEforModel11 DataSummary=ObsModel11 FitStatistics=AdjrsqModel11
Effects=OverallSigModel11;
proc surveyreg data=multi;
	where year>1999;
	class County year /ref=first;
	Model11: Model veryUnhealthyperct= DID DID*poor County Year /Solution AdjRsq;
run;
```

```
ods output ParameterEstimates=PEforModel12 DataSummary=ObsModel12 FitStatistics=AdjrsqModel12
Effects=OverallSigModel12;
proc surveyreg data=single;
	where year>1999;
	class County year /ref=first;
	Model12: Model veryUnhealthyperct= DID2 DID2*poor County Year /Solution AdjRsq;
run;

ods output ParameterEstimates=PEforModel13 DataSummary=ObsModel13 FitStatistics=AdjrsqModel13
Effects=OverallSigModel13;
proc surveyreg data=multi;
	where year>1999;
	class County year /ref=first;
	Model13: Model hazardousperct= DID DID*poor County Year /Solution AdjRsq;
run;

ods output ParameterEstimates=PEforModel14 DataSummary=ObsModel14 FitStatistics=AdjrsqModel14
Effects=OverallSigModel14;
proc surveyreg data=single;
	where year>1999;
	class County year /ref=first;
	Model14: Model hazardousperct= DID2 DID2*poor County Year /Solution AdjRsq;
run;

Data Table_Long;
	length Model $10; /* Makes sure the variable Model has the right length and its values are not truncated */
	length Parameter $30; /* Makes sure the variable Parameter has the right length and its values are not
truncated */
	set PEforModel3 PEforModel4 PEforModel5 PEforModel6 PEforModel7 PEforModel8 PEforModel9
PEforModel10 PEforModel11 PEforModel12 PEforModel13 PEforModel14 indsname=M; /*"indsname" creates an
indicator variable (here I call it "M") that tracks the name of databases use in the "set" statement */
	where Substr(Parameter,1,6) ne "County" and Substr(Parameter,1,4) ne "Year" ;
	*THisISM=M;

	if	M="WORK.PEFORMODEL3" then Model="Model3";
		else if M="WORK.PEFORMODEL4" then Model="Model4";
		else if M="WORK.PEFORMODEL5" then Model="Model5";
		else if M="WORK.PEFORMODEL6" then Model="Model6";
		else if M="WORK.PEFORMODEL7" then Model="Model7";
		else if M="WORK.PEFORMODEL8" then Model="Model8";
		else if M="WORK.PEFORMODEL9" then Model="Model9";
		else if M="WORK.PEFORMODEL10" then Model="Model10";
		else if M="WORK.PEFORMODEL11" then Model="Model11";
		else if M="WORK.PEFORMODEL12" then Model="Model12";
		else if M="WORK.PEFORMODEL13" then Model="Model13";
		else Model="Model14";

		if Probt le 0.01 then Star="***";
		else if probt le 0.05 then Star="**";
	   else if probt le 0.1 then Star="*";
	   else Star="";

	EditedResults=cats(Put(Estimate,comma16.3),star);
	output;
```

```
		EditedResults=cats("(",put(StdErr,comma16.3),")");
		output;

run;

proc sort data=Table_Long out=Table_Long_Sorted;
		by Model Parameter;
run;

data	Model3Results(rename=(EditedResults=Model3))
			Model4Results(rename=(EditedResults=Model4))
			Model5Results(rename=(EditedResults=Model5))
			Model6Results(rename=(EditedResults=Model6))
			Model7Results(rename=(EditedResults=Model7))
			Model8Results(rename=(EditedResults=Model8))
			Model9Results(rename=(EditedResults=Model9))
			Model10Results(rename=(EditedResults=Model10))
			Model11Results(rename=(EditedResults=Model11))
			Model12Results(rename=(EditedResults=Model12))
			Model13Results(rename=(EditedResults=Model13))
			Model14Results(rename=(EditedResults=Model14));
		set Table_Long_Sorted;
		if Model="Model3" then output Model3Results;
			else if Model="Model4" then output Model4Results;
			else if Model="Model5" then output Model5Results;
			else if Model="Model6" then output Model6Results;
			else if Model="Model7" then output Model7Results;
			else if Model="Model8" then output Model8Results;
			else if Model="Model9" then output Model9Results;
			else if Model="Model10" then output Model10Results;
			else if Model="Model11" then output Model11Results;
			else if Model="Model12" then output Model12Results;
			else if Model="Model13" then output Model13Results;
			else output Model14Results;

