Do Regulators Strategically Avoid Pollution Hotspots when Siting Monitors? Evidence from Remote Sensing of Air Pollution*

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Abstract

Ambient air pollution monitors are used to track pollution, and the data are used in regulatory settings and research. We identify a principal-agent problem where the local regulator has an incentive to avoid siting monitors in polluted areas but the ability to do so is dampened in nonattainment counties. To test for strategic behavior, we employ satellite-derived pollution estimates to characterize pollution at non-monitored locations. Leveraging the discontinuity at the nonattainment threshold, we find evidence of avoidance by local regulators in attainment counties. Our results suggest that monitoring data in attainment counties systematically understates ambient pollution compared to nonattainment counties.

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Policies that regulate ambient air pollution rely on stationary, *in situ* monitors that measure concentrations of target pollutants. The network of monitors provides regulators, researchers and the public with data that describe the distribution of pollution over space and time. The data are used by researchers across many disciplines, including atmospheric science, public health, and economics, but to our knowledge there has been no previous research on how the locations of monitors used for compliance are chosen. The literature in economics, as well as other fields, implicitly treats monitor locations as exogenous and the readings as random samples. However, in a federalist system such as the United States, the local regulator (e.g. a state-, sub-state agency) can exercise some discretion in the siting decision, and the local regulator has an incentive to avoid detecting pollution due to a principal-agent problem. In this paper, we show that local regulators have an incentive to strategically avoid pollution hotspots when siting new monitors, and we test for strategic behavior using remote sensing estimates of pollution.

Our focus is on the United States, where ambient air pollution is regulated by the Clean Air Act and its Amendments (CAAA)[1]. Under the CAAA, states, tribes and local governments are charged with ensuring that local ambient air quality complies with National Ambient Air Quality Standards (NAAQS) set by the EPA. The NAAQS are set and occasionally updated based on scientific advances concerning human health impacts, and the standards are achieved through a variety of federal and local regulations targeting emissions from stationary and nonpoint sources. Areas found out of compliance with the NAAQS (typically counties, but occasionally smaller regions) are designated as "nonattainment" areas, which then must come back into compliance through additional regulatory actions. Importantly, while each state is charged with designing its own monitoring network, there is considerable flexibility in exactly how a state chooses the *locations* for its ambient pollution monitors, particularly if the county has historically been in attainment. A local regulator has an incentive to avoid detecting a pollution hotspot, and this incentive is particularly strong for counties at risk of exceeding the NAAQS threshold.

Nonattainment designation, and the resulting reduction in pollution due to additional regulatory pressure, has played an important role in the literature on the economics of pol-

[1] 40 C.F.R. Subchapter C, Parts 50-97

lution and regulation. Nonattainment designation itself has been used as an instrumental variable (and the threshold has been used in a regression discontinuity design) in several papers to identify hedonic models and distributional effects of regulations (Chay and Greenstone 2005; Grainger 2012), to identify impacts on health or mortality (Chay and Greenstone 2003), or to examine labor market impacts (Walker 2013). Nonattainment status has been shown to be costly for polluting firms (Becker 2005; Greenstone 2002), which face additional regulatory pressure to reduce emissions, though estimates suggest that the social benefits far outweigh the costs.[2] Nonattainment designation affects the distribution of pollution *within* affected counties, as designation leads to targeted regulatory efforts (Auffhammer et al. 2009).[3] Other literature focuses on how firms choose their location decisions in response to county-level nonattainment. For example, Kahn (1997), Kahn and Mansur (2013), Henderson (1996), List et al. (2003) and Becker and Henderson (2000) study impacts of regulations, including on new plant siting choices. Nonattainment designation is also costly for the local regulator; roughly two-thirds of the administrative costs are borne by EPA, but the remaining costs fall on local governments. Under the CAAA, counties found to be out of compliance with the NAAQS are required to come back into compliance by submitting a State Implementation Plan, which details how the state plans to bring the air quality in the violating county back to acceptable levels. If the county fails to come back into attainment, EPA has authority to impose penalties on states such as withholding federal highway funding. As a result, a budget-constrained regulator may wish to avoid costly nonattainment designation by simply avoiding monitoring pollution hotspots.[4]

For an area *already* in nonattainment, new monitor sitings are typically placed as part of the State Implementation Plan (SIP) or Federal Implementation Plan (FIP), which describes in detail how an area will come back into attainment with the NAAQS. The SIP process

[2] Central estimates from the EPA suggest that the benefits of the CAAA between 1990 and 2020 are orders of magnitude larger than the costs. Damages are estimated at $56 Billion, whereas benefits (mostly from health and avoided mortality) are roughly 30 times higher (USEPA 1999).

[3] Grainger (2012) and Bento et al. (2015) both leverage the within-county variation in the pollution reduction to look at distributional impacts of the regulations.

[4] It is not obvious that targeting a hotspot would be "optimal" for a regulator, as she is solving a multi-objective optimization problem, which may include protecting human health as well as other objectives, such as obtaining information for modeling and prediction.

involves not only taking a detailed inventory of emissions sources, but often also increasing its monitoring capacity to ensure that ambient air pollution does not exceed federal guidelines. Thus a regulator siting a new monitor in an area already designated as nonattainment does not have the same degree of flexibility in her siting decision, as the siting decision is typically subject to additional federal oversight.

The minimum number of monitors in a given Core-Based Statistical Area (CBSA) is determined by the CAAA. The area's population, industrial composition, the amount of thru-traffic, as well as other indicators, determine the minimum number of monitors, and local regulatory agencies typically do not place additional monitors, as the cost of additional monitoring would fall on the state. We also note that the decision to re-site or remove a monitor requires EPA approval, and monitors may only be removed from a location if the state can demonstrate that the monitor has historically fallen well below the NAAQS thresholds and the probability of future violations is small.[5]

Because ambient pollution monitors only provide data on pollution levels at monitor-specific locations, we use remote-sensing data to learn about pollution levels throughout the United States, with a particular focus on alternative candidate locations for monitors at the time of siting (which we define later in the empirical section).[6] We compare ambient pollution (as measured remotely) at the monitor site to pollution levels in surrounding areas within the county. We show that, *within an attainment county*, a new pollution monitor is more likely to be sited in an area with low pollution levels relative to other candidate locations in that county. To test for strategic siting of monitors, we leverage the disconinuity at the NAAQS threshold and find that new monitors in attainment areas tend to avoid pollution relative to nonattainment areas. We then estimate linear probability models at different spatial levels to determine whether relative pollution levels influence the siting decision. We find evidence of strategic siting, which suggests that many counties would be designated as nonattainment if monitors were resited to dirtier locations within the same region.

[5] In the empirical section we consider removal of monitors as well as new sitings.

[6] An alternative approach would be to use an atmospheric model to estimate pollution at locations without monitors, such as the Community Multiscale Air Quality model. These models are typically validated and/or calibrated using AQS monitoring data, however, so if monitors are strategically sited, it is possible that the models would miss the heterogeneity in pollution due to strategic siting behavior.

We argue that our findings have important implications for policy as well as empirical research using monitoring data. First, depending on the type of county, measurements of ambient pollution from *in situ* monitors may be systematically biased, as local regulators have an incentive to avoid polluted areas when siting new monitors. Regression Discontinuity estimates suggest a significant decrease in avoidance behavior for counties just above the NAAQS threshold. Second, we demonstrate that the bias in attainment county monitoring data persists beyond the newly-sited monitors. Point estimates suggest that a one standard deviation increase in the remotely-sensed pollution at the grid cell level in an attainment county is associated with a 40-70% decrease in the likelihood that that grid cell is monitored. Third, nonattainment status is, at least for marginal counties, endogenous, as the local regulator in an attainment county can avoid pollution hotspots when siting ambient pollution monitors. Fourth, there are areas of the country that are likely out of compliance with federal standards but, because monitors in those counties do not capture peak pollution levels, remain classified as being in attainment. As a result, a large share of the population is likely exposed to pollution levels above the NAAQS threshold but these regions are effectively misclassified as being in compliance. Finally, our results suggest that there are potentially large gains from additional oversight or guidance from the federal government when local regulators choose where to site new monitors. Given the recent advances in the remote sensing for ambient air pollution and the improvements in mobile pollution monitoring technologies, these information sources could be leveraged to better guide monitor placement decisions, which would result in improved monitoring data and more efficient air pollution regulation.

1 Background

Air pollution regulations can be classified into two general categories: regulations targeting emissions, and ambient air quality regulations. In this paper we are concerned with the latter, in particular nonattainment designation and the monitor placement choices of local regulators. We are aware of no previous studies concerning strategic siting of ambient pollution monitors. A legal perspective, including a discussion of microclimates, is in Carlson (2018). Muller and Ruud (2016) study how monitored ozone levels in one period affect the siting or removal of monitors in subsequent periods. A major difference, however, is that they employ only AQS monitoring data, while our approach employs remote sensing data to compare pollution levels at the monitored location to the surrounding area. There is also evidence that strategic emissions by point sources of pollution may create a bias in monitoring data for particulate matter. Zou (2017) employs aerosol optical depth estimates of fine particulates to study pollution at monitored locations on days when the monitor is not operating. He finds evidence of strategic *emissions* by upwind firms by leveraging the once-every-six-days monitoring schedule for particulate matter in the United States.[7] Our focus is on strategic avoidance of pollution in the siting of stationary monitors, which to our knowledge has not been previously addressed in the literature.

Ambient pollution monitors, which are sited and maintained by local regulatory authorities, are used to provide continuous monitoring of ambient air pollution.[8] In general monitors are only placed when mandated, because the cost of a new monitor is substantial and borne by the local authority.[9] Monitors are generally placed on trailers or on rooftops, and they must have adequate space for the associated electrical and computer equipment. Furthermore, a site must have a source of power for heating and cooling the instruments and computers, and the instruments must be regularly calibrated and maintained by on-site engineers. The quality standards for these monitors are high, and other monitoring data (such as from mobile monitors) cannot currently be used for regulatory compliance; EPA provides guidance on the standards that a monitor must meet. Once placed, a monitor is difficult to remove, and in practice the monitor's location is effectively viewed as a permanent decision by the local regulator.

Importantly, the local regulator is given considerable discretion in determining its moni-

[7]We note that NO_2 and ozone, the pollutants of interest in this paper, do not follow this sampling pattern.

[8]The World Health Organization (WHO 1999) lists multiple objectives that should be met by a monitoring system, including population exposure and health impact assessment; identifying threats to natural ecosystems; determining compliance with national or international standards; informing the public about air quality and establishing alert systems; providing objective input to air quality management and to transport and land-use planning; identifying and apportioning sources; developing policies and setting priorities for management action; developing and validating management tools such as models and geographical information systems; quantifying trends to identify future problems or progress in achieving management or control targets.

[9]Furthermore, because nonattainment can be triggered by a "bad day" at a single location, there is little incentive to increase the network size within a county.

toring strategy. For the criteria pollutants regulated under the Clean Air Act, the Code of Federal Regulations sets guidelines for how a monitoring network should be established.[10] Our discussion here focuses on NO_2 because our remote sensing data do particularly well at detecting NO_2, but the same flexibility is present in the rules guiding the placement of monitors for other criteria pollutants.[11] While there are federal guidelines regarding the placement of ambient pollution monitors, there remains considerable flexibility in the siting choice. States (or substate regulatory agencies) are required to establish a plan to place, or to identify, an area-wide NO_2 monitor; NO_2 monitors should be placed to characterize vulnerable and susceptible populations; and core-based statistical areas (CBSAs) are required to have varying numbers of near-road monitors, depending on the population and traffic density along major freeways.[12] Area-wide monitors, which are meant to be representative of a larger spatial scale, have additional rules in the Code of Federal Regulations (CFR). Specifically, the local regulatory agency shall "monitor a location of expected highest NO_2 concentrations representing the neighborhood or larger spatial scales." Furthermore, under the CFR, emissions inventories and meteorological analysis should be used to identify appropriate candidate locations within a core-based statistical area (CBSA) for establishing an area-wide monitoring station.

For areas already designated as nonattainment, new monitor placements are typically subject to increased federal scrutiny under the local State Implementation Plan (SIP),[13] which must be approved by EPA. This often requires expanding a state's pollution monitoring network with an additional focus of monitoring of areas of concern.

The flexibility in determining the precise location of each monitor in the network is the focus of this paper. The Appendix provides a simple analytical model that generates the

[10] For NO_2 monitors, for example, see 40 U.S.C. 1(C)§58.

[11] Not all monitors are used to sample each of the six criteria pollutants. Depending on local conditions and emissions sources, some monitors track multiple pollutants, whereas others may target specific pollutants.

[12] Specifically, CBSAs with 1,000,000 people or 500,000 people and significant traffic require a single monitor, and a second monitor is required if the CBSA population exceeds 2.5 Million (or if thru-traffic increases substantially).

