VOG: Using Volcanic Eruptions to Estimate the Impact of Air Pollution on Student Learning Outcomes *

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Abstract

We pair variation stemming from volcanic eruptions with the census of Hawaiʻi's public schools student test scores to estimate the impact of $PM_{2.5}$ and SO_2 on student performance. Increased particulate pollution decreases test scores. These results are concentrated among schools located in south Hawaiʻi, which has the highest level of pollution on average. The effects of $PM_{2.5}$ are larger for the poorest pupils by a factor of at least four. We demonstrate that poor air quality disproportionately impacts the human capital accumulation of economically disadvantaged children.

Key Words: Vog, Particulates, Test Scores, Kriging, Environmental Justice
JEL Classification: I22, I24, Q52

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1 Introduction

Researchers and policymakers have increasingly sought to understand the consequences of poor air quality. An abundance of evidence suggests pollution can have severe adverse effects on health, fertility, and mortality outcomes.[1] A smaller yet growing set of studies has identified labor productivity losses, where pollution harms workers across both physically demanding (e.g. fruit picking (Graff Zivin and Neidell, 2012) and pear-packing (Chang et al., 2016)) and mentally demanding (e.g. baseball umpiring (Archsmith et al., 2018)) occupations.[2]

However, despite some evidence of air pollution sharply reducing cognitive performance (Zhang et al., 2018), there are only a handful of empirical investigations into how pollution directly affects student test scores. This is a pity as student scores not only are a marker of cognitive performance but they also often have long term consequences. A better understanding of this topic, therefore, has implications for how air quality impacts human capital acquisition and subsequent labor market outcomes.

In this study, we investigate how air quality affects student performance on standardized tests. There is a growing number of studies on the effects of specific pollutants (primarily particulates) on student test scores. Work from Ebenstein et al. (2016) uses Israeli data from 2000 to 2002 to find drops in high school exit exam test scores and worsened longer run outcomes in response to poor air quality.[3] Similar results come from Amanzadeh et al. (2020) who utilize data from Iran. Carneiro et al. (2021) show that higher concentrations of particulates result in lower scores on college entry examinations in Brazil. Using data from the US, Marcotte (2017)

[1] Several studies have found a positive association between pollution and fertility abnormalities (Nieuwenhuijsen et al., 2014; Slama et al., 2013; Perin et al., 2010). See Carré et al. (2017) for a review of the literature. Burnett et al. (1999) and Koken et al. (2003) find increases in air pollution leads to an increase in cardiorespiratory hospitalizations. Linares et al. (2010) find children who attend schools closer to major air pollution sources were more likely to develop respiratory and lung abnormalities. Di et al. (2017) finds increases in pollution (even at levels below the national standard) were associated with an increase in mortality for US Medicare beneficiaries, especially amongst racial minority groups.

[2] Other studies examining labor productivity loss include He et al. (2019) (textile industry workers), Chang et al. (2019) (call center workers), and Lichter et al. (2017) (professional soccer players). For a comprehensive review of the literature on "non-health" effects of air pollution, we refer the reader to Aguilar-Gomez et al. (2022).

[3] These effects were especially large for those of lower socioeconomic status.

found decreased performance among kindergartners on testing days with both worse pollen and fine airborne particulate matter. Pham and Roach (2023) utilize natural variation across the US to investigate how PM2.5 pollution harms third through eighth grader achievement.[4,5] Outside student performance outcomes, related studies from Currie et al. (2009), Liu and Salvo (2018), Chen et al. (2018), and Komisarow and Pakhtigian (2022) find increased student absences in response to poor air quality. Relative to the volume of research on the health impacts of poor air quality, there is still a dearth of studies on this particular topic.

An important feature of our study is that we pay close attention to how poor air quality affects poorer students within schools. It has long been understood that air pollution disproportionately impacts the poor and disadvantaged minorities in the United States despite recent progress (Currie et al., 2020). Importantly, work that demonstrates disproportionate effects of poor air quality on test scores by socioeconomic status is limited. Moreover, the results that we do have often conflict leaving the issue still up for debate. Ebenstein et al. (2016) finds that Israeli students of lower socioeconomic status experience larger declines in test scores due to higher pollution. They attribute this finding to higher rates of asthma among those of lower socioeconomic classes.[6] However, seminal work by Case et al. (2002) shows that asthma is more prevalent among children with richer parents in the United States. On the other hand, Heissel et al. (2022) show that economically disadvantaged students (as proxied by eligibility for federal programs such as free and reduced lunch) experience smaller impacts on test scores compared

[4] At the postsecondary level, Bedi et al. (2021) investigate the impacts of $PM_{2.5}$ on grammatical reasoning tests of university students in Brazil, while Yao et al. (2023) look at university student test scores from China's College English Test.

[5] A related literature looks at the effects of various "human made" polluters and interventions on student outcomes. For example, Stafford (2015) investigates how school renovations, such as mold remediation and ventilation improvements, impacted student test scores in Texas. Austin et al. (2019) identify the effects of retrofitting school busses to reduce emissions on student test scores in Georgia. Persico and Venator (2021) investigate how the introduction and disappearance of a local Toxic Release Inventory affects student test scores in Florida. Also using data from Florida, Heissel et al. (2022) identify the effects of traffic on student test scores and other shorter run outcomes. Gilraine and Zheng (2022) identify the effects of installing air filters in classrooms in Los Angeles. Finally, Duque and Gilraine (2022) investigate how the presence of coal power plants affect math test scores in North Carolina, and similarly, Jacqz (2022) identify the effects of toxic chemical releases on student test score performance (ten years later).

[6] Marcotte (2017) also shows that the effects of particulate pollution are largest for asthmatic students.

to their more advantaged peers; however, they also experience more absences and behavioral issues. Wen and Burke (2022) find no differences in the effects of wildfire smoke exposure across differing student economic status. Accordingly, there is not a clear consensus within the literature suggesting that poor air quality disproportionately impacts learning outcomes of poorer students.