		drop Model;
		keep Parameter EditedResults;
run;

data Table_Wide;
		merge Model3Results Model4Results Model5Results Model6Results Model7Results Model8Results
Model9Results Model10Results Model11Results Model12Results Model13Results Model14Results;
		by Parameter;

		if parameter="DID" then order=1;
		else if parameter="DID*Poor" then order=2;
		else if Parameter="DID2" then Order=3;
		else order=4;

		if mod(_n_,2)=1 then Regressors=Parameter;

run;

proc sort data=Table_Wide out=Table_Wide_Sorted(drop=Order Parameter);
		by Order;
run;
```

```
/*The row for the number of observations*/
Data NumberofObs;
	merge ObsModel3(rename=(NValue1=NVModel3) drop=CValue1)
ObsModel4(rename=(NValue1=NVModel4) drop=CValue1)
	ObsModel5(rename=(NValue1=NVModel5) drop=CValue1) ObsModel6(rename=(NValue1=NVModel6)
drop=CValue1)
	ObsModel7(rename=(NValue1=NVModel7) drop=CValue1) ObsModel8(rename=(NValue1=NVModel8)
drop=CValue1)
	ObsModel9(rename=(NValue1=NVModel9) drop=CValue1)
ObsModel10(rename=(NValue1=NVModel10) drop=CValue1)
	ObsModel11(rename=(NValue1=NVModel11) drop=CValue1)
ObsModel12(rename=(NValue1=NVModel12) drop=CValue1)
	ObsModel13(rename=(NValue1=NVModel13) drop=CValue1)
ObsModel14(rename=(NValue1=NVModel14) drop=CValue1);
	where Label1="Number of Observations";

	Model3=put(NVModel3,comma16.);
	Model4=put(NVModel4,comma16.);
	Model5=put(NVModel5,comma16.);
	Model6=put(NVModel6,comma16.);
	Model7=put(NVModel7,comma16.);
	Model8=put(NVModel8,comma16.);
	Model9=put(NVModel9,comma16.);
	Model10=put(NVModel10,comma16.);
	Model11=put(NVModel11,comma16.);
	Model12=put(NVModel12,comma16.);
	Model13=put(NVModel13,comma16.);
	Model14=put(NVModel14,comma16.);
	keep Label1  Model3 Model4 Model5 Model6 Model7 Model8 Model9 Model10 Model11 Model12
Model13 Model14;
run;

/*The row for thr adjusted R-Squared*/
Data Adjrsq;
	merge AdjrsqModel3(rename=(cvalue1=Model3)drop=nvalue1)
AdjrsqModel4(rename=(cvalue1=Model4)drop=nvalue1)
	AdjrsqModel5(rename=(cvalue1=Model5)drop=nvalue1)
AdjrsqModel6(rename=(cvalue1=Model6)drop=nvalue1)
	AdjrsqModel7(rename=(cvalue1=Model7)drop=nvalue1)
AdjrsqModel8(rename=(cvalue1=Model8)drop=nvalue1)
	AdjrsqModel9(rename=(cvalue1=Model9)drop=nvalue1)
AdjrsqModel10(rename=(cvalue1=Model10)drop=nvalue1)
	AdjrsqModel11(rename=(cvalue1=Model11)drop=nvalue1)
AdjrsqModel12(rename=(cvalue1=Model12)drop=nvalue1)
	AdjrsqModel13(rename=(cvalue1=Model13)drop=nvalue1)
AdjrsqModel14(rename=(cvalue1=Model14)drop=nvalue1);
	where Label1="Adjusted R-Square";
run;

/*The row for the F-test related to the Overall Significance of the model*/
Data  OSM3(rename=(EditedValue=Model3)) OSM4(rename=(EditedValue=Model4))
OSM5(rename=(EditedValue=Model5)) OSM6(rename=(EditedValue=Model6))
OSM7(rename=(EditedValue=Model7)) OSM8(rename=(EditedValue=Model8))
OSM9(rename=(EditedValue=Model9)) OSM10(rename=(EditedValue=Model10))
OSM11(rename=(EditedValue=Model11)) OSM12(rename=(EditedValue=Model12))
```