[13] Under some circumstances "EPA may promulgate comprehensive control measures...in the absence of State-adopted provisions", a process known as a FIP. See Chapter 1 of (EPA). We also note that some areas, such as "maintenance areas" may also have additional federal oversight although they are technically in attainment. Our binary categorization, if anything, would bias against finding an effect.

main hypothesis that we test in this paper, namely that a regulator in an attainment county would avoid hotspots relative a nonattainment county, all else equal. In the next section we move to a description of the data sources before proceeding to our empirical tests.

2 Data

2.1 AQS Monitoring Data

The Air Quality System (AQS) data from the US Environmental Protection Agency contain the universe of ambient pollution monitors that are used for compliance with the CAAA. The monitor-level data include the longitude and latitude positioning and hourly pollution readings of each active ozone and NO_2 monitor. The spatial distributions of ozone monitors for the United States are shown in figure 1.[14] The figure includes all monitors active for at least one year from 2005-2016 in the contiguous United States. Monitor coverage tends to follow populated areas due to federal guidelines, with rural areas being largely unmonitored.

Important for this study are nonattainment designations. The nonattainment designation occurs at the county-year level when a primary or secondary standard is violated for one of the criteria pollutants. We use the Greenbook from EPA, which provides data on the period of violation, by criteria pollutant, for each county in the United States. Our primary definition of nonattainment status includes designation for either ozone or fine particulates, as NO_x is a precursor to both.[15]

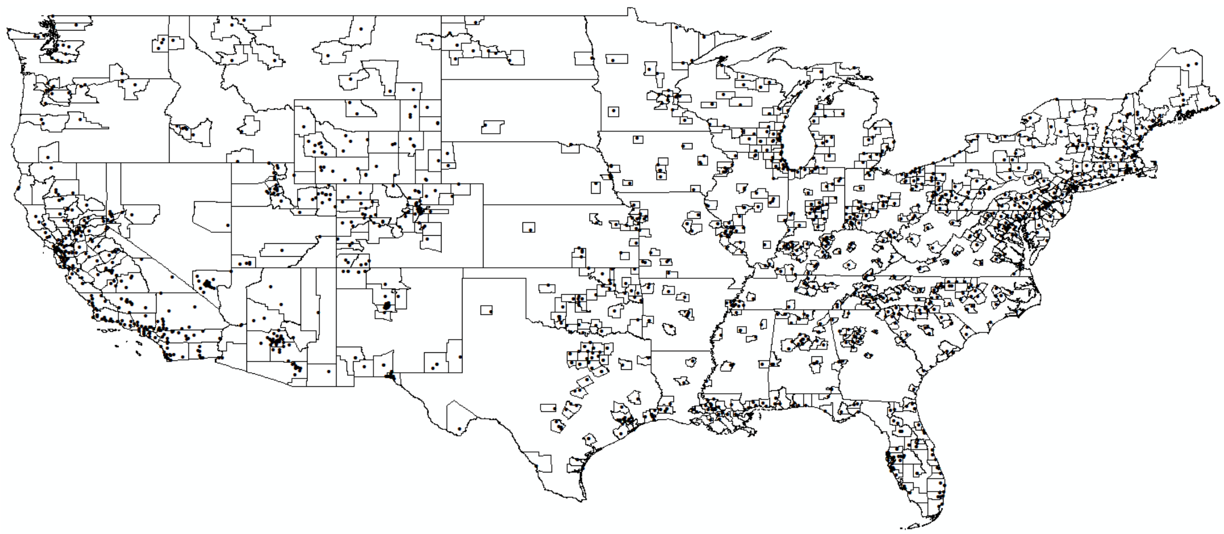
Table 1 provides descriptive statistics on the number of active, newly-sited, and retired monitors in our data range. Newly-sited monitors are simply defined as monitors that were not active in the previous year. Retired monitors are defined as monitors that were inactive in the subsequent years, including monitors that are re-sited in subsequent years to nearby areas.[16] From 2005-2016, 492 monitors were newly sited in the contiguous United States that

[14] All coordinates are translated to the WGS84 coordinate system using GIS software. Many (but not all) monitors capture readings for multiple pollutants. For all active monitors from 2005-2016, 507 of the 1,575 monitors measure ozone exclusively while multi-pollutant monitors tend to measure PM (PM_{10} and $PM_{2.5}$) and NO_2 the most out of the other criteria pollutants.

[15] We also note that there have been no NO_2 nonattainment designations since the late 1970s.

[16] In this paper we focus on sitings of new monitors; subsequent research will examine retirements and

Figure 1: Air Quality System Pollution Monitors: Ozone



Notes: Black dots denote the distribution of ozone monitors in the AQS database from 2005-2016 for the contiguous United States. The associated counties for monitor sitings are also delineated.

measure ozone and nitrogen dioxide concentrations. The number of newly sited monitors spiked in 2011 with 93, and has since fallen through 2016.[17] We do not include roadside monitors (following EPA's definition) and include monitors that measure both NO_2 and ozone so that the samples are consistent across analyses.

The monitoring data are reported hourly, but for our purposes we also include annual averages, 8-hour averages, and several percentiles and order statistics following the NAAQS for each pollutant. The standard for ozone, for example, is based on the annual fourth-highest daily maximum 8-hour concentrations, averaged over three years.[18] There are currently no

pollution dynamics.

[17]We note that the conservation of flow (the total number of monitors in the next year does not add to the number in the previous year plus any net change due to siting and retiring) does not hold for the first level of the table due to years with unreported data (e.g. mechanical issues or cleaning). Of the total number of newly sited monitors, approximately 34% were sited in counties in nonattainment at the time of siting, while the other 66% were sited in attainment counties. In the *New* column, the number of monitored counties is less than the number of newly sited monitors due to multiple monitors sited in the same county. Roughly 30% of the total number of counties getting a new monitor were in nonattainment designation which suggests that nonattainment counties get a proportional number of monitors relative to the number of counties in each category. The total number of monitors and counties across designation statuses are not mutually exclusive in the *All* case. 200 counties and 392 monitors flip between nonattainment and attainment designations in our sample period.

[18]The nonattainment designation in our data follows the contemporaneous standard, so 2005 nonattain-

Table 1: AQS Descriptive Statistics: Ozone

		New	Retired	All
Number of Monitors	*2005*	37	38	1123
	2006	44	33	1127
	2007	64	41	1154
	2008	46	33	1146
	2009	51	31	1171
	2010	46	39	1192
	2011	93	28	1247
	2012	30	68	1248
	2013	25	23	1199
	2014	13	34	1195
	2015	25	41	1189
	2016	18		1169
Total Monitors	*Attainment*	327	226	1022
	NA	165	183	846
	Total	492	409	1868
Total Counties	*Attainment*	248	183	666
	NA	108	115	368
	Total	356	298	1034
Avg. 4th Max	*Attainment*	0.065	0.066	0.067
	NA	0.071	0.068	0.075
	Total	0.067	0.067	0.071

Notes: *New* denotes the number of newly sited monitors in our sample period, *Retired* refers to those that do not appear again in the data following the last record and *All* aggregates across all monitors with available data for a given year. The conservation of flow does not hold in the first level of the table due to years that are unreported due to mechanical issues or cleaning. For instance, if the current period has more monitors than anticipated (the number of monitors in the previous period plus or minus the net change due to siting and retiring), then monitors were turned off in the previous period. The total number of monitors and counties across designation status are not mutually exclusive in the *All* case. We pick out all monitors and counties that have ever been associated with nonattainment vs. attainment from 2005-2016. The count of *New* and *Retired* monitors (both by monitor and the county they were placed/removed from) is assessed at the time of siting or retiring. The NAAQS in place in 2005 was the 1997 standard of 0.08 ppm. The threshold was reduced to 0.075 ppm in 2008 and 0.070 ppm in 2015.

counties in nonattainment for NO_2. The bottom tier of table 1 provides the difference in pollution readings averaged across all years in our sample for all monitors, newly-sited monitors and retired monitors across county types. As expected, nonattainment counties

ment, for example, follows the NAAQS in place in 2005, which was the 1997 standard of 0.08 ppm. The threshold was reduced to 0.075 ppm in 2008 and 0.070 ppm in 2015.

have higher levels of ozone readings than attainment counties, with the average just above the ambient pollution standard. Moreover, newly-sited monitors tend to have lower pollution levels than preexisting monitors. Retired monitors have the smallest readings on average, which is consistent with federal guidelines defining when a monitor may be removed.

2.1.1 Monitoring Objectives

The discussion so far has abstracted away from monitor "types," but in practice there are several networks of monitors, the objectives of which vary. These networks include the State and Local Air Monitoring Stations (SLAMS), the National Air Monitoring Stations (NAMS), and the Photochemical Assessment Monitoring Stations (PAMS). While NAMS monitors are generally meant to be representative of a broader region, PAMS monitors are used to better calibrate models of ozone formation and are often placed upwind of peak ozone pollution as indicators of "background" concentrations. SLAMS monitors are those operated by local regulatory agencies with the primary purpose of comparing ambient pollution concentrations with the NAAQS. In our empirical specifications we consider the set of all AQS monitors as well as restricting our attention to the siting of SLAMS monitors.

The AQS metadata also include the specific objective for each monitor. The most prominent monitoring objectives in the AQS data include monitors sited for population exposure to ambient pollution and targeting highest concentrations (i.e. "hotspots"). Table 2 describes the number of monitors sited with a particular objective.[19] We define *other* to include monitors sited for "background pollution" (typically pollution levels from sources outside the jurisdiction, before local sources are taken into account); regional transport pollution; downwind/upwind exposure; and unlisted objectives. About 23% of newly-sited monitors in attainment counties list "highest concentration" as the objective; the proportion is similar (21%) for newly-sited monitors in nonattainment counties.

[19] There are instances in the data where multiple objectives are provided for a given monitor (for instance, siting a monitor for population exposure and highest concentration).

Table 2: Number of Monitors Sited for Different Objectives

		Highest Concentration	Population Exposure	Other
New	*Attainment*	78	111	144
	NA	37	103	40
All	*Attainment*	430	608	280
	NA	519	695	87

Notes: *New* denotes the number of newly sited monitors in our sample period and *All* aggregates across all monitors with available data for a given year. The designation status for monitor counts in the *All* case are not mutually exclusive due to counties which change status. Monitors are also not exclusively in each objective category due to instances of multiple objectives listed in the data. We pick out all monitors and counties that have ever been associated with nonattainment vs. attainment from 2005-2016. The count of *New* monitors is assessed at the time of siting.

2.2 Satellite Data: BEHR and OMI

Our characterization of the problem requires information on pollution levels not only at the monitored site, but also in the surrounding areas. We are interested in local comparisons of the monitored site to other candidate locations within the same county. We employ a state-of-the-science remote sensing dataset from the Berkeley High Resolution (BEHR) group (Laughner et al. 2018) for nitrogen dioxide and estimates from NASA's OMI (Ozone Monitoring Instrument) for formaldehyde from 2005-2015.[20] The BEHR data provide fine resolution pollution estimates regridded to a 0.05° x 0.05° grid cell level (roughly equaling a 5 x 5km cell).[21]

It is worth emphasizing that our empirical specifications will use data based on this 0.05° x 0.05° grid. As such, our characterization of the regulator's decision is still somewhat coarse. We test whether the average concentrations at the grid cell level has an impact on the probability of a new monitor being sited. At this level of aggregation, the decision is modeled at a neighborhood (or even suburb) level. Our estimates will therefore be conservative in

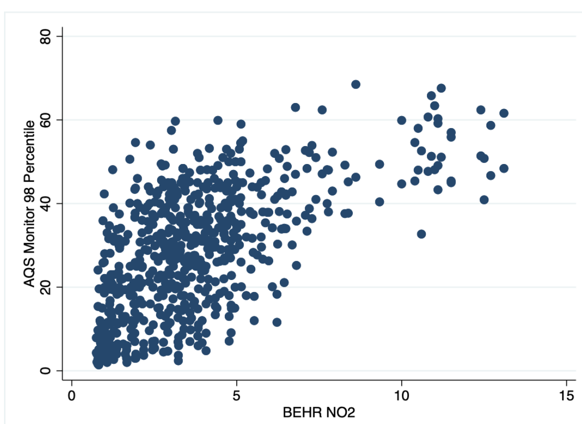
[20]At the time of writing, BEHR data are only available for part of 2016, and therefore excluded from the remainder of the analysis.

[21]We restrict data collected for pollution estimates to be within only monitored counties for the contiguous United states for years 2005-2015. A variety of quality control checks were built into our data extraction programs. Aside from following basic quality flags, we followed the BEHR recommendations for cleaning the data and dropping observations from our empirical specifications (for example, using only observations with limited cloud coverage).

the sense that we are not modeling the decision to site an ambient pollution monitor at a busy intersection vs. one block away; rather, at this level of resolution we are modeling the choice to avoid that area of the city (or county) altogether.