The context of our study is the islands of O‘ahu and Hawai‘i in the state of Hawai‘i. This is a particularly advantageous setting for several reasons. One is Hawai‘i's rich, plausibly exogenous variation in air quality. Another is that despite its reputation for moderate climate, Hawai‘i can claim ten of the world's fourteen classifications for climate zones (microclimates) - the only place in the world with such diversity in one small area.[7]

Hawai‘i provides a unique and powerful opportunity to estimate the effects of two pollutants, particulate matter ($PM_{2.5}$) and sulfur dioxide (SO_2), on cognitive performance. We do so using SO_2 emissions from Kilauea volcano which is located on the island of Hawai'i. These gaseous emissions eventually form particulate matter in the form of sulfate aerosols. This pollution is called vog and is similar to smog pollution in many cities. Because this species of particulates is high in sulfuric acid, they resemble particulates from sources that produce sulfate aerosols such as coal-fired power plants.[8] Importantly, 8% of the world's population faces potential risks from volcanic eruptions and so, our estimates will have a direct bearing on these other settings (Choumert-Nkolo et al., 2021).

The emission of SO_2 from the Kilauea volcano represents a rare case of truly unpredictable variation in air pollution in the United States. Based on local wind conditions and whether the

[7]Source: Hawai‘i Magazine, *https://www.Hawaiimagazine.com/content/Hawaii-has-10-worlds-14-climate-zones-explorers-guide-each-them*, (*accessed 16 Sep. 2020*)

[8]See Halliday et al. (2019) for further detail on the similarities and differences between vog and other man-made pollutants. In short, smog that is composed of sulfate aerosols (such as smog near coal-fired power plants) is very similar to Kilauea vog. Still, there are differences based on particle size, shape, chemistry, and absorption of copollutant, though this is true of smog pollution across the US. For example, the smog in Pennsylvania cannot be directly compared to smog in New York or California, as there are differences in the physical and chemical properties of particulate pollution across regions and sources. Particulates in vog are likely to be more acidic than typical city smog, though the health implication for this is ambiguous. In general, Hawai‘i has much lower NOx, ozone, CO, soot, and volatile organics than other cities as well.

volcano is emitting, the air quality of Hawai'i can shift from hazardous to pristine in a matter of hours across differing parts of the islands. Previous research has leveraged this high frequency variation on a day-to-day basis to find increased emergency room admissions due to respiratory reasons on days with higher pollution levels (Halliday et al., 2019).[9]

An additional advantage of our setting is that average pollution levels are far below Environmental Protection Agency (EPA) ambient air quality standards throughout most of the state. Identifying and understanding the effects of pollution at lower baseline levels is important as this can help to inform and potentially update EPA standards. Moreover, lower pollution levels also better reflect modal households in the US. While prior literature has focused entirely on air quality within higher-baseline polluted environments, average pollutant levels in our study are comparable to pollution within the US. In 2021, the US average seasonally-weighted concentration of particulate matter ($PM_{2.5}$) pollution was 8.47 micrograms per cubic meter (μg/m^3).[10,11] In our sample, Hawai'i island saw similar mean $PM_{2.5}$ levels with an average of 8.08 $\mu g/m^3$ while mean levels on O'ahu are slightly lower at 4.35 $\mu g/m^3$.

We pair this variation in particulates with the census of public school student test scores in the State of Hawai'i. These data were obtained from the Hawai'i Data eXchange Partnership (DXP), a collaboration between the University of Hawai'i, the Executive Office of Early Learning, and the State of Hawai'i Department of Education. Because we have a census, we will have enough power to detect even small impacts of air pollution. The data track students from elementary to middle and high-school from 2015 through 2018. Math and English literacy assessments are given in grades three through eight, and again in grade eleven. In total, the data include nearly 450,000 student-test-year observations. These data allow us to estimate day-of measures of air

[9] Halliday et al. (2019) articulate the numerous advantages of using variation in vog to study the impact of pollution. For example, vog is emitted naturally, whereas the majority of the literature relies on variation in human activity (e.g. from cars, airplanes, factories) which may plausibly suffer from endogeneity biases. Another advantage comes from temporal variation: vog can vary on a day-to-day basis, whereas most other types of pollutants are highly serially correlated.

[10] For example, in Ebenstein et al. (2016) the average level of $PM_{2.5}$ on student test days was 21.05 μg/m^3.

[11] Source: US Environmental Protection Agency, *https://www.epa.gov/air-trends/particulate-matter-pm25-trends*, (*accessed 25 Apr. 2021*)

quality on student performance across varying ages, assessment types, and air quality conditions.

An important feature of this study is that we employ three separate techniques to predict pollution exposure at a school. The first of these, Kriging, comes from geostatistics (Cressie, 1990; Montero et al., 2015). The Kriging procedure leverages information on the spatial correlation in pollution as well as the distance between the relative locations of the pollution monitoring stations and the schools. We also exploit the fact that the presence of northeasterly winds, or trade winds, affects the spatial distribution of pollution in Hawai‘i. In general, trade winds lower pollution levels throughout most of the archipelago. While Kriging is common in the geostastistics literature, it is not common in environmental economics.[12] We also employ predictors that use inverse distance weighting and uniform weighting for monitoring stations that are near a school which are more common in economics. We show that Kriging works well near Kilauea on the island of Hawai‘i, particularly for SO_2, but performs poorly on the island of O’ahu.