```
OSM13(rename=(EditedValue=Model13)) OSM14(rename=(EditedValue=Model14));
	set OverallSigModel3 OverallSigModel4 OverallSigModel5 OverallSigModel6 OverallSigModel7 
OverallSigModel8 OverallSigModel9 OverallSigModel10 OverallSigModel11 OverallSigModel12 
OverallSigModel13 OverallSigModel14 indsname=M;
	where Effect="Model";
	if ProbF le 0.01 then Star="***";
		else if probf le 0.05 then Star="**";
	   else if probf le 0.1 then Star="*";
	   else Star="";
	ThisISM=M;

	Label1="OverallSignificance";
	EditedValue=cats(put(FValue,comma16.2),Star);

	if M="WORK.OVERALLSIGMODEL3" then output OSM3;
	else if M="WORK.OVERALLSIGMODEL4" then output OSM4;
	else if M="WORK.OVERALLSIGMODEL5" then output OSM5;
	else if M="WORK.OVERALLSIGMODEL6" then output OSM6;
	else if M="WORK.OVERALLSIGMODEL7" then output OSM7;
	else if M="WORK.OVERALLSIGMODEL8" then output OSM8;
	else if M="WORK.OVERALLSIGMODEL9" then output OSM9;
	else if M="WORK.OVERALLSIGMODEL10" then output OSM10;
	else if M="WORK.OVERALLSIGMODEL11" then output OSM11;
	else if M="WORK.OVERALLSIGMODEL12" then output OSM12;
	else if M="WORK.OVERALLSIGMODEL13" then output OSM13;
	else output OSM14;

	keep Label1 EditedValue;
run;

Data OverallSig;
	merge OSM3 OSM4 OSM5 OSM6 OSM7 OSM8 OSM9 OSM10 OSM11 OSM12 OSM13 OSM14;
	by Label1;
run;


data OtherStat;
	set NumberofObs AdjRsq OverallSig;
	rename Label1=Regressors;
run;

data Table_Wide_Sorted_withStat;
	set Table_Wide_Sorted OtherStat;
run;

proc format;
	value $VariableName(default=50)
				"DID"="Multi-Sector CAT"
				"DID2"="Single-Sector CAT"
				"DID*Poor"="Multi*Poor"
				"DID2*Poor"="Single*Poor";

Run;

ods excel file="/home/u62973430/MySAS/Hon Project/ProjectResults.xlsx" options(Embedded_Titles="ON" 
Embedded_Footnotes="ON"); /*Use the path to your MySAS folder */
```

```
Title "  ";
footnote justify=left"Source:.
Notes: robust standard errors are in parentheses. *, **, and *** indicate
10%, 5%, and 1% significance levels, respectively. Model 1 good air quality. Model 2 represents moderate air
quality.
Model 3 represents unhealthy for sensitive groups air quality. Model 4 represents unhealthy air quality.
Model 5 represents very unhealthy air quality. Model 6 represnets hazardous air quality,";

proc print data=Table_Wide_Sorted_withStat noobs;
	var regressors;
	var Model3-Model14 / style(header)={Just=Center} style(data)={Just=Center tagattr="type:string"};
	format Regressors $VariableName.;
run;
ods excel close;
/*****************************************************************/
ods output ParameterEstimates=PEforModel15 DataSummary=ObsModel15 FitStatistics=AdjrsqModel15
Effects=OverallSigModel15;
proc surveyreg data=multi;
	where year>1999;
	class County year/ref=first;
	Model15: Model Goodperct= DID poor*did avgtemp precip County year/Solution AdjRsq;
run;

ods output ParameterEstimates=PEforModel16 DataSummary=ObsModel16 FitStatistics=AdjrsqModel16
Effects=OverallSigModel16;
proc surveyreg data=single;
	where year>1999;
	class County year /ref=first;
	Model16: Model Goodperct=DID2 poor*DID2 avgtemp precip County Year /Solution AdjRsq;
run;

ods output ParameterEstimates=PEforModel17 DataSummary=ObsModel17 FitStatistics=AdjrsqModel17
Effects=OverallSigModel17;
proc surveyreg data=multi;
	where year>1999;
	class County year/ref=first;
	Model17: Model Goodperct= DID poor*did avgtemp precip pop persinc County year/Solution AdjRsq;
run;

ods output ParameterEstimates=PEforModel18 DataSummary=ObsModel18 FitStatistics=AdjrsqModel18
Effects=OverallSigModel18;
proc surveyreg data=single;
	where year>1999;
	class County year /ref=first;
	Model18: Model Goodperct=DID2 poor*DID2 avgtemp precip pop persinc County Year /Solution AdjRsq;
run;

ods output ParameterEstimates=PEforModel19 DataSummary=ObsModel19 FitStatistics=AdjrsqModel19
Effects=OverallSigModel19;
proc surveyreg data=multi;
	where year>1999;
	class County year/ref=first;
	Model19: Model Goodperct= DID poor*did avgtemp precip pop persinc auto bus truck motorcycle County
year/Solution AdjRsq;
run;
```