Remote sensing estimates of NO_2 perform well when ground-truthed to ground level measurements of pollution, as documented in the atmospheric science literature (e.g.Russell et al. (2011), Bechle et al. (2013)). The BEHR NO_2 data do particularly well when comparing concentrations within a smaller region, such as at the county or city levels, consistent with our empirical application. The BEHR data are measured as column densities (molecules/cm^2), while ground level pollution is monitored in either parts per billion (ppb) for NO_2 or ozone, or $\mu g/m^3$ for particulates. We use the annual average NO_2 estimates rather than daily or weekly due to challenges in interpretation of remote sensing data at a high temporal resolution (Laughner et al. 2016). When comparing the primary standard for NO_2 at the monitor level (i.e. the 98^{th} percentile of hourly concentrations in a year) and the remotely-sensed NO_2 column density for the grid cell containing the monitor, we find an overall correlation coefficient of about 0.58 for the years 2005-2015. This comparison is plotted in Figure 2 for the year 2015.[22]

Figure 2: Remote Sensing BEHR vs AQS NO_2 (98 Percentile) for 2015



Notes: This scatter plot shows AQS nitrogen dioxide concentrations at the monitor level (the 98th percentile, which corresponds to the primary standard) versus the BEHR column density for nitrogen dioxide. AQS units are ppb, and BEHR units are molecules per square centimeter.

Because the remote sensing estimates are comparable within small areas with relatively

[22] Additional information on remote sensing of NO_2 is provided in the Appendix.

homogeneous physical characteristics, we use the column densities to generate a comparison of pollution at the monitored location to grid cells within that county or sub-county "zone." That is, we consider *within-zone* variation of pollution estimates around each monitor; we take the observed value in grid cell i in county c (or in a sub-county zone) and year t, subtract the average for that county (or zone), and scale it by the county- (or zone-) level standard deviation. Let X_{ict} be the remotely-sensed pollution level for the pollutant of interest in grid cell i, in county c and year t. The z-score for pollutant is then given by $z_{ict} = (X_{ict} - \bar{X}_{ct})/\sigma_{ct}$. We emphasize that z-scores are calculated only using remote sensing pollution estimates.

Because the calculation of z-scores is impacted by outliers, we also consider a grid cell's BEHR value as a percentile, again relative to the surrounding zone or county. This maintains the property of being a localized comparison while being more robust to the presence of outliers. We will use the notation P_{ict} to denote the percentile for grid cell i's BEHR NO_2 estimate relative to all other grid cells in county c and year t. As is the convention, a value of $P_{ict} = 20$ would mean that grid cell i's BEHR estimate is greater than 20% of the values from other grid cells in county c and year t.

2.3 NO_2 and Ozone Overview

The AQS monitoring data include criteria pollutants such as NO_2 and ozone (O_3). Because ozone is not directly measured in the BEHR data and the NASA OMI ozone estimates are reported at too coarse a resolution for our purposes, we use a combination of BEHR and NASA's OMI aerosol data to proxy for ozone.[23] As such, a brief overview of ozone formation is useful in order to understand our empirical treatment of ozone.

Tropospheric ozone is not directly emitted but formed through a combination of volatile organic compounds (VOCs) and nitrogen oxides (NO_x) in the presence of sunlight, particularly ultraviolet light. The BEHR data include NO_2 (a subset of nitrogen oxides), while NASA OMI data include formaldehyde ($HCHO$, a proxy for VOCs). The atmospheric sci-

[23] The coarseness of the OMI ozone estimates is the reason we adopt a proxy here. As we are interested in relative concentrations only, the average estimated remote sensing ozone values at a coarser resolution are not useful for our purposes.

ence literature has recently used these precursors as indicators for ozone productivity.[24] In general, more formaldehyde and more NO_x (plus sunlight) translate into higher levels of tropospheric ozone.

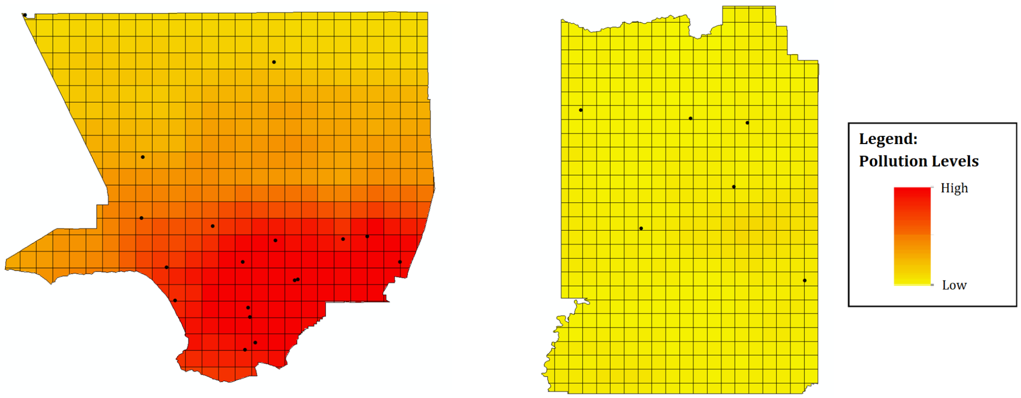
As a proxy for local ozone productivity, we take the product of $HCHO$ and NO_2. Although ozone formation is more complicated due to the underlying chemistry, across our sample the correlation coefficient is 0.30 across 2005-2015 between the AQS data (i.e. the fourth-highest value in a year/monitor) and our proxy at the grid cell level. Like our treatment of NO_2, however, we are most interested in a grid cell's pollution concentrations relative to nearby grid cells. Consider Figure 3 for an example of our ozone proxy and subsequent county level z-score calculations for both Los Angeles County, California and Uintah County in Utah, a large natural gas producer. Both regions have similar AQS pollution profiles. The average of annual AQS readings for the 4th-maximum value across monitors within each county are 0.079 ppm for Los Angeles County and 0.076 ppm for Uintah County, while the corresponding maximum values are 0.118 ppm and 0.117 ppm, respectively. However, as is evident from figure 3a, remote sensing estimates for our ozone proxy are not comparable across the regions due to differences in physical characteristics. Los Angeles County has a much steeper pollution gradient, reaching a maximum over the densely populated urbanized area in the southern parts of the county, whereas across Uintah County the pollution gradient is more nuanced. In order to adjust for these differences and focus on within-county (or, in alternative specifications, within-zone) heterogeneity in pollution, we normalize the data using county-level z-scores in figure 3b.

Our proxy for ozone also coincides well with national trends for ozone pollution. In Figure 4, we plot the BEHR NO_2 column density estimates, $HCHO$ estimates mapped onto BEHR grid cells, and the product of the two (i.e. our proxy for ozone productivity). In the figures the darker red portions of the map indicate higher levels of BEHR pollution and lighter yellow portions represent lower levels of pollution. Highly polluted areas tend to be concentrated around urban areas like New York City, Los Angeles and Chicago. The

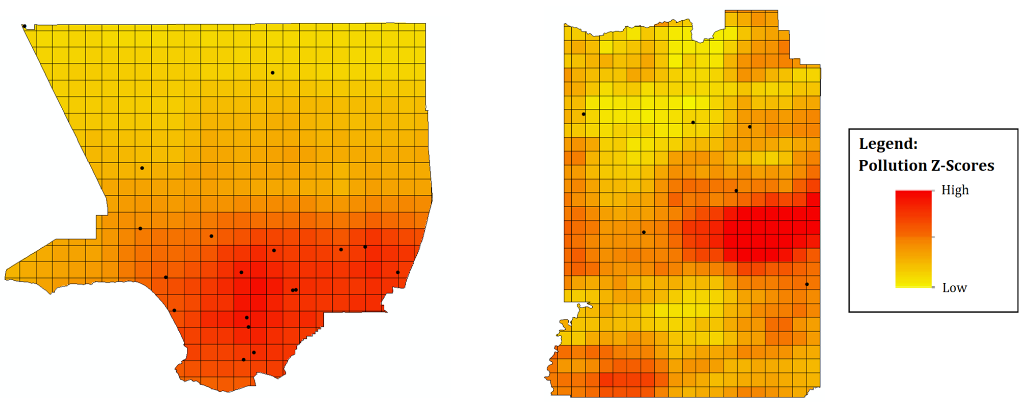
[24] For example, see Jin and Holloway (2015). They use the Formaldehyde-NOx Ratio (FNR) to determine areas that are particularly productive, ruling out values that indicate either VOC- or NOx-limited conditions. This is beyond the scope of the current paper, though we note that in alternative specifications we make similar exclusions to the data, and our results are robust to such changes.

Figure 3: Remote Sensing Estimates and County-Level Z-scores

(a) Ozone Proxy



(b) County Level Z-Scores

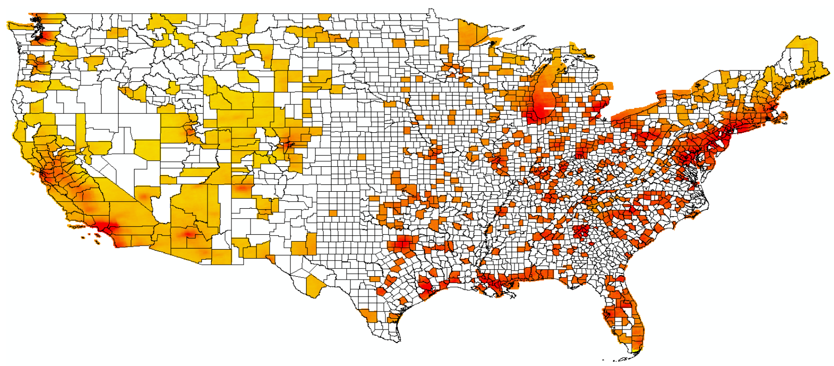


Notes: The left side of each sub-figure represents Los Angeles County, California and the right side shows Uintah County, Utah. Black dots represent ozone monitors as part of the AQS active any time during 2005-2016. Grids are defined by the BEHR satellite dataset. Darker reds indicate higher positive values of pollution and z-scores, while lighter yellows indicate lower levels.

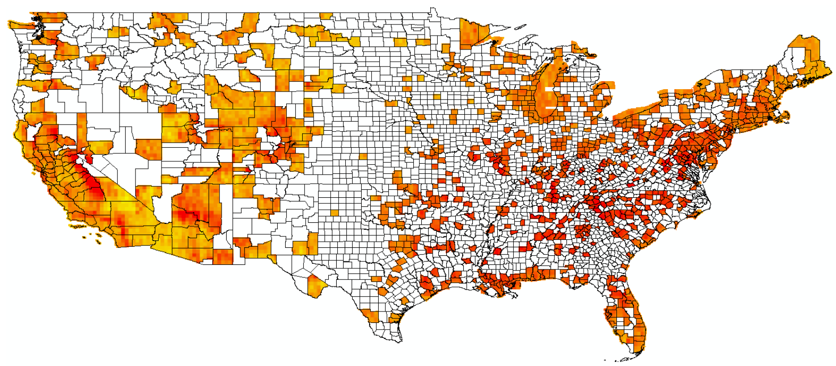
middle map shows that formaldehyde concentrations tend to be highest in the southeast. The combination of both in the form of an interaction term is displayed in the bottom map. Areas with the highest values for our ozone proxy align extremely well with nonattainment designations for ozone.

Figure 4: Ozone Formation (2015)

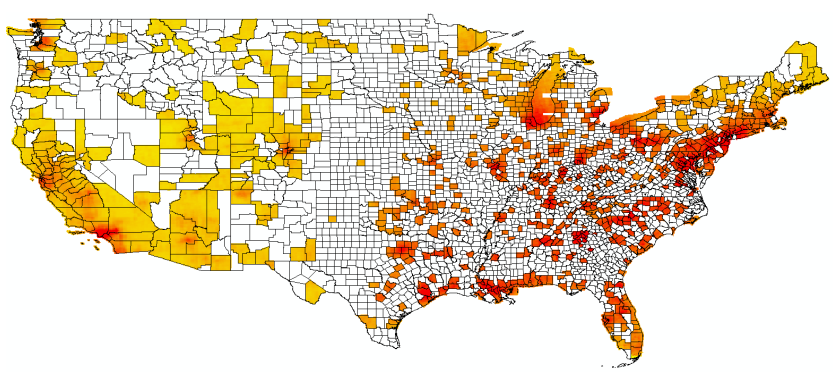
(a) Nitrogen Dioxide BEHR Estimates



(b) Formaldehyde NASA OMI Estimates



(c) Ozone Proxy



Notes: Column densities for NO_2 and $HCHO$ in 2015 are illustrated for monitored counties in the top and middle figures, respectively. The bottom figure shows the interaction of NO_2 and $HCHO$, our proxy for ozone. Red indicates higher levels of pollution while yellow indicates lower levels.

2.3.1 Summary Statistics

Aside from the remote sensing and AQS data, we use a variety of controls from the American Community Survey (ACS)[25] to study both the socioeconomic factors affecting monitor placement and federal guidelines prescribing monitors to characterize pollution near vulnerable and susceptible populations. Variables from the ACS include the poverty rate, total population, median household income, and race and ethnicity. We also include other spatial indicators from GIS shapefiles, including county borders, state borders, air districts, the proportion of surface water in a grid cell, and whether a particular area is classified as urban or tribal. There are a total of 124 air management districts which is a combination of state, sub-state, and tribal jurisdictions.[26]

Table 3 provides summary statistics on the key variables used in the analysis. Descriptive statistics are shown at the county level for counties that receive a new monitors at some point during our period of study. We also distinguish between counties that are already in nonattainment (*NA*) at the time of siting and those that are not (*Attainment*). There are 313 new monitor sitings in attainment counties and 161 new sitings in nonattainment counties in our sample period, comprising 0.4% of the total number of grid cells across newly-monitored counties. Means (and standard deviations in parentheses) in these columns reflect the average across all grid cells, by county type, that received a new monitor that year. As a point of comparison we also calculate the same descriptive statistics for one sub-county zone definition (35 km radius).