For the full sample of student test scores, we estimate a small but statistically significant impact of particulates on student test scores. A one standard deviation increase in $PM_{2.5}$ reduces test scores by 0.26-0.50 percent of a standard deviation. We then find that the effects are significantly tied to mean levels of pollutant exposure within schools. For example, schools with average $PM_{2.5}$ levels under nine $\mu g/m^3$ (roughly the average of $PM_{2.5}$ levels in the United States) see a drop in test scores of about 0.17 to 0.35 percent of a standard deviation for every standard deviation increase in $PM_{2.5}$. When subsetting our regression sample to schools with average $PM_{2.5}$ levels above nine $\mu g/m^3$, we see a reduction of 1.02-1.22 percent of a standard deviation with respect to a one standard deviation increase in $PM_{2.5}$. Furthermore, our findings are concentrated amongst schools in south Hawai‘i, the region of the state that sees the highest level of pollution exposure on average. This suggests that the damages from pollutants increase precipitously with average exposure, yet are still present in environments that have relatively low levels of mean exposure.

The effects of SO_2 are more muted and nuanced. For the full sample, we do not find effects.

[12] Lleras-Muney (2010) is the only economics study that we know of that employs the technique.

However, we do estimate statistically significant effects on south Hawai‘i. These estimates also have a higher magnitude. A one standard deviation increase in SO_2 pollution decreases test scores in south Hawai‘i by 0.62 to 1.70 percent of a standard deviation. One important caveat with the results in south Hawai‘i (which includes Kilauea) is that we find that both $PM_{2.5}$ and SO_2 adversely impact student outcomes. Because both pollutants are highly correlated, we have not separately identified the effects on each pollutant.[13]

Lastly, and perhaps most importantly, we find that the effects of pollution are particularly concentrated among economically disadvantaged students. Poorer pupils experience at least four times the effect of $PM_{2.5}$ when compared to their more advantaged counterparts. Interestingly, we find little difference in the effects of particulates across schools by the fraction of the school's students who were disadvantaged, suggesting that the economically disadvantaged student gap is not driven by differences in school resources (e.g. classroom air conditioning). We also note that this is less of an issue in Hawai‘i as there is one statewide school district in which schools are not funded by local property taxes. So, we conclude that disadvantaged students *within* the same school are significantly more harmed by pollution than their more advantaged counterparts. This result has obvious implications for environmental justice and our understanding of how environmental laws, regulations, and policies may disproportionately harm people from lower income and/or minority groups.

[13] We note that the inability to cleanly identify one pollutant from another is a common issue in the literature. In this regard, this paper is no different. Halliday et al. (2019) were able to cleanly identify the effects on particulates on emergency medical care. However, their design used data exclusively from O'ahu where the only pollutant is $PM_{2.5}$. In the current setting, a large portion of the impacts occur close to Kilauea where SO_2 levels are extremely high as well.

2 Data and Background

2.1 Student Learning Outcome Measurements

We measure student learning outcomes using data from the Hawai‘i Data eXchange Partnership (DXP), a collaboration between five of Hawai‘i's state agencies (Department of Health, Department of Labor and Industrial Relations, Department of Education, Department of Human Services, and University of Hawai‘i). The data from the DXP consists of all students in Hawai‘i's public school system spanning elementary through secondary education. The data include education performance measures as well as demographic characteristics of the student. Test score data come from the Smarter Balanced Assessment (SBA). The SBA is an annual assessment of college and career readiness that includes modules on math and English literacy. It has been administered to students in grades three through eight and grade ten since 2015.[14] We standardize test scores to a mean of zero and a standard deviation of one at the grade-module-year level. Our data on student learning outcomes span the years 2015-2018.

Though the SBA is mandatory for all public school students, test dates are unique at the student level. Each school year, the DOE provides a one to three month testing window within which schools are required to administer the modules. Each school is then individually responsible for determining the exact date that students take their assessments. Importantly, schools determine their exam dates at the beginning of the school year, well before the school can forecast potential weather conditions or vog levels on the exam date. Schools typically have students within the same grade take the same module on the same date, though larger schools often space students within the same grade across multiple testing dates. The two modules (math and reading) are always taken on separate dates. In some circumstances, school faculty are authorized to have some students take the exams earlier or later than their peers. Since students with cognitive

[14] Prior to 2015, the DOE administered the Hawai‘i State Reading and Math Assessment (HSA) to measure student performance. The HSA was administered to students in grades three through eight and ten. Though our data includes test scores from the HSA, we do not have data on test dates, and thus we strictly focus on utilizing data from the SBA.

disabilities are subject to alternative assessments, we drop them from our sample.

2.2 Air Quality Measurements

We employ data on particulates ($PM_{2.5}$) and sulfur dioxide (SO_2) obtained from the State of Hawai‘i Department of Health (DOH).[15] Particulates are measured in micrograms per cubic meter ($\mu g/m^3$). $PM_{2.5}$ measures particulates that are 2.5 micrometers in diameter or smaller. SO_2 is measured in parts per billion (ppb). The DOH reports measures of each pollutant at hourly frequencies. For our analysis, we aggregate the pollutant measures from each DOH monitoring station to 24-hour averages and merge these data with the DXP data using the date that students took their assessments.

2.3 Summary Statistics

Table 1 displays summary statistics from the DXP student data. At the student-year level, the mean month of the math and reading exam is just over four, indicating that students tend to take both of their assessments in April. Half of student-years in the public school system come from economically disadvantaged families and around six percent received English language services. Table 1 also reveals Hawai‘i's ethnically diverse population. Nearly a quarter of students identify as Native Hawaiian and just under another quarter identify as Filipino. Another 18% of students identify as non-Filipino Asian, 10% as Pacific Islander, 18% as White, and 8% identify as another ethnicity. The data includes 116,374 unique individuals enrolled across 230 schools.

Summary statistics for pollution are presented in Table 2 by monitoring station.[16] Overall, $PM_{2.5}$ averages are relatively similar across the islands of O'ahu, Maui, and Kauai. Hawai‘i island sees slightly higher levels of $PM_{2.5}$ in certain areas due to Kilauea's volcanic activity. The

[15] We do not use data on PM_{10} as the state only had three stations monitoring it.