```
ods output ParameterEstimates=PEforModel20 DataSummary=ObsModel20 FitStatistics=AdjrsqModel20
Effects=OverallSigModel20;
proc surveyreg data=single;
	where year>1999;
	class County year /ref=first;
	Model20: Model Goodperct=DID2 poor*DID2 avgtemp precip pop persinc auto bus truck motorcycle
County Year /Solution AdjRsq;
run;

Data Table_Long;
	length Model $10; /* Makes sure the variable Model has the right length and its values are not truncated */
	length Parameter $30; /* Makes sure the variable Parameter has the right length and its values are not
truncated */
	set PEforModel15 PEforModel16 PEforModel17 PEforModel18 PEforModel19 PEforModel20
indsname=M; /*"indsname" creates an indicator variable (here I call it "M") that tracks the name of databases use in
the "set" statement */
	where Substr(Parameter,1,6) ne "County" and Substr(Parameter,1,4) ne "Year" ;
	*THisISM=M;

	if	M="WORK.PEFORMODEL15" then Model="Model15";
		else if M="WORK.PEFORMODEL16" then Model="Model16";
		else if M="WORK.PEFORMODEL17" then Model="Model17";
		else if M="WORK.PEFORMODEL18" then Model="Model18";
		else if M="WORK.PEFORMODEL19" then Model="Model19";
		else Model="Model20";

		if Probt le 0.01 then Star="***";
		else if probt le 0.05 then Star="**";
	   else if probt le 0.1 then Star="*";
	   else Star="";

	EditedResults=cats(Put(Estimate,comma16.3),star);
	output;

	EditedResults=cats("(",put(StdErr,comma16.3),")");
	output;

run;

proc sort data=Table_Long out=Table_Long_Sorted;
	by Model Parameter;
run;

data
		Model15Results(rename=(EditedResults=Model15))
		Model16Results(rename=(EditedResults=Model16))
		Model17Results(rename=(EditedResults=Model17))
		Model18Results(rename=(EditedResults=Model18))
		Model19Results(rename=(EditedResults=Model19))
		Model20Results(rename=(EditedResults=Model20));
	set Table_Long_Sorted;
	if Model="Model15" then output Model15Results;
		else if Model="Model16" then output Model16Results;
		else if Model="Model17" then output Model17Results;
		else if Model="Model18" then output Model18Results;
		else if Model="Model19" then output Model19Results;
```

```
			else output Model20Results;

		drop Model;
		keep Parameter EditedResults;
run;

data Table_Wide;
		merge Model15Results Model16Results Model17Results Model18Results Model19Results
Model20Results;
		by Parameter;

		if parameter="DID" then order=1;
		else if parameter="DID*Poor" then order=2;
		else if Parameter="DID2" then Order=3;
		else if Parameter="DID2*Poor" then Order=4;
		else if Parameter="Precip" then Order=5;
		else if Parameter="Avgtemp" then Order=6;
		else if Parameter="Pop" then Order=7;
		else if Parameter="Persinc" then Order=8;
		else if Parameter="auto" then Order=9;
		else if Parameter="bus" then Order=10;
		else if Parameter="truck" then Order=11;
		else if Parameter="motorcycle" then Order=12;
		else order=13;

		if mod(_n_,2)=1 then Regressors=Parameter;

run;

proc sort data=Table_Wide out=Table_Wide_Sorted(drop=Order Parameter);
		by Order;
run;

/*The row for the number of observations*/
Data NumberofObs;
		merge  ObsModel15(rename=(NValue1=NVModel15) drop=CValue1)
		ObsModel16(rename=(NValue1=NVModel16) drop=CValue1)
ObsModel17(rename=(NValue1=NVModel17) drop=CValue1)
		ObsModel18(rename=(NValue1=NVModel18) drop=CValue1)
ObsModel19(rename=(NValue1=NVModel19) drop=CValue1)
		ObsModel20(rename=(NValue1=NVModel20) drop=CValue1);
		where Label1="Number of Observations";