When considering all active monitors and aggregating across years, 0.9% of the grid cells in attainment counties contain an ozone monitor, compared to 1.4% of the grid cells in nonattainment counties. Zonal means and standard deviations are defined analogously; they include only grid cells within 35km of the sited monitor (and within the same county). This alternative specification effectively restricts the relevant within-county comparison to a smaller subset of grid cells for larger counties, which typically lie in western states. Though

[25] We use the 5 year estimate tables for 2007-2011 at the Census block level, which are mapped onto the BEHR grid cells assuming that the population characteristics are uniformly distributed within the block.

[26] For example, California has 23 Air Pollution Control Districts and 12 Air Quality Management Districts for a total of 35 districts. Most states have only one.

Table 3: Summary Statistics

	County Level				35km Zones			
	New Mon. Grid Cells		All Mon. Grid Cells		New Mon. Grid Cells		All Mon. Grid Cells	
	Attainment	*NA*	*Attainment*	*NA*	*Attainment*	*NA*	*Attainment*	*NA*
New Monitors	0.00425	0.00436			0.0111	0.0124		
	(0.0651)	(0.0659)			(0.105)	(0.111)		
AQS Monitors			0.00866	0.0140			0.0202	0.0377
			(0.0927)	(0.117)			(0.141)	(0.190)
BEHR NO_2	1.587	3.096	2.226	3.244	2.139	4.991	2.824	4.532
	(1.060)	(2.860)	(1.322)	(2.521)	(1.271)	(4.118)	(1.370)	(3.140)
Population (1000s)	1.292	1.621	1.316	1.478	1.586	1.728	1.514	1.690
	(0.665)	(1.977)	(0.686)	(1.186)	(0.839)	(1.166)	(0.768)	(1.166)
Pct. White	85.39	78.56	84.05	81.27	86.30	76.61	85.74	79.30
	(20.76)	(19.06)	(22.05)	(21.01)	(16.28)	(19.25)	(16.70)	(19.24)
Pct. Black	1.903	4.369	3.737	4.370	3.970	5.967	5.512	6.451
	(7.217)	(8.106)	(10.02)	(9.601)	(10.75)	(10.36)	(12.02)	(12.23)
Pct. Asian	0.576	2.917	0.822	2.150	1.117	5.427	1.133	4.000
	(1.566)	(5.664)	(2.108)	(4.526)	(2.644)	(8.075)	(2.184)	(6.797)
Poverty Rate (%)	12.72	12.28	13.52	12.06	11.18	11.20	11.80	11.12
	(9.178)	(9.470)	(9.492)	(9.806)	(7.802)	(8.977)	(7.577)	(8.658)
Median HH Income (1000s)	53.04	57.36	50.95	58.01	57.88	68.89	55.67	66.69
	(17.14)	(24.94)	(17.04)	(25.36)	(17.19)	(26.47)	(17.57)	(26.82)
Observations	76855	37812	839396	479251	54218	54497	628657	625178

Standard deviations are listed in parentheses beneath mean values.

we use z-scores in our empirical analysis, the "raw" remote sensing pollution values (NO_2 column densities and our ozone proxy), scaled to $10^{15} mol/cm^2$, are included for the sake of comparison. As expected, attainment counties tend to have lower levels of remotely-sensed pollution estimates for NO_2 and ozone than nonattainment counties, suggesting that the remotely-sensed estimates reflect the same general trends as the *in situ* AQS monitoring data.

3 Empirical Evidence

3.1 Preliminary Evidence

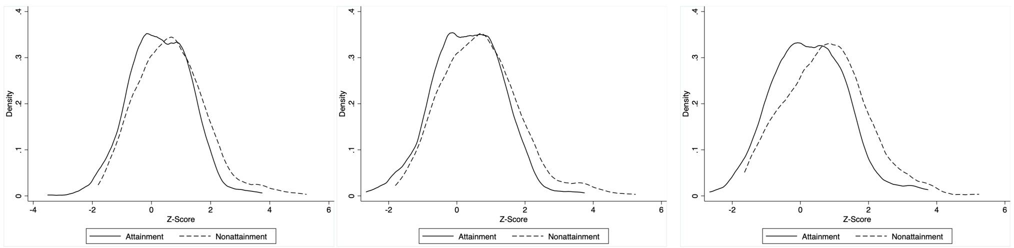
We are interested in testing the hypothesis that regulators in attainment counties act strategically in choosing the location of new ambient pollution monitors. This requires making a comparison relative to some baseline siting behavior. As discussed earlier, our comparison is relative to nonattainment counties, where the set of locations in the siting decision is more constrained.

Our main variable of interest is the z-score for remotely-sensed pollution. Recall that we calculate the z-score locally, comparing the pollution estimate at each grid cell to the surrounding area. In our baseline specification the comparison is made to all other grid cells in that same county, whereas in alternative specifications we restrict the comparison group to grid cells within some radius r of the monitor (and still within that same county), where we vary r from 10 km to 50 km.[27]

If siting behavior in attainment and nonattainment counties were the same, we would expect no difference in the distributions of z-scores between the two county types. As preliminary evidence of differences in pollution targeting behavior, we simply take the z-scores for *monitored* grid cells in the most recent year of our data (2015), and we plot the ker-

[27] The number of grid cells within a zone or county varies. The number of grid cells in 2015 (across all monitors) are as follows: in the 10 km-radius zone definition, the mean and median number of grid cells in a zone are 12, and the standard deviation is about 1.8; for the 35 km-radius zone specification, the median number of grid cells in a zone is 80, the mean is 85, and the standard deviation is roughly 33. In the county-level specification, the corresponding median, mean and standard deviation are 116, 234, and 446, respectively.

Figure 5: Kernel Densities for BEHR NO_2 Z-Scores in 2015



(a) All Monitors (b) SLAMS Monitors (c) High Conc. Monitors

Notes: Each figure shows the kernel density estimate for the distribution of county-level z-scores at monitored grid cells, separately for nonattainment and attainment counties, for our remote sensing measurement of NO_2 described in the text. The plot on the left includes all monitors, the middle SLAMS network monitors, and the plot on the right includes only "high concentration" monitors.

nel densities, by attainment status. In addition we plot separately the distributions for SLAMS network monitors, and monitors specifically designated to target high pollution concentrations. As shown in figures 5a - 5c, the distributions for attainment and nonattainment counties diverge, following the pattern predicted by our analytical model (see the Appendix). In each case, the distribution for attainment counties lies to the left of the distribution for nonattainment counties, indicating that monitors in attainment counties are in relatively clean locations compared to nonattainment counties. In all three cases a two-sample Kolmogorov-Smirnov test (Kolmogorov 1933; Smirnov 1939) of the equality of distributions rejects equality at the 0.1% level.[28]

3.2 Regression Discontinuity

In the cross-sectional comparisons monitor sites between attainment and nonattainment counties, it is possible that nonattainment counties simply happened to have monitors in dirtier locations (which in turn caused these counties to be designated as nonattainment). In what follows we turn our focus to new monitor sitings.

The incentive to avoid polluted areas is arguably highest for counties that are near the threshold for being designated as nonattainment. In order to leverage the discontinuity

[28] In 2015, the respective mean BEHR z-scores for attainment and nonattainment are 0.55 and 0.63 for all AQS monitors, 0.50 and 0.58 for SLAMS monitors, and 0.52 and 0.62 for monitors with "High Concentration" as the primary objective. The difference is significant at the 5% level in each case.

between attainment and nonattainment, we need to construct a continuous running variable that characterizes a county's pollution level relative to the NAAQS (according to preexisting monitors) for several pollutants associated with NO_2. This is because a county could be in nonattainment for one pollutant (say, ozone) but not another (say, $PM_{2.5}$), and the newly-sited monitors typically do not measure just one pollutant. Recall that our primary remotely-sensed pollutant is NO_2, which is a precursor to both ozone and fine particulates, but the NO_2 standards have not been violated during our period of study.

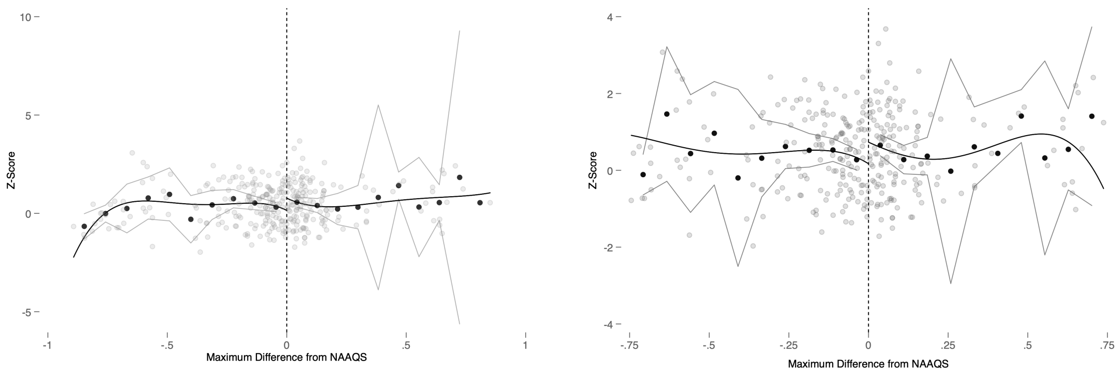
We proceed as follows. At the county level we calculate "design values" for ozone, $PM_{2.5}$, and NO_2 relative to the corresponding NAAQS in each year. We consider both primary and secondary standards, so there are a total of five design values calculated for each county-by-year with sufficient data. We then take the maximum (in percentage terms) difference between the design value and the NAAQS for each of the criteria pollutants (both primary and secondary standards) at the county level. This is our running variable in the Regression Discontinuity (RD) analysis.

We then estimate an RD model with the z-score for NO_2 for newly-sited monitors as the dependent variable. Because the monitor siting decision would be in response to the lagged distance to nonattainment designation, we consider the impact of the lagged maximum percentage difference between the design value and the NAAQS for the three criteria pollutants. WIthin 20% of the threshold, the mean z-score for monitored locations below the NAAQS is 0.4, while the mean above the NAAQS threshold is 0.6. We first consider observations within 100% of the NAAQS. The scale of the resulting plot is large due to the influence of a few outliers, so we also illustrate the results using only observations within 75% of the NAAQS. The resulting sample sizes are 318 and 307 observations, respectively. The results are shown in Figure 6.

The results of the RD estimation show that a discontinuous increase in the z-score at the threshold. Point estimates suggest an increase in the z-score for the new monitors of 0.4 in the first specification, and 0.38 in the second, both significant at the 5% level, following Calonico, Cattaneo, and Titiunik (2014) for bias corrected RD.

The RD estimate suggests that the effect of nonattainment is to increase the average z-score of monitored grid cells by nearly half a standard deviation. Put differently, the

Figure 6: Regression Discontinuity Plots



(a) Within 100% of NAAQS

(b) Within 75% of NAAQS

Notes: The vertical axis is the z-score of NO_2 at a newly-sited monitor (remotely sensed) relative to other grid cells in that county and year. The horizontal axis shows the maximum distance (times 100%) from the NAAQS threshold for NO_2, O_3 and $PM_{2.5}$ (primary and secondary standards) for that county the year prior to siting.

flexibility in monitor siting for *attainment* counties means that the local regulators site new monitors in areas with significantly less pollution than elsewhere in the county. For counties with sufficient variation in pollution, this avoidance behavior for regulators in counties with monitored pollution levels just below the NAAQS is critical, as it may allow the county to avoid nonattainment designation. This is a point we will return to.

3.3 New Monitor Sitings: LPM

How does the local regulator choose a monitor location, and is there evidence that regulators in attainment counties avoid hotspots (relative to regulators in nonattainment counties)? Over our period of study, there are 474 new AQS monitors for ozone,[29] which we exploit for our empirical test. For each monitor, we use the z-score in the year it was sited as the main independent variable, and we test the null hypothesis that attainment and nonattainment monitors are sited based on similar criteria.