[16] Hawai‘i Island also has a monitoring station at Kamehameha Schools Hawai‘i that began collecting data on $PM_{2.5}$ and SO_2 in 2019. Our sample of test scores ends in 2018 so we do not use this information to construct pollution predictions. However, we do use it to construct the Kriging weights and for our cross-validation exercise.

Table 1: Summary Statistics (Hawai‘i Data eXchange Partnership Student Measures)

	Mean	Std. Dev.
Panel A: Student-Year Level Statistics		
Month of Math Exam	4.43	0.77
Month of Reading Exam	4.11	0.71
Economically Disadvantaged	0.50	0.50
Received English Language Services	0.06	0.24
Panel B: Student Level Statistics		
Female	0.50	0.50
Asian (Non-Filipino)	0.16	0.37
Filipino	0.24	0.43
Native Hawaiian	0.24	0.43
Pacific Islander	0.09	0.29
White	0.19	0.39
Other Ethnicity	0.08	0.27
Unique Individuals	116,397	
Schools	230	
Years	2015 - 2018	

Notes: Data on student summary statistics comes from the Hawai‘i Data eXchange Partnership for the years 2015-2018. Economically disadvantaged students refer to those who qualify for federal programs such as free and reduced lunch. Those who received English language services are students who enrolled in the State of Hawai‘i Department of Education’s English Learner Program for the academic school year.

Table 2: Summary Statistics (Pollutant Measures)

	$PM_{2.5}$		SO_2	
Station	Mean	Std. Dev.	Mean	Std. Dev.
Hawai'i Island				
Hilo	8.41	5.62	3.87	8.16
Honaunau				
Kailua Kona				
Kona	11.12	4.42	3.25	1.96
Mountain View	3.65	3.18	1.75	2.43
Ocean View	12.60	4.79	18.60	16.06
Pahala	4.77	2.61	28.94	18.89
Hawai'i Island Average	8.08	2.80	12.09	6.57
O'ahu				
Honolulu	3.66	2.41	0.38	0.48
Kapolei	4.90	2.01	0.14	0.34
Pearl City	4.05	2.04		
Sand Island	4.92	1.90		
O'ahu Average	4.35	1.73	0.26	0.34
Sample Average	6.69	1.98	9.04	4.92

Notes: Data on pollutant measures come from the State of Hawai'i Department of Health for the years 2015-2018. Measures of $PM_{2.5}$ and SO_2 are reported for each pollutant monitoring station. The particulate $PM_{2.5}$ is reported in $\mu g/m^3$ and SO_2 is reported in ppb.

Pahala monitoring station is located less than 20 miles south of the Kilauea volcano. Because of the Pahala monitoring station's close proximity to the volcano's active vents, average levels of SO_2 in Pahala are nearly three times the state average. For the full sample, the average $PM_{2.5}$ is 6.69 μg/m^3 (with a standard deviation of 1.98) and the average SO_2 is 9.04 ppb (with a standard deviation of 4.92).

2.4 Emissions from Kilauea: Jan 2015 - Jun 2018

In Figure 1, we display time series plots of SO_2 levels near Kilauea from two adjacent monitoring stations: Ocean View and Pahala. We display daily pollution levels over our sample period which spans January 2015 to June 2018. In each figure, we display the one hour National

Ambient Air Quality Standards (NAAQS) level for SO_2 from the EPA of 75 ppb. Note that we display one *day* averages and so any levels above the NAAQS line reflect particularly poor air quality.

While the figure does indicate a fairly steady emission of SO_2 over the sample period, it also does show three specific events with increased volcanic activity (United States Geological Survey, 2018; National Park Service, 2018). First, in April 2015, the lava lake at the summit spilled onto the floor of Halema‘uma‘u Crater several times causing increased emissions of SO_2. The lake level abruptly dropped by May 10. Next, the lava lake rose at the start of 2016 and again subsequently declined. Finally, the summit of Pu‘u‘o‘o collapsed on April 30, 2018 causing lava to drain away from the summit. This lava was subsequently released by a magnitude 6.9 earthquake which caused a fissure near a residential area. Lava then covered 13.7 square miles of land, destroyed 700 homes, and added 875 acres of land to the island (National Park Service, 2018).