		Model15=put(NVModel15,comma16.);
		Model16=put(NVModel16,comma16.);
		Model17=put(NVModel17,comma16.);
		Model18=put(NVModel18,comma16.);
		Model19=put(NVModel19,comma16.);
		Model20=put(NVModel20,comma16.);
		keep Label1 Model15 Model16 Model17 Model18 Model19 Model20;
run;

/*The row for thr adjusted R-Squared*/
Data Adjrsq;
		merge AdjrsqModel3(rename=(cvalue1=Model3)drop=nvalue1)
AdjrsqModel4(rename=(cvalue1=Model4)drop=nvalue1)
```

```
            AdjrsqModel5(rename=(cvalue1=Model5)drop=nvalue1)
AdjrsqModel6(rename=(cvalue1=Model6)drop=nvalue1)
            AdjrsqModel7(rename=(cvalue1=Model7)drop=nvalue1)
AdjrsqModel8(rename=(cvalue1=Model8)drop=nvalue1)
            AdjrsqModel9(rename=(cvalue1=Model9)drop=nvalue1)
AdjrsqModel10(rename=(cvalue1=Model10)drop=nvalue1)
            AdjrsqModel11(rename=(cvalue1=Model11)drop=nvalue1)
AdjrsqModel12(rename=(cvalue1=Model12)drop=nvalue1)
            AdjrsqModel13(rename=(cvalue1=Model13)drop=nvalue1)
AdjrsqModel14(rename=(cvalue1=Model14)drop=nvalue1);
            where Label1="Adjusted R-Square";
run;

/*The row for the F-test related to the Overall Significance of the model*/
Data
OSM15(rename=(EditedValue=Model15)) OSM16(rename=(EditedValue=Model16))
OSM17(rename=(EditedValue=Model17)) OSM18(rename=(EditedValue=Model18))
OSM19(rename=(EditedValue=Model19)) OSM20(rename=(EditedValue=Model20));
            set OverallSigModel15 OverallSigModel16 OverallSigModel17 OverallSigModel18 OverallSigModel19
OverallSigModel20 indsname=M;
            where Effect="Model";
            if ProbF le 0.01 then Star="***";
                        else if probf le 0.05 then Star="**";
               else if probf le 0.1 then Star="*";
               else Star="";
            ThisISM=M;

            Label1="OverallSignificance";
            EditedValue=cats(put(FValue,comma16.2),Star);

            if M="WORK.OVERALLSIGMODEL15" then output OSM15;
            else if M="WORK.OVERALLSIGMODEL16" then output OSM16;
            else if M="WORK.OVERALLSIGMODEL17" then output OSM17;
            else if M="WORK.OVERALLSIGMODEL18" then output OSM18;
            else if M="WORK.OVERALLSIGMODEL19" then output OSM19;
            else output OSM20;

            keep Label1 EditedValue;
run;

Data OverallSig;
            merge OSM15 OSM16 OSM17 OSM18 OSM19 OSM20;
            by Label1;
run;


data OtherStat;
            set NumberofObs AdjRsq OverallSig;
            rename Label1=Regressors;
run;

data Table_Wide_Sorted_withStat;
            set Table_Wide_Sorted OtherStat;
run;

proc format;
```

```
	value $VariableName(default=50)
				"DID"="Multi-Sector CAT"
				"DID2"="Single-Sector CAT"
				"DID*Poor"="Multi*Poor"
				"DID2*Poor"="Single*Poor";

Run;

ods excel file="/home/u62973430/MySAS/Hon Project/AppendixGood.xlsx" options(Embedded_Titles="ON"
Embedded_Footnotes="ON"); /*Use the path to your MySAS folder */
Title " Table 5: Good Days with Controls ";
footnote justify=left"NOAA National Centers for Environmental information, n.d., U.S. Bureau of Economic
Analysis, 2022; US Environmental Protection Agency, 2023; Winter, D.,2022 and own calculations.
 Notes: Robust standard errors are in parentheses. *, **, and *** indicate10%, 5%, and 1% significance levels,
respectively. Models 1 and 2 represent good air quality, Models 3 and 4 represent moderate air quality, Models 5
and 6 represent unhealthy for sensitive groups air quality, Models 7 and 8 represent unhealthy air quality, Models 9
and 10 represent very unhealthy air quality, and Models 11 and 12 represent hazardous air quality.
";

proc print data=Table_Wide_Sorted_withStat noobs;
	var regressors;
	var Model15-Model20 / style(header)={Just=Center} style(data)={Just=Center tagattr="type:string"};
	format Regressors $VariableName.;
run;
ods excel close;
```