We define $NewMonitor_{ict}$ as an indicator taking a value of 1 if a monitor is placed in grid i, in county c (or "zone" z for some radius r, as discussed earlier), and year t; otherwise

[29]There are no two new monitors sited within the same grid cell for the period covered by our data. This differs when considering the universe of existing ozone monitors between 2005-2015.

it takes a value of zero. We restrict the sample to county- (or "zone-") year pairs that include new monitor placements. We then define $Attainment_{ct}$ as an indicator for county c being in attainment of the standard in year t, leaving nonattainment as the excluded category. The linear probability model specification is given by

$$
\begin{aligned}
NewMonitor_{ict} &= \alpha zscore_{ict} + \beta zscore_{ict} * Attainment_{ct} \\
&+ \delta_{ct} + \sum_{j} \theta_j X_{ij} + \epsilon_{ict},
\end{aligned}
$$

where $zscore_{ict}$ is the z-score for the pollutant of interest (either remotely-sensed NO_2 or the ozone proxy), δ_{ct} denotes the county-by-year (or in other specifications, zone-by-year) fixed effect, X_{ij} represents control variables such as local demographics and economic variables, and ϵ_{ict} is a random disturbance term. Note that an attainment indicator does not enter the estimating equation separately, as it would be collinear with the county-by-year fixed effects. The key coefficient of interest is β, which provides a direct test of whether monitors in attainment counties systematically avoids pollution relative to nonattainment counties.[30]

We estimate this for NO_2, including all monitors in the baseline specification, and restricting the sample to SLAMS monitors in an alternative specification. In addition, as an alternative to the local z-score, we estimate an analogous model with the grid cell's percentile relative to other grid cells in that county-by-year (or zone-by-year). These results are shown in the following four tables.

The key parameter of interest is the interaction term in the third row ($zscore*Attainment$ in Tables 5 and 7 or $Pctile*Attainment$ in Tables 6 and 8, respectively). Across specifications we see that, on average, regulators in attainment counties tend to site monitors in cleaner areas than regulators in nonattainment counties. The magnitudes are large when considering the baseline proportion of grid cells in the sample that are monitored. A one standard deviation increase in pollution decreases the probability of a new monitor being sited in that

[30]We note briefly that our definition of nonattainment includes ozone and particulates, as NOx is a precursor to both. In the Appendix we show our main specifications, but including a broader definition of nonattainment to include any criteria pollutant. The key findings are unchanged by redefining nonattainment in this fashion.

Table 4: County Level Regressions for New Monitor Sitings: NO2 Z-scores, All AQS Monitors

	(1)	(2)	(3)	(4)	(5)	(6)
Z-score(NO2)	0.00391***	0.00397***	0.00361***	0.00352***	0.00389***	0.00378***
	(0.000537)	(0.000556)	(0.000644)	(0.000677)	(0.000773)	(0.000774)
Attainment*Z-score(NO2)	-0.00231***	-0.00237***	-0.00200***	-0.00185***	-0.00212***	-0.00201***
	(0.000495)	(0.000499)	(0.000603)	(0.000650)	(0.000698)	(0.000707)
Population		-0.000266	-0.000311*	-0.000213	-0.000228	-0.000183
		(0.000176)	(0.000180)	(0.000168)	(0.000153)	(0.000156)
Pct. White			-0.0000363*	-0.0000134	-0.000000114	0.00000749
			(0.0000204)	(0.0000156)	(0.0000222)	(0.0000193)
Pct. Black			0.000207	0.000192	0.000178	0.000174
			(0.000134)	(0.000135)	(0.000133)	(0.000133)
Pct. Asian			0.0000482	0.0000789	0.000130	0.000134
			(0.000120)	(0.000119)	(0.000128)	(0.000126)
Poverty Rate				0.000162***		0.0000986*
				(0.0000602)		(0.0000569)
Median HH Income					-0.000102***	-0.0000838***
					(0.0000267)	(0.0000253)
Constant	0.00349***	0.00387***	0.00644***	0.00250	0.00915***	0.00629***
	(0.00000159)	(0.000251)	(0.00197)	(0.00166)	(0.00217)	(0.00211)
Fixed Effects	County-year	County-year	County-year	County-year	County-year	County-year
Clustering	Air Districts	Air Districts	Air Districts	Air Districts	Air Districts	Air Districts
Observations	48956	48956	48956	48956	48956	48956

Each column shows estimates from a separate linear probability model. The dependent variable is an indicator variable for a new monitor. An observation is an individual grid cell. See the text for details. Heteroskedastic robust standard errors, clustered at the air district level, are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: County Level Regressions for New Monitor Sitings: NO2 Percentiles, All AQS Monitors

	(1)	(2)	(3)	(4)	(5)	(6)
Pctile(NO2)	0.000119***	0.000120***	0.000108***	0.000105***	0.000119***	0.000115***
	(0.0000201)	(0.0000209)	(0.0000205)	(0.0000211)	(0.0000242)	(0.0000243)
Attainment*Pctile(NO2)	-0.0000688***	-0.0000701***	-0.0000574***	-0.0000525**	-0.0000630***	-0.0000589**
	(0.0000194)	(0.0000198)	(0.0000202)	(0.0000214)	(0.0000220)	(0.0000225)
Population		-0.000226	-0.000289	-0.000190	-0.000207	-0.000161
		(0.000162)	(0.000173)	(0.000165)	(0.000153)	(0.000158)
Pct. White			-0.0000361*	-0.0000130	-0.000000247	0.00000755
			(0.0000200)	(0.0000157)	(0.0000217)	(0.0000188)
Pct. Black			0.000225*	0.000210	0.000198	0.000194
			(0.000133)	(0.000134)	(0.000132)	(0.000133)
Pct. Asian			0.0000861	0.000116	0.000166	0.000170
			(0.000104)	(0.000105)	(0.000115)	(0.000113)
Poverty Rate				0.000164***		0.000102*
				(0.0000606)		(0.0000564)
Median HH Income					-0.000101***	-0.0000823***
					(0.0000272)	(0.0000257)
Constant	-0.0000507	0.000248	0.00291	-0.00110	0.00526***	0.00234
	(0.000634)	(0.000548)	(0.00181)	(0.00174)	(0.00186)	(0.00190)
Fixed Effects	County-year	County-year	County-year	County-year	County-year	County-year
Clustering	Air Districts	Air Districts	Air Districts	Air Districts	Air Districts	Air Districts
Observations	48956	48956	48956	48956	48956	48956

Each column shows estimates from a separate linear probability model. The dependent variable is an indicator variable for a new monitor. An observation is an individual grid cell. See the text for details. Heteroskedastic robust standard errors, clustered at the air district level, are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: County Level Regressions for New Monitor Sitings: NO2 Z-scores, SLAMS Monitors

	(1)	(2)	(3)	(4)	(5)	(6)
Z-score(NO2)	0.00438***	0.00446***	0.00400***	0.00385***	0.00428***	0.00413***
	(0.000642)	(0.000658)	(0.000754)	(0.000798)	(0.000894)	(0.000891)
Attainment*Z-score(NO2)	-0.00265***	-0.00273***	-0.00231***	-0.00212**	-0.00243***	-0.00228**
	(0.000685)	(0.000672)	(0.000793)	(0.000849)	(0.000876)	(0.000886)
Population		-0.000361	-0.000461*	-0.000327	-0.000379**	-0.000314*
		(0.000221)	(0.000233)	(0.000200)	(0.000170)	(0.000170)
Pct. White			-0.0000748*	-0.0000239	-0.0000313	-0.00000949
			(0.0000418)	(0.0000395)	(0.0000432)	(0.0000414)
Pct. Black			0.000268	0.000270	0.000239	0.000246
			(0.000164)	(0.000167)	(0.000162)	(0.000164)
Pct. Asian			0.0000366	0.0000956	0.000138	0.000152
			(0.000141)	(0.000145)	(0.000153)	(0.000152)
Poverty Rate				0.000238***		0.000146**
				(0.0000763)		(0.0000680)
Median HH Income					-0.000121***	-0.0000946***
					(0.0000326)	(0.0000302)
Constant	0.00434***	0.00488***	0.0104**	0.00315	0.0137***	0.00851**
	(0.00000146)	(0.000326)	(0.00393)	(0.00374)	(0.00402)	(0.00357)
Fixed Effects	County-year	County-year	County-year	County-year	County-year	County-year
Clustering	Air Districts	Air Districts	Air Districts	Air Districts	Air Districts	Air Districts
Observations	29767	29767	29767	29767	29767	29767

Each column shows estimates from a separate linear probability model. The dependent variable is an indicator variable for a new monitor. An observation is an individual grid cell. See the text for details. Heteroskedastic robust standard errors, clustered at the air district level, are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: County Level Regressions for New Monitor Sitings: NO2 Percentiles, SLAMS Monitors

	(1)	(2)	(3)	(4)	(5)	(6)
Pctile(NO2)	0.000132***	0.000134***	0.000118***	0.000113***	0.000130***	0.000124***
	(0.0000226)	(0.0000235)	(0.0000227)	(0.0000236)	(0.0000274)	(0.0000273)
Attainment*Pctile(NO2)	-0.0000829***	-0.0000849***	-0.0000702**	-0.0000645**	-0.0000769***	-0.0000718**
	(0.0000254)	(0.0000254)	(0.0000268)	(0.0000279)	(0.0000284)	(0.0000287)
Population		-0.000311	-0.000431*	-0.000294	-0.000350**	-0.000282*
		(0.000201)	(0.000221)	(0.000191)	(0.000165)	(0.000167)
Pct. White			-0.0000697*	-0.0000172	-0.0000256	-0.00000260
			(0.0000415)	(0.0000398)	(0.0000432)	(0.0000418)
Pct. Black			0.000295*	0.000295*	0.000266	0.000273*
			(0.000163)	(0.000165)	(0.000161)	(0.000162)
Pct. Asian			0.0000846	0.000143	0.000184	0.000198
			(0.000120)	(0.000126)	(0.000134)	(0.000134)
Poverty Rate				0.000246***		0.000156**
				(0.0000790)		(0.0000709)
Median HH Income					-0.000122***	-0.0000935***
					(0.0000330)	(0.0000307)
Constant	0.0000815	0.000480	0.00589	-0.00157	0.00871**	0.00334
	(0.000886)	(0.000799)	(0.00371)	(0.00384)	(0.00369)	(0.00350)
Fixed Effects	County-year	County-year	County-year	County-year	County-year	County-year
Clustering	Air Districts	Air Districts	Air Districts	Air Districts	Air Districts	Air Districts
Observations	29767	29767	29767	29767	29767	29767

Each column shows estimates from a separate linear probability model. The dependent variable is an indicator variable for a new monitor. An observation is an individual grid cell. See the text for details. Heteroskedastic robust standard errors, clustered at the air district level, are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

cell by roughly 50 percent.

3.4 Robustness to Spatial Specification

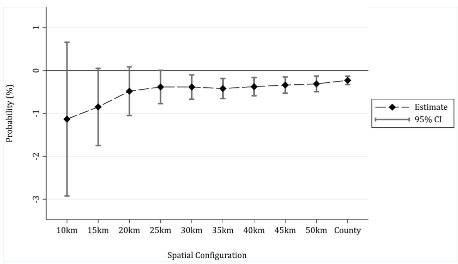
The results so far focus on county-level comparisons. We now consider the impact of changing the size of the "zone" within which the z-scores or percentiles are calculated. This serves two purposes. First, the county-level specifications will include few monitors and many unmonitored cells. Defining the set of alternative locations with a smaller radius will address this problem. Second, the county-level definition assumes that all candidate grid cells within the county are candidates for monitoring; in practice, the local regulator may be interested in some smaller subregion, so choosing a smaller radius addresses this issue.

To illustrate the impact of alternative radii choices, we show the coefficient of interest from column 1 (i.e. the simplest specification) of the previous tables. Figure 7a shows the coefficients and standard errors for the baseline specification for a variety of radii all the way up to the county level. As the radius increases, the coefficient tends toward the county-level definition of a "zone". The coefficients are generally significant at the 5% level. Larger standard errors are calculated for zones with smaller radii due to these zones being defined by only a few grid cells.[31] The interpretation of coefficients varies across specifications due to differences in the proportion of cells that are monitored in each specification. As such, Figure 7b shows the parameter estimate relative to the baseline proportion of monitored grid cells in each sample. As shown in the figure, the results are generally robust across the choice of comparison groups in our z-score calculations.

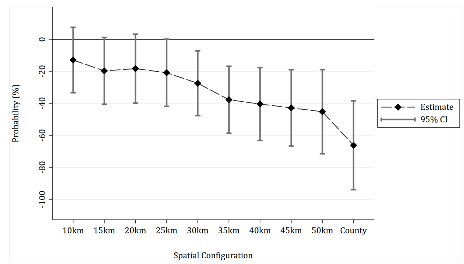
Figures 7c-7d show the respective parameter estimates and marginal probability impacts of grid cell-level NO_2 percentiles. The point estimates suggest that a ten percentage point increase in a grid cell's percentile decreases the probability of a new monitor being sited in that cell by roughly 10-20 percent.

Figures 8a-8d show the analogous parameter and marginal effects for the subsample of monitors that are part of the SLAMS network (used for compliance with the NAAQS). The magnitudes are similar to the full set of monitors, though the estimates are not always

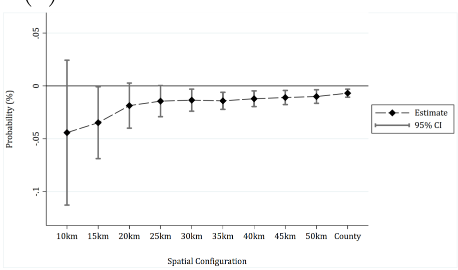
[31] Recall that the grid cells are 0.05^o by 0.05^o, which translates to roughly 5km by 5km, so a 10km radius specification is very limiting.