3 Research Design

3.1 Measuring Pollution at Schools

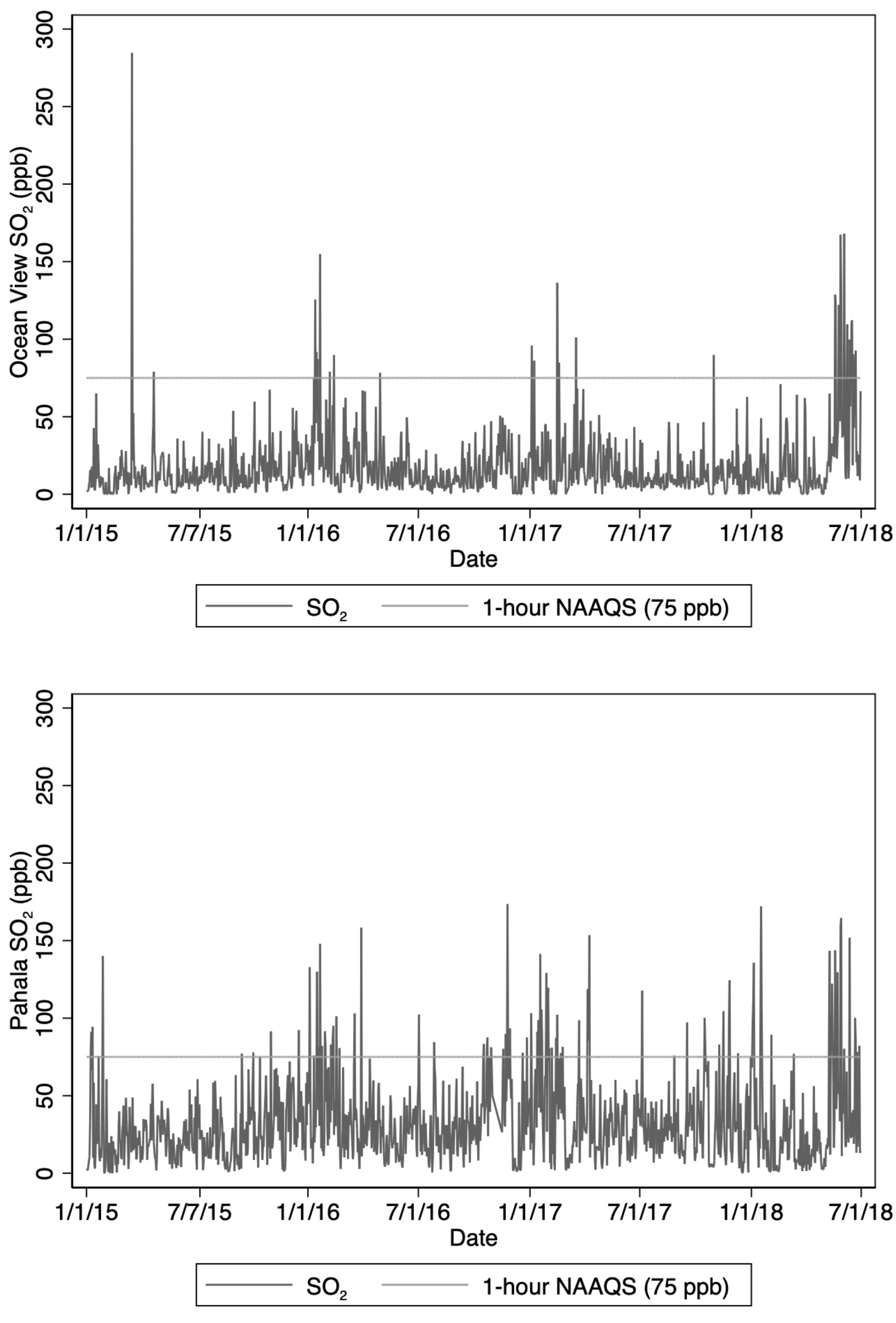
We employ three methods to predict pollution exposure at schools which we subscript with s. Denoting the measured pollution at monitoring station m on day t with Π_{mt}, we can write all three predictors using the generic form

$$\widehat{P}_{st} = \sum_{m \in N(s)} \lambda_{sm}(X_t)\Pi_{mt} \tag{1}$$

where $N(s)$ is a neighborhood of school s and X_t is a set of time varying regressors which can possibly be empty.[17] We restrict the weights to sum to unity so that $\sum_{m \in N(s)} \lambda_{sm}(X_t) =$

[17] In fact, kriging is a "universal" predictor in that it uses all available measurements to make predictions. However, in non-stationary environments such as this, it is advisable to use more local measures. With this in mind, we

Figure 1: Average Daily SO_2 Levels Near Kilauea



Notes: Each figure displays time series plots of daily averages of SO_2 levels at the Ocean View and Pahala monitoring stations over the period Jan 2015 to Jun 2018.

1. Negative weights, however, are permitted. Under stationarity conditions, the means of the pollution measures from each station and school (if they existed) will be the same. Under these conditions, predictors of this form are unbiased.

The first two methods employ inverse distance weights (ID-weights) and uniform weights (U-weights). ID-weights are computed as

$$\lambda_{sm} = \frac{d_{sm}^{-1}}{\sum_{n \in N(s)} d_{sn}^{-1}}$$

where d_{sm} is the distance between school s and monitoring station m. ID-weights are very common in environmental economics. U-weights are computed as

$$\lambda_{sm} = \frac{1}{\#N(s)}.$$

U weights simply deliver the arithmetic mean using local monitoring stations.

The third method we employ uses Kriging, which is a common technique in geostatistics (Cressie, 1990). We call these weights K-weights. These weights have nice theoretical properties and be easily modified to accommodate covariates. With the exception of Lleras-Muney (2010), we know of no other economists who have employed K-weights in the pollution literature. One of the contributions of the paper, therefore, is to investigate in an empirical application how K-weights perform when compared to their better known cousins: ID- and U-weights.

The K-weights that we compute use pollution measurements from monitoring stations in conjunction with variation in Hawai‘i's trade wind patterns to predict pollution at each of Hawai‘i's schools. Theoretically, Kriging delivers the best linear unbiased predictor (BLUP) of unobserved pollution at each school (Cressie, 1990).[18] Normally, Kriging weights depend solely on the spatial correlations of pollution measurements across monitoring stations. However, we ex-

employ three neighborhoods: O'ahu, south Hawai‘i (includes Kilauea), and north Hawai‘i (the rest of the island of Hawai‘i).

[18] In simulation studies and under proper conditions, it also has also been shown superior to other commonly used prediction methods such as inverse distance weighting (Zimmerman et al., 1999).

tend the procedure so that we can incorporate external variables (wind direction in our case) to generate more accurate predictions. This addresses a common critique of ID- and U-weights, namely, that they do not address the spatial correlation in pollution nor can they cannot easily accommodate covariates such as wind direction or relative location.

The K-weights that we employ depend on the distance between school s and monitoring station m (previously notated as d_{sm}), the relative location of the monitoring station vis-a-vis the school (l_{sm}), and the wind direction on that day (NE_t). We denote the weight given to monitoring station m to predict pollution at school s as $\lambda(d_{sm}, l_{sm}, NE_t) \equiv \lambda_{sm}(NE_t)$. In the spirit of Halliday et al. (2019), we employ the variable NE_t, a binary variable indicating that the winds on that day were northeasterly. As previously discussed, such winds are called "trade winds" and tend to improve air quality throughout the state.