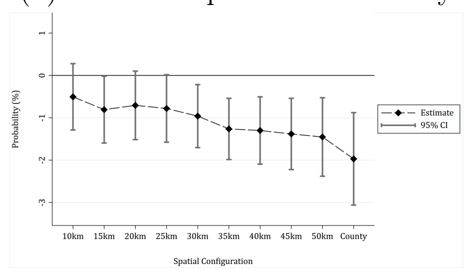
(a) Z-Score Parameter Estimates



(b) Z-Score Impact on Probability



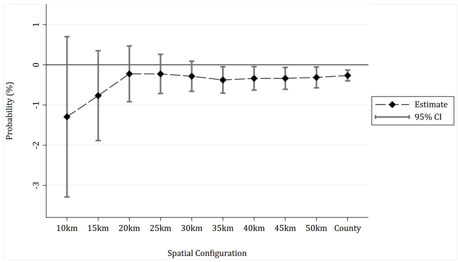
(c) Percentile Parameter Estimates



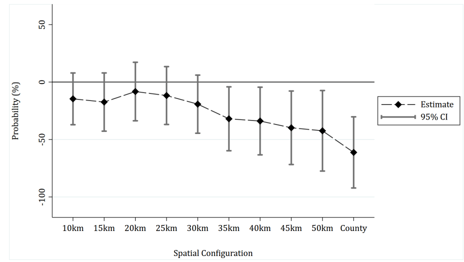
(d) Percentile Impact on Probability

Figure 7: Robustness Across Zone Sizes (NO_2): New AQS Monitors

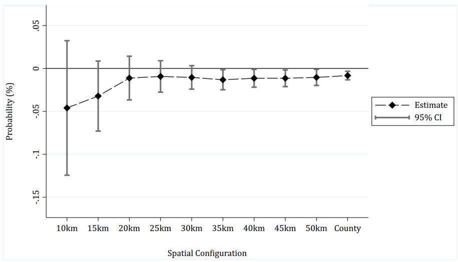
Notes: Parameter estimates are shown for the interaction term $Attainment * Zscore$ or $Attainment * Percentile$ from the baseline specification (i.e. column 1 in the tables) for different "zone" sizes, ranging from 10 km radii to full counties. Error bars indicate the 95% confidence interval. Relative Probability estimates show the parameter values adjusted for the baseline proportion of grid cells containing a monitor in that sample.



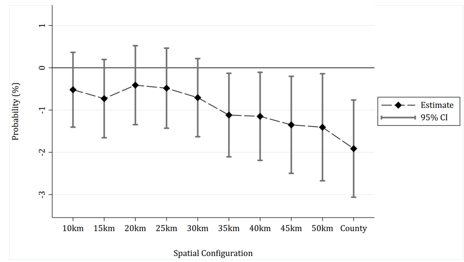
(a) Z-Score Parameter Estimates



(b) Z-Score Impact on Probability



(c) Percentiles Parameter Estimates



(d) Percentiles Impact on Probability

Figure 8: Robustness Across Zone Sizes (NO_2): New SLAMS Monitors

Notes: Parameter estimates are shown for the interaction term $Attainment * Zscore$ or $Attainment * Percentile$ from the baseline specification (i.e. column 1 in the tables) for different "zone" sizes, ranging from 10 km radii to full counties. Error bars indicate the 95% confidence interval. Relative Probability estimates show the parameter values adjusted for the baseline proportion of grid cells containing a monitor in that sample.

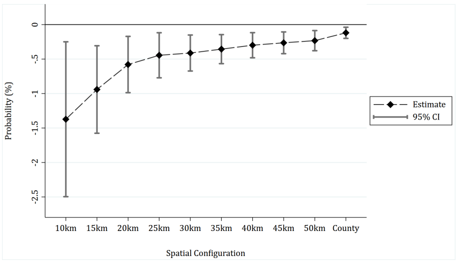
significant for specifications with zones defined by small radii.

The results indicate that, relative to siting behavior in a nonattainment county, an increase in pollution in a given grid cell relative to the surrounding region (defined either with z-scores or percentiles) leads to a large decrease in the probability of that grid cell being sited.

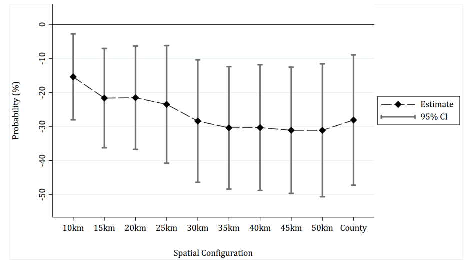
3.5 Ozone Results

In addition to the z-scores and percentiles based on remotely-sensed NO_2, we also estimate the impact of relative ozone concentrations using the proxy developed in the data section. Here we illustrate the relative impacts on the probability of siting across spatial configurations.

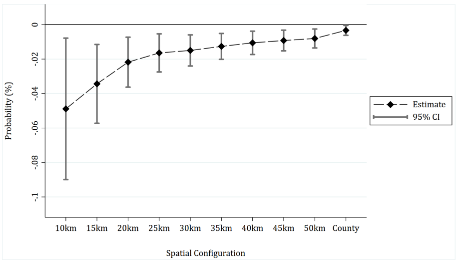
The estimates follow the general pattern of the NO_2 estimates, though magnitudes are slightly smaller. A one standard deviation increase in a grid cell's pollution decreases the



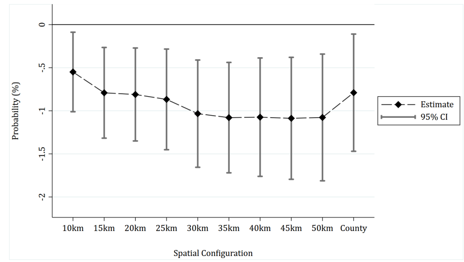
(a) Z-Score Parameter Estimates



(b) Z-Score Impact on Probability



(c) Percentile Parameter Estimates



(d) Percentile Impact on Probability

Figure 9: Robustness Across Zone Sizes (Ozone): New AQS Monitors

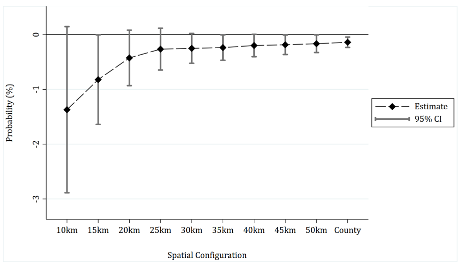
Notes: Parameter estimates are shown for the interaction term $Attainment * Zscore$ or $Attainment * Percentile$ from the baseline specification (i.e. column 1 in the tables) for different "zone" sizes, ranging from 10 km radii to full counties. The z-score or percentiles are calculated for our remotely-sensed proxy for ozone, $NO_2 \times HCHO$, as discussed in the Data section. Error bars indicate the 95% confidence interval. Relative Probabilty estimates are adjusted for the baseline proportion of grid cells containing a monitor in that sample.

probability of a new monitor being sited by 20-30%. Alternatively, a ten percentage point increase in a grid cell's percentile value decreases the probability of a new monitor siting by 5-10%. The results using the full sample of monitors and SLAMS monitors are similar in magnitude, but in some specifications the estimate is borderline significant at the 5% level in the SLAMS specifications.

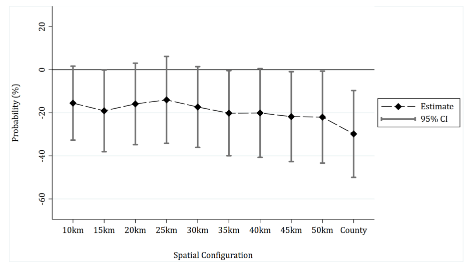
4 Implications

4.1 Cross-Sectional Bias

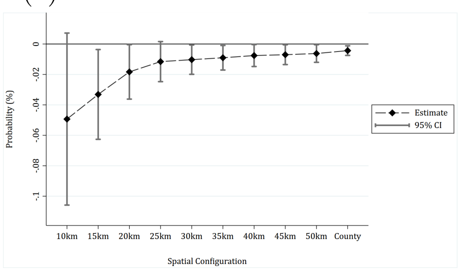
So far we have focused on newly-sited monitors, but how well do the locations of monitors reflect pollution in the surrounding area? One simple way to address this question is to simply estimate a cross-sectional linear probability model for the baseline specification for each year



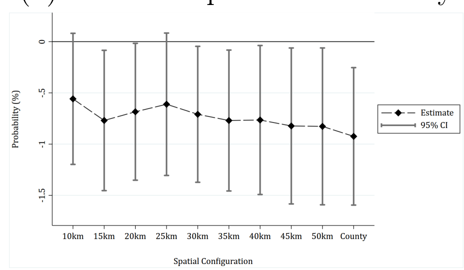
(a) Z-Score Parameter Estimates



(b) Z-Score Impact on Probability



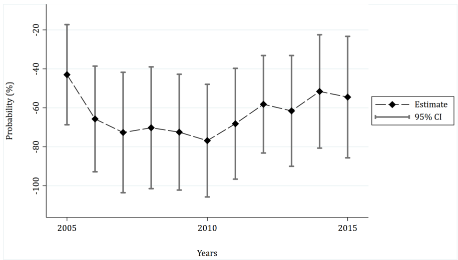
(c) Percentiles Parameter Estimates



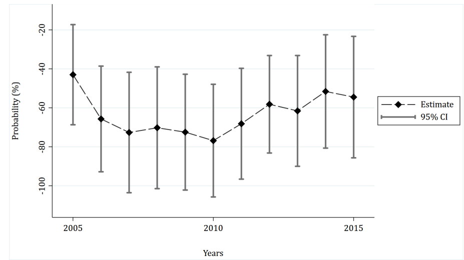
(d) Percentiles Impact on Probability

Figure 10: Ozone Estimates Across Zone Sizes (Ozone): New SLAMS Monitors

Notes: Parameter estimates are shown for the interaction term $Attainment * Zscore$ or $Attainment * Percentile$ from the baseline specification (i.e. column 1 in the tables) for different "zone" sizes, ranging from 10 km radii to full counties. The z-score or percentiles are calculated for our remotely-sensed proxy for ozone, $NO_2 \times HCHO$, as discussed in the Data section. Error bars indicate the 95% confidence interval. Relative Probabilty estimates are adjusted for the baseline proportion of grid cells containing a monitor in that sample.



(a) All AQS Monitors



(b) SLAMS Monitors

Figure 11: Cross-Sectional Marginal Impacts on for Monitoring Probability (NO_2)

Notes: Parameter estimates are shown for the interaction term $Attainment * Zscore$ from the baseline specification (i.e. column 1 in the tables) for all monitors in each year in our data. Error bars indicate the 95% confidence interval. The coefficients have been adjusted for the baseline proportion of grid cells containing a monitor in that sample.

in our sample. To make our estimates comparable to the estimates for new monitors, we again scale the coefficients to adjust for the baseline proportion of grid cells containing a monitor in each sample.

When estimating our baseline specification for *all* monitors instead of *new* monitors, the impact is roughly twice as large. That is, a one standard deviation increase in pollution (relative to the county) implies a 40-70% lower likelihood that the grid cell contains a monitor. This suggests that not only are regulators strategically avoiding siting monitors near hotspots in attainment counties, but the probability of a monitor in an attainment county being near a hotspot is significantly lower in attainment counties in any given year. Stated differently, relative to nonattainment counties, monitors in attainment counties systematically understate pollution levels.

5 Implications

So far we have tested the hypothesis that ambient pollution monitors are placed similarly in nonattainment and attainment counties. The results strongly suggest that, relative to nonattainment counties, regulators tend to avoid relatively polluted areas when siting new monitors in attainment counties. If monitors systematically avoid the dirtiest areas in attainment counties, this suggests that there are counties that exceed NAAQS thresholds for criteria pollutants, but the monitoring data for these counties do not reflect these "hotspots".

A natural follow-up question then would be, how has strategic monitoring affected nonattainment designation? Or, stated differently, how many counties are likely in violation of NAAQS but remain designated as being in attainment? To address this, we first note that the remote sensing pollution estimates rely on column densities, which are measured in different units than the AQS monitoring data (and the NAAQS thresholds). Thus we cannot directly use remote sensing estimates to determine which areas are likely above the threshold for ozone concentrations, or for other pollutants, for that matter.

The RD point estimate indicated a 0.4 increase in the county-level z-score when moving across the NAAQS threshold from attainment to nonattainment. Combining the AQS monitoring data, the remote sensing pollution estimates, and using the RD coefficient, we can now estimate a rough counterfactual scenario, where the monitors in attainment counties were sited as they are in nonattainment counties.

We first use estimates from a fixed effects regression of the AQS ozone design values (i.e. the 4^{th} highest daily value) on the remote sensing ozone proxy (BEHR*HCHO), which are shown in the Appendix. Call the resulting coefficient of interest β. Then for, each monitor in an attainment county in 2015, we add $0.4 \times \sigma_c \times \beta$, where σ_c is the county-level standard deviation in the remotely-sensed ozone proxy for 2015. This gives us a counterfactual ozone concentration for each attainment county in 2015. We then can compare these readings to the NAAQS for 2015 (70 ppb). Taking the point estimates at face value, we find that 670 monitors in in 255 attainment counties would be in violation of the NAAQS. The combined population in these counties is 43.5 million people. In comparison, in 2015 there were 42 million people residing in 210 nonattainment counties for ozone. A map illustrating the counties above the threshold under counterfactual monitoring those designated nonattainment in 2015 is shown in Figure 12.

Taken together, this suggests that resiting monitors in attainment counties, targeting pollution more as in nonattainment counties, would more than double the number of nonattainment counties and double the population residing in nonattainment counties. Any such thought experiment comes with a number of caveats, including uncertainty in the prediction. However, given that our analysis is at a relatively coarse level of spatial aggregation,

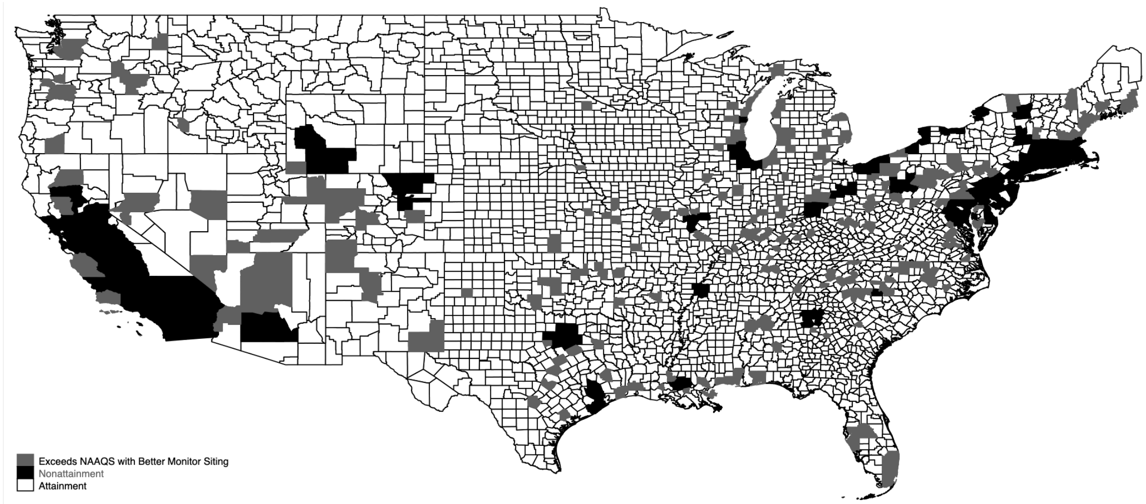


Figure 12: Counties Potentially Exceeding the Ozone NAAQS

there are undoubtedly many counties that remain in attainment due to strategic monitor siting–the empirical question of precisely how many will be left for future work.

6 Conclusions

Under the Clean Air Act and its Amendments, states must comply with federal National Ambient Air Quality Standards, but states (or tribal, or other local regulators) are also charged with developing and maintaining their own monitoring network that is used for compliance with the federal standards. We argue that this creates an incentive for strategically siting new pollution monitors, depending on whether the county is in attainment or nonattainment with the NAAQS. Most importantly, a regulator in an attainment county has an incentive to avoid pollution hotspots when siting monitors, whereas a regulator for a nonattainment area may be compelled to target pollution (at least in a relative sense) due to additional federal oversight.

To test the hypothesis, we use a novel approach that utilizes both monitoring data and remote sensing estimates of local air pollution. Focusing on new monitor sitings, we calculate a local z-score for pollution (either NO_2 or a proxy for ozone based on remote sensing estimates) that compares pollution in the grid cell where a new monitor is placed to pollution in the surrounding region. We show that new monitors in attainment counties are placed in relatively clean areas relative to new monitors in nonattainment areas.

There are several caveats worth highlighting. First, our tests for strategic behavior rely on differences in the ability of local regulators to avoid pollution between attainment and nonattainment counties. Local regulators for nonattainment counties may still face similar incentives, so our findings should be interpreted relative to that comparison group. Second, there could be endogenous siting of monitors *due to* a local pollution source (for example, for source attribution, or to monitor emissions from a large point source); to the extent that this type of monitoring is present, it would bias against finding any strategic behavior. Finally, our estimates rely on remote sensing data at a somewhat coarse resolution. That we find an impact at this level of analysis suggests that strategic siting is a problem, and if finer data were available the impact would likely be even more pronounced. Similarly, because of the coarseness in the remote sensing data, we are not detecting avoidance behavior at the level of avoiding a congested intersection or a particularly dirty point source; instead, our findings suggest that regulators avoid siting in dirty regions within a county.

Our findings have several practical implications worth further discussion. First, existing estimates of air pollution may be systematically biased because of the incentive structure facing local regulators. Part of the difference in observed pollution levels between nonattainment and attainment counties may be partially driven by systematic avoidance in attainment counties; that is, new *in situ* monitors in attainment counties tend to understate pollution levels. Furthermore, projections and models that are calibrated to monitors may miss important variation in pollution within attainment counties. Taking this further, there are counties that are not in compliance with federal air quality standards, but because of strategic siting decisions, they remain classified as being in attainment. Recent work points to large benefits associated with reductions in NO_x (and ozone) concentrations (Deschênes et al. 2017), so misclassifying an area as attainment due to strategic monitoring could have significant health costs.

Even under relatively conservative assumptions, we estimate that a significant proportion of counties would be in nonattainment if monitors were re-sited. Furthermore, we reiterate that our estimates are based on data from a relatively coarse grid (0.05^o). Our estimates suggest that moving monitors to alternative grid cells within the county would trigger nonattainment; we are not suggesting moving monitors next to major intersections or point sources of emissions, but rather to grid cells with high average concentration levels. Our results are robust to a variety of alternative specifications, and conducting the analysis at a finer spatial resolution would likely lead to even starker evidence of avoidance behavior in attainment counties.

There are also implications for applied researchers using monitoring data. First, health and morbidity studies that rely on monitoring data may have a systematic bias due to strategic monitor placement. Part of the difference between measured pollution levels in attainment and nonattainment counties could be attributed to differences in regulator behavior. In other words, nonattainment designation itself is an endogenous outcome. In other dimensions, where researchers focus on the discontinuity at the NAAQS nonattainment threshold, future work should recognize that local regulators may strategically site air quality monitors and that the nonattainment designation itself is endogenous. This suggests that economists studying pollution should exercise caution in interpreting estimates based on ambient monitoring data in some settings. Future work should focus on quantifying the bias in the monitoring data.

What can be done to improve the siting of monitors and realign incentives? Assuming states will maintain their own monitoring programs and that *in situ* monitoring data will remain the gold standard for compliance, the EPA could mandate that remote sensing estimates of pollution be used in guiding which sites are chosen by local authorities. Rather than states exercising discretion in the monitor siting decision, remote sensing estimates of local pollution could be used to determine a subset of the region where a monitor ought to be placed. This would remove some of the ability of local regulators to strategically site monitors, and it would improve the monitoring network's capacity to detect pollution, target regulatory pressure, and protect human health.

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A Analytical Model

The local regulator has competing incentives when siting a monitor. Our approach is similar in spirit to the analytical model of (Rabassa 2008), who looks at local enforcement of the CAAA through emissions inspections. We consider the local regulator's problem when choosing the location for an additional ambient air pollution monitor. We hold fixed other regulatory efforts regarding emissions to focus on the incentives relevant to ambient monitoring. The local regulator seeks to minimize the costs of pollution, including costs to human health, the costs of monitoring effort, and the costs associated with nonattainment designation.[32] Though this decision is over some set of locations, we omit location subscripts for ease of exposition.

The regulator's objective function contains several arguments, which we consider in turn. First, $h(A)$ is the health damage from ambient pollution A. Health damages are assumed to be increasing in A at an increasing rate: $h' > 0, \ \ h'' > 0$. Point source emissions $e(\bar{R}, M)$ are a function of emissions regulations, R (which we hold constant at some level $\bar{R}$), and ambient pollution monitoring effort, M—the regulator's decision variable. We assume that $e' \equiv \frac{\partial e}{\partial M} < 0$ and $e'' > 0$. Lastly, $c(\bar{R}, M)$ is the monetary cost of overall regulatory efforts, where $c' \equiv \frac{\partial c}{\partial M} > 0$, and $c'' > 0$. Monitoring effort, $M \in [0, 1]$, measures how well the monitored ambient air quality represents the incidence of emissions on local residents. A higher value of M is associated with increased targeting of ambient pollution.

We assume that ambient pollution at a given location is impacted by point source emissions and a random component (e.g. due to local meteorological conditions or variation in traffic). The random component is assumed to be distributed according to $\epsilon \sim N(0, \sigma_\epsilon)$, where $f(\epsilon)$ denotes the probability density function and $F(\epsilon)$ is the corresponding cumulative distribution function.

We define A as the "true" ambient pollution level, but $\tilde{A}$ is the value obtained by the monitor. The true value of ambient pollution is given by $A = e(\bar{R}, M) + \epsilon$, whereas detected pollution is impacted by the monitoring decision, such that $\tilde{A} = Me(\bar{R}, M) + \epsilon$. To model

[32]Regulatory efforts are being held constant, though additional monitoring may affect emissions through existing regulations if "smokestack" regulations are tied to ambient pollution levels. As such we do not include abatement costs of firms in the objective function.

nonattainment, we set a threshold for ambient pollution, A_c. Exceeding this value will trigger nonattainment designation, which we assume results in a discrete penalty Z paid to the federal regulator.

Therefore the local regulator faces the following minimization problem:

$$\begin{aligned}\min_{M} &\int_{-\infty}^{A_c - Me(\bar{R},M)} \Big[h(A) + c(\bar{R}, M)\Big] f(\epsilon) d\epsilon \\ &+ \int_{A_c - Me(\bar{R},M)}^{\infty} \Big[h(A) + c(\bar{R}, M) + Z\Big] f(\epsilon) d\epsilon \\ &= \mathbb{E}\big[h(A)\big] + c(\bar{R}, M) + \big[1 - F(A_c - Me(\bar{R}, M))\big] Z \end{aligned} \tag{1}$$

Differentiating with respect to M, the first-order condition is given by

$$\mathbb{E}\left[\frac{\partial h}{\partial e}\right] \frac{\partial e}{\partial M} + \frac{\partial c}{\partial M} + \underbrace{f\big(A_c - Me(\bar{R}, M)\big) \underbrace{\left(e + M\frac{\partial e}{\partial M}\right)}_{\text{Marg. Eff. of Monitoring}} Z}_{\text{Marginal Nonattainment Effect}} = 0 \tag{2}$$

We denote the net marginal contribution of monitoring efforts to the monitored ambient pollution levels, $(e + Me')$, as the *Marginal Effect of Monitoring*. This term represents the increase in ambient concentrations net of the decrease in point source emissions due to increased monitoring. We also highlight the *Marginal Effect of Nonattainment* to emphasize the role of the discrete "penalty", Z, on the local regulator's choice of monitoring location.

We now have the following proposition.

Proposition 1. *If the marginal effect of monitoring is non-negative and weakly increasing in M, and if expected ambient pollution is below or at the nonattainment threshold, then optimal monitoring efforts are decreasing in expected pollution levels; i.e.,* $\frac{\partial M^*}{\partial \mathbb{E}[A]} < 0$.

Proof. The corresponding second order condition from the cost minimization problem above is given by:

$$
\begin{aligned}
\mathbb{E}[h']e'' - \mathbb{E}[h'']e'^2 + c'' \\
-Zf'\big(A_c - Me(\bar{R}, M)\big) \cdot (e + Me')^2 \\
+Zf\big(A_c - Me(\bar{R}, M)\big) \cdot (2e' + Me'')
\end{aligned}
\tag{3}
$$

From equation (2) we have

$$
\mathbb{E}[h'] = -\frac{f\big(A_c - Me(\bar{R}, M)\big) \cdot \big(e + Me'\big)Z + c'}{e'}, \tag{4}
$$

which is substituted into the second-order condition above, yielding

$$
\begin{aligned}
e''\left(-\frac{f\big(A_c - Me(\bar{R}, M)\big) \cdot (e + Me')Z + c'}{e'}\right) - \mathbb{E}[h'']e'^2 + c'' \\
-Zf'\big(A_c - Me(\bar{R}, M)\big) \cdot (e + Me')^2 \\
+Zf\big(A_c - Me(\bar{R}, M)\big) \cdot (2e' + Me'').
\end{aligned}
\tag{5}
$$

By assumption the marginal effect of monitoring is non-negative and weakly increasing in monitoring effort, so the following two conditions must hold:

$$
\begin{aligned}
e + Me' &\geq 0 \\
2e' + Me'' &\geq 0.
\end{aligned}
\tag{6}
$$

The first expression in (6) can be interpreted as there being a bound on the reduction that could be achieved from a marginal increase in monitoring. Similarly, the second inequality suggests that an increase in monitoring effort may decrease emissions, but because we are holding constant the level of regulatory effort at $\bar{R}$, there is a limit to the reduction that would be induced by increased monitoring. Ambient pollution levels do not exceed the threshold $\mathbb{E}[A] \leq A_c$ (and hence $\tilde{A} \leq A_c$), so it is the case that $f'(\cdot) \leq 0$. Under such conditions, the second-order condition is non-negative, which allows for the first-order condition to be sufficient for optimality.