While K-weights must sum to one, they can be negative or greater than unity. This allows the predictions to take on a value outside of the simplex generated by the pollution measurements. In principle, this is a positive feature of Kriging - not a deficiency. To see this, we note that the monitoring stations on the island of O'ahu are all in urban Honolulu on the southern shore of the island (see Figure 2). However, many schools on this island are in rural parts of the island and/or on the northern facing shores placing them outside of the simplex generated by the monitoring stations. Because the weights are not constrained to be between zero and one, the predictions at these rural schools can be smaller (or larger than) than *all* of the Π_{mt} used to construct $\widehat{P}_{st}$. Other common predictors used in this literature such as nearest neighbor or inverse distance weighting do not share this property. On the other hand, schools located far away from monitoring stations may lead to extreme values for weights (despite the fact that they sum to unity) which may not be desirable in certain applications.

To illustrate the relative locations of the schools and the monitoring stations, we present Figures 2 and 3. These figures plot each school's location and each monitoring station's location (denoted by the solid red circles) on the islands of O'ahu and Hawai‘i, respectively. Schools on O'ahu are empty circles. Schools on south Hawai‘i are empty triangle whereas those on north

Hawai‘i are crosses. These correspond to the three neighborhoods (denoted $N(s)$ in equation (1)) for which we compute the ID-, U-, and K-weights. The figure illustrates that the schools in our sample are often located well outside of the simplex generated by the monitoring stations.

We now briefly discuss the GMM procedure that we use to estimate the Kriging weights. A detailed treatment of this can be found in Appendix A.1. Denoting $M(s) \equiv \#N(s)$, we define

$$\lambda_s(b) \equiv (\lambda_{s1}(b), ..., \lambda_{sM(s)}(b), \alpha_b)'$$

which is a vector that includes the Kriging weights, $\lambda_{sm}(b)$ for $b \in \{0, 1\}$ (b is an indicator for northeasterly winds), and the Lagrangian multiplier on the constraint that the weights must sum to one denoted by α_b for $b \in \{0, 1\}$. The weights depend on the semivariogram between stations m and n on trade wind and non-trade wind days. The semivariogram is one minus the spatial correlation between the two locations and equals zero at a given location *i.e.* when $m = n$. We denote this measure by $\gamma_{mn}(b)$. The Kriging weights can then be derived as $\lambda_s(b) = \Gamma(b)^{-1}\Gamma_s(b)$ where

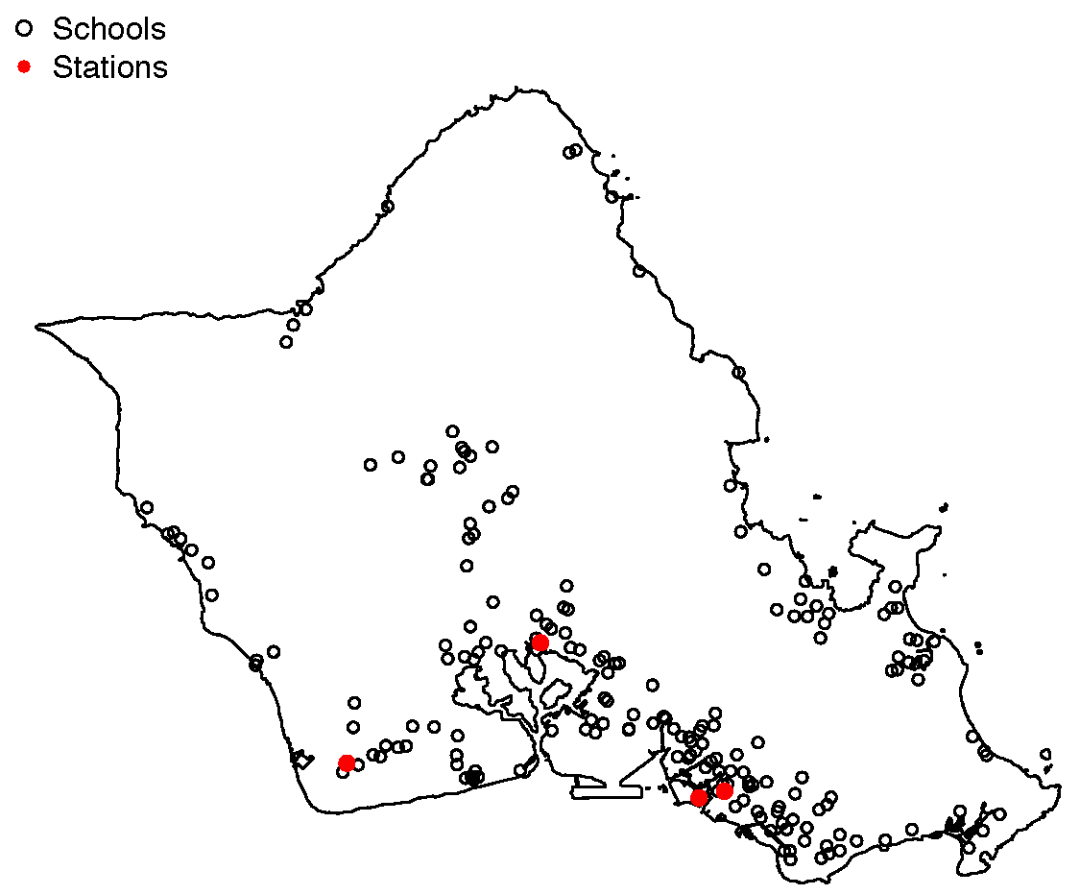
$$\Gamma(b) \equiv \begin{bmatrix} \gamma_{11}(b) & \dots & \gamma_{1M(s)}(b) & 1 \\ \vdots & \ddots & \vdots & \vdots \\ \gamma_{M(s)1}(b) & \dots & \gamma_{M(s)M(s)}(b) & 1 \\ 1 & \dots & 1 & 0 \end{bmatrix}$$

and

$$\Gamma_s(b) \equiv \begin{bmatrix} \gamma_{1s}(b) \\ \vdots \\ \gamma_{M(s)s}(b) \\ 1 \end{bmatrix}.$$

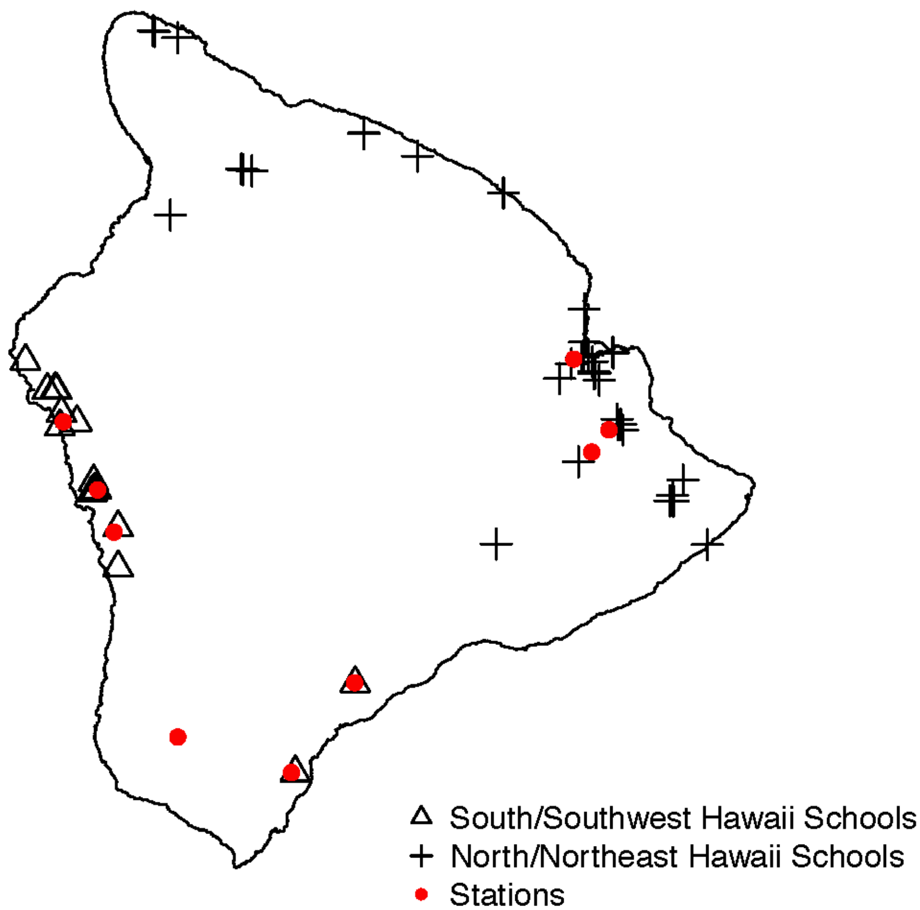
Hence, the task of computing the Kriging weights hinges on computing the semivariogram for $NE_t = 1$ and $NE_t = 0$. We refer the reader to the appendix for details on the derivation and, specifically, what optimization problem delivers these weights.

Figure 2: Schools and Monitoring Stations on O'ahu



Notes: This figure displays all pollutant monitoring stations and schools located on the island of O'ahu.

Figure 3: Schools and Monitoring Stations on Hawai‘i Island



Notes: This figure displays all pollutant monitoring stations and schools located on the island of Hawai‘i.

To compute the semi-variograms in $\Gamma(b)$ and, especially, $\Gamma_s(b)$ (which requires out-of-sample prediction), we postulate a parametric model indexed by a vector. To estimate this parameter, first, we compute the empirical semivariagrams for trade wind ($NE_t = 1$) and non-trade wind days ($NE_t = 0$). Next, we model the spatial correlation between stations m and n as

$$1 - \gamma_{mn}(NE_t) = \exp\left(-d_{mn} \times \left(\phi NE_t + \sum_{j\in\mathcal{L}}(\delta_j 1_{mn}(j) + \beta_j \times 1_{mn}(j) \times NE_t)\right)\right)$$

where $\mathcal{L} \equiv \{NE, SE, SW, NW\}$ (which collects the relative location variables) and $1_{mn}(j)$ is an indicator for the location of n relative to m where m is held fixed. This functional form allows the spatial correlation: (1) to decline with the distance between locations; (2) to decline when trade winds are blowing; (3) to depend on relative locations according to wind direction. The semivariogram is zero when $d_{mn} = 0$. We then note that estimation of the parametric model can proceed using a simple Poisson regression or Generalized Linear Model (with a log link function) package in Stata or R and is relatively easy to implement.

3.2 Covariogram Estimates

We plot the covariograms for $PM_{2.5}$ and SO_2 in Figures A1 and A2. Each figure has four plots corresponding to the relative locations of the monitoring stations: NE, SE, SW, and NW. For any pair of stations, (m, n), the location corresponds to m relative to n. We also plot the covariograms for trade and non-wind days in each plot. Each dot in these plots is a pair of stations.[19]

In Figure A1, we see a large degree of spatial correlation in $PM_{2.5}$. In the diagonal plots corresponding to relative locations NE and SW, we see that the spatial correlation remains above

[19]The GMM procedure that we use only employs the bottom triangle of the covariance matrix since the information in the upper triangle is redundant. This implies, however, that the samples used in the off-diagonal plots in the top right and bottom left plots of Figures A1 and A2 are different and so the estimations are also different. For example, for a pair of stations (m, n), if m is northeast of n then $1_{mn}(NE) = 1$ and $1_{mn}(SW) = 0$. On the other hand, for (n, m), we would have $1_{mn}(NE) = 0$ and $1_{mn}(SW) = 1$. The same is true for the plots on the diagonal of the figure (not the covariance matrix). This is highly technical point but some readers may have wondered why these plots are different. This is why.

0.2 for up to a distance of 60 miles. In the off-diagonal plots corresponding to NW and SE, the spatial correlations remain well above zero when there are no trade winds, but they are substantially smaller when the trade winds are blowing. Overall, this figure strongly indicates that trade winds result in lower spatial correlations in $PM_{2.5}$.

Figure A2 shows a much more muted degree of spatial correlation for SO_2. When the monitoring stations are either to the northeast or southeast, the figure shows that there is essentially no spatial correlation in SO_2. When the stations are to the northwest or the southwest, there appears to be moderate spatial correlation through about 100 miles and trade winds modestly dampen it. The more modest degree of spatial correlation in SO_2 makes it more difficult to predict SO_2 exposure at schools. All told, the spatial correlations in $PM_{2.5}$ are more informative than they are in SO_2. This most likely underscores our subsequent difficulties predicting SO_2 using any of our predictors.

3.3 Pollution Predictions: Summary Statistics

In Table 3, we provide the means and standard deviations of the predictions of pollution at each school on days with and without trade winds using K-, ID-, and U-weights.[20] We provide descriptive statistics for the three neighborhoods for which we computed the weights: O'ahu, south/southeast Hawai'i, and north/northeast Hawai'i. Using K-weights, the table shows that on trade wind days levels of $\text{PM}_{2.5}$ are lower on O'ahu and north Hawai'i across all three of our pollutant measure methods. However, we do not see lower particulate levels on trade wind days on south Hawai'i. Presumably, the reason for this is that many of the schools on south Hawai'i are located to the west of Kilauea and, so the trade winds blow $PM_{2.5}$ towards those schools. Finally, we see a similar pattern for SO_2 with lower levels on trade wind days on O'ahu and north Hawai'i.

[20] We replaced the prediction with a zero when the Kriging prediction was negative. We also replaced all predictions above the 99th percentile with a missing value. In the raw pollution data, 22.10% of $PM_{2.5}$ predictions were negative and 1.08% of SO_2 predictions were negative. These numbers might seem large but we note per Halliday et al. (2019) many days in those data essentially had very low pollution levels.

We note that the standard deviations of the K-weighted predictors of $PM_{2.5}$ are higher on O'ahu than they are for the ID- and U-weighted predictors. This is particularly the case on trade wind days on O'ahu for which the standard deviation is 6.12 $\mu g/m^3$ using K-weights whereas it is 1.63 and 1.56 $\mu g/m^3$ using ID- and U-weights, respectively. This might reflect that the K-weights are larger in absolute value for some of the more remote schools on O'ahu located far away from the monitoring stations, thereby, necessitating a large degree of extrapolation. On the other hand, the standard deviations of the ID- and U-weighted predictors of $PM_{2.5}$ on south and north Hawai'i are more similar.

However, the standard deviations of the K-weighted means of SO_2 are fairly comparable to those using ID- and U-weights on O'ahu but substantially *lower* on South and North Hawai'i. Their comparability on O'ahu presumably reflects the low spatial correlation in SO_2 on O'ahu. On the other hand, the standard deviations of predictors are substantially lower when employing K-weights throughout the island of Hawai'i than they they are for either the ID- and U-weighted predictors. In general, we found that that the K-weights weights for SO_2 were less likely to negative or greater than one (presumably due to lower spatial correlation) than they were for $PM_{2.5}$. This is probably underlies the lower standard deviations of the K-weight predictors for SO_2.

3.4 Cross-Validation Exercise

We now conduct a simple cross-validation exercise to investigate the accuracy of our three predictors. For the monitoring stations in each of our three groups (O'ahu, south Hawai'i, and north Hawai'i), we exclude information from one station and then we use the remaining stations in the group to predict its pollution levels. We then compare the actual pollution levels that were measured by the station with the predicted pollution levels.

To gauge the accuracy of the prediction, we compute two sets of statistics. The first is the R^2 from a regression of the actual pollution measure onto the predicted pollution measure. The

Table 3: Summary Statistics (Pollutant Measures) by Tradewind Status

	O'ahu		S/SW Hawai'i		N/NE Hawai'i	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
No Tradewinds						
PM_{25} (kriging)	4.20	3.11	7.71	6.79	7.07	5.21
PM_{25} (inverse distance)	3.97	2.50	7.72	6.74	7.08	5.30
PM_{25} (uniform weights)	3.97	2.46	7.53	6.23	7.08	5.32
Tradewinds						
PM_{25} (kriging)	2.94	6.12	8.87	6.44	5.65	4.01
PM_{25} (inverse distance)	3.19	1.63	9.11	7.15	5.60	4.00
PM_{25} (uniform weights)	3.23	1.56	8.80	6.84	5.55	3.98
No Tradewinds						
SO_2 (kriging)	0.80	0.78	4.96	4.52	3.55	4.03
SO_2 (inverse distance)	0.81	0.79	8.33	11.52	5.76	10.52
SO_2 (uniform weights)	0.81	0.77	13.06	13.92	5.83	10.38
Tradewinds						
SO_2 (kriging)	0.60	0.63	6.79	4.94	1.36	0.98
SO_2 (inverse distance)	0.60	0.64	11.43	13.83	1.52	2.16
SO_2 (uniform weights)	0.61	0.63	18.03	14.67	1.51	2.11

Notes: Data on pollutant measures come from the State of Hawai'i Department of Health. Measures of $PM_{2.5}$ and SO_2 are reported for O'ahu, West/Northwest Hawai'i island, and East/Southeast Hawai'i for days with and without tradewinds (northeasterly winds). The particulate $PM_{2.5}$ is reported in $\mu g/m^3$ and SO_2 is reported in *ppb*. O'ahu stations include Honolulu, Kapolei, Pearl City, and Sand Island stations. South/Southwest Hawai'i stations include Honaunau, Kailua Kona, Kona, Naalehu, Ocean View, and Pahala stations. North/