By the first-order condition, the optimal monitoring location, M^*, is defined by the location where marginal benefits equal marginal costs. The *marginal nonattainment effect* —the marginal increase of expected penalty payments due to a unit increase in pollution exposure—decreases the benefits of an additional unit of monitoring effort, due to a positive marginal effect of monitoring. This means that the marginal benefits of monitoring air pollution are *smaller* than in the case when we ignore the penalty for noncompliance. In other words, e and Z contribute toward a positive marginal nonattainment effect, and as a result, $\frac{\partial M^*}{\partial e} < 0$, $\frac{\partial M^*}{\partial \mathbb{E}[A]} < 0$, $\frac{\partial M^*}{\partial Z} < 0$.

□

Taken together, these results indicate that the local regulator has an increase in expected pollution leads to a decrease in monitoring effort. Stated differently, the local regulator has an incentive to avoid siting ambient pollution monitors where they may trigger nonattainment status (i.e. in relatively "dirty" locations within that county).

A.1 The Case of Nonattainment Counties

The regulator's problem in a county *already* designated as nonattainment is inherently different. The nonattainment penalty (i.e. Z) has already been imposed, but importantly for our empirical setting, we note that future monitoring efforts may be constrained, or even dictated, by the State Implementation Plan (SIP) (or Federal Implementation Plan, FIP). We do not derive any formal propositions for the regulator in this case. We simply note that by constraining the monitoring effort in the maximization problem in (1) to some minimum level (i.e. $M \in [\underline{M}, 1]$, where the constraint binds) would lead to different behaviors for a regulator in a nonattainment county as compared to the attainment case above.

B Data Appendix (For Online Publication)

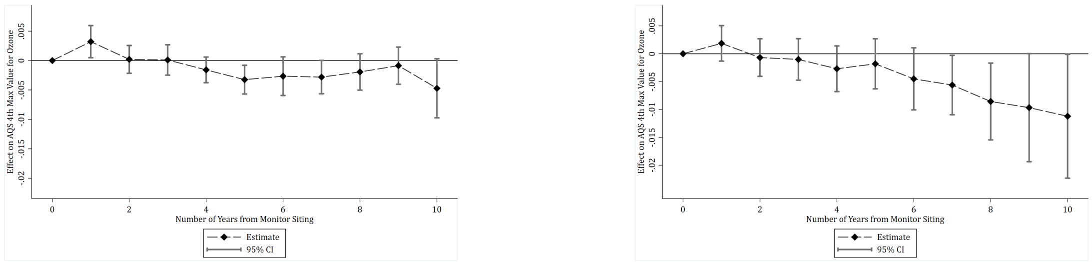
To illustrate the relationship between the remote sensing (BEHR) data and the ambient *in situ* AQS monitoring data, we begin with the BEHR data. As discussed in the main text, the BEHR data provide estimates of the column density of NO_2 in molecules per square centimeter. This makes a direct comparison of the remotely-sensed tropospheric column density and ground-level concentrations (measured in parts per billion) difficult, though an extensive literature investigates the performance of remote sensing alternative algorithms in predicting ground-level concentrations in various locations.

It is far beyond the scope of this paper to fully describe the methods behind remote sensing of air pollution, so we encourage the interested reader to refer to XXX. Here we briefly describe the relationship between the remote sensing data and monitoring data used in the main text.

B.1 NO_2 Data

The BEHR NO_2 column density is reported at a $0.05^o x 0.05^o$ grid, where the variable $behr_{it}$ reflects the average estimated column density for grid cell i and year t. A small subset of these grid cells in the United States contains an AQS ambient air pollution monitor. The primary standard for NO_2 is the 98th percentile, and when comparing the AQS reading for the primary standard at the monitor level (i.e. the 98th percentile) and the remotely-sensed NO_2 column density for the grid cell containing the monitor, we find an overall correlation coefficient of about 0.58 for the years 2005-2015.

As discussed in the literature, the remote sensing estimates perform well locally (often within a metropolitan area, where additional ambient measurements are taken during a "campaign"). In the following table we demonstrate how the BEHR data perform in regressions of the primary standard (measured at the monitor) on remote sensing data. Inclusion of county- and year fixed effects is shown in the second two columns, as our primary regressions in the text use relative scores (z-scores or percentiles) to compare pollution levels within a county-by-year and to standardize units across space.



(a) Attainment Counties (b) Nonattainment Counties

Figure 13: AQS Event Study: Monitor Sitings

Notes: The coefficients and 95% confidence intervals are from a nonparametric event study regression to show the changes in NO_2 as measured by newly-sited monitors. The horizontal axis shows the years since the monitor was sited.

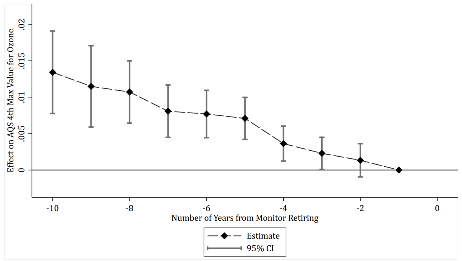
B.2 Ozone Data

Remote sensing estimates of ozone are typically made available at a coarser resolution, but because we are interested in within-county-year variation, we construct a measure based on formaldehyde (a proxy for volatile organic compounds) and NO_2, a proxy for availability of NO_x. As discussed in the text, we take the product of $HCHO$ (from OMI) and NO_2 (BEHR), which we then normalize using z-scores or percentiles. Although ozone formation is more complicated due to the underlying chemistry, across our sample the correlation coefficient is 0.30 across 2005-2015 between the AQS data (i.e. the fourth-highest value in a year/monitor) and our proxy at the grid cell level.

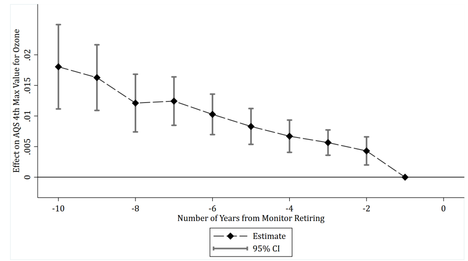
B.3 Post-Siting and Pre-Retirement/Resiting of Monitors

To illustrate trends in pollution in the AQS data after monitoring for newly-sited monitors, we estimate a nonparametric "event study" regression with year fixed effects, monitor fixed effects, and indicators for the number of years post-siting. Post-monitoring there appears to be a reduction in NO_2 at the monitor, though the coefficients are more often significant in the nonattainment counties.

Similarly, to show the trends in pollution at the monitored locations in the years leading up to a monitor's retirement or resiting, we show an analogous event study plot. The plots show a decrease in concentrations leading up to the removal of monitors in both nonattain-



(a) Attainment Counties



(b) Nonattainment Counties

Figure 14: AQS Event Study: Monitor Sitings

Notes: The coefficients and 95% confidence intervals are from a nonparametric event study regression to show the changes in NO_2 as measured by retired/resited AQS monitors. The horizontal axis shows the years leading up to the removal of a monitor.

ment and attainment counties, which is consistent with the Code of Federal Regulations.

Table 8: AQS Nitrogen Dioxide and BEHR Data

	(1)	(2)	(3)
BEHR NO2	17.59***	15.21***	11.21***
	(2.373)	(2.834)	(2.360)
County FE		X	X
Year FE			X
Constant	64.73***		
	(11.71)		
Observations	3558	3558	3558

Heteroskedastic-robust standard errors clustered by county in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: AQS Ozone and Remote Sensing

	(1)	(2)	(3)	(4)
Ozone Proxy (behr*hcho)	0.0000930***	0.000131***	0.000198***	0.000142***
	(0.00000925)	(0.0000398)	(0.0000272)	(0.0000315)
BEHR NO2			-0.000756**	-0.000924***
			(0.000382)	(0.000305)
NASA HCHO			-0.00161***	-0.000115
			(0.000141)	(0.000198)
County FE		X	X	X
Year FE				X
Constant	0.0668***			
	(0.000695)			
Observations	51444	51444	51444	51444

Heteroskedastic-robust standard errors, clustered by county, shown in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Additional Results

In this section we define counties as nonattainment for *any* criteria pollutant.

Table 10: New Monitor Sitings: County-Level NO2 Z-scores, SLAMS Monitors, Alternative Nonattainment Definition

	(1)	(2)	(3)	(4)	(5)	(6)
Z-score(NO2)	0.00416***	0.00423***	0.00379***	0.00367***	0.00408***	0.00394***
	(0.000705)	(0.000722)	(0.000792)	(0.000819)	(0.000906)	(0.000902)
Attainment*Z-score(NO2)	-0.00242***	-0.00249***	-0.00209**	-0.00194**	-0.00223**	-0.00211**
	(0.000744)	(0.000735)	(0.000831)	(0.000873)	(0.000890)	(0.000900)
Population		-0.000352	-0.000456*	-0.000321	-0.000374**	-0.000308*
		(0.000220)	(0.000233)	(0.000200)	(0.000170)	(0.000169)
Pct. White			-0.0000750*	-0.0000233	-0.0000312	-0.00000885
			(0.0000419)	(0.0000397)	(0.0000435)	(0.0000415)
Pct. Black			0.000270	0.000271	0.000240	0.000248
			(0.000165)	(0.000167)	(0.000162)	(0.000164)
Pct. Asian			0.0000474	0.000105	0.000149	0.000162
			(0.000141)	(0.000144)	(0.000152)	(0.000151)
Poverty Rate				0.000241***		0.000150**
				(0.0000767)		(0.0000690)
Median HH Income					-0.000121***	-0.0000944***
					(0.0000324)	(0.0000301)
Constant	0.00434***	0.00486***	0.0104**	0.00303	0.0137***	0.00836**
	(0.00000161)	(0.000324)	(0.00394)	(0.00376)	(0.00402)	(0.00357)
Fixed Effects	County-year	County-year	County-year	County-year	County-year	County-year
Clustering	Air Districts	Air Districts	Air Districts	Air Districts	Air Districts	Air Districts
Observations	29767	29767	29767	29767	29767	29767

Each column shows estimates from a separate linear probability model. The dependent variable is an indicator variable for a new monitor. An observation is an individual grid cell. See the text for details. Heteroskedastic robust standard errors, clustered at the air district level, are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: New Monitor Sitings: County-Level NO2 Percentiles, SLAMS Monitors, Alternative Nonattainment Definition

	(1)	(2)	(3)	(4)	(5)	(6)
Pctile(NO2)	0.000123***	0.000126***	0.000110***	0.000106***	0.000122***	0.000117***
	(0.0000235)	(0.0000243)	(0.0000235)	(0.0000242)	(0.0000277)	(0.0000275)
Attainment*Pctile(NO2)	-0.0000728***	-0.0000747***	-0.0000607**	-0.0000566*	-0.0000680**	-0.0000637**
	(0.0000259)	(0.0000259)	(0.0000272)	(0.0000283)	(0.0000284)	(0.0000289)
Population		-0.000303	-0.000426*	-0.000288	-0.000345**	-0.000276
		(0.000199)	(0.000221)	(0.000190)	(0.000164)	(0.000166)
Pct. White			-0.0000703*	-0.0000171	-0.0000261	-0.00000250
			(0.0000417)	(0.0000400)	(0.0000436)	(0.0000420)
Pct. Black			0.000295*	0.000295*	0.000266	0.000273*
			(0.000164)	(0.000166)	(0.000161)	(0.000163)
Pct. Asian			0.0000954	0.000153	0.000195	0.000208
			(0.000121)	(0.000127)	(0.000135)	(0.000135)
Poverty Rate				0.000249***		0.000159**
				(0.0000790)		(0.0000715)
Median HH Income					-0.000122***	-0.0000928***
					(0.0000329)	(0.0000307)
Constant	0.0000884	0.000476	0.00593	-0.00162	0.00875**	0.00324
	(0.000928)	(0.000848)	(0.00373)	(0.00385)	(0.00373)	(0.00350)
Fixed Effects	County-year	County-year	County-year	County-year	County-year	County-year
Clustering	Air Districts	Air Districts	Air Districts	Air Districts	Air Districts	Air Districts
Observations	29767	29767	29767	29767	29767	29767

Each column shows estimates from a separate linear probability model. The dependent variable is an indicator variable for a new monitor. An observation is an individual grid cell. See the text for details. Heteroskedastic robust standard errors, clustered at the air district level, are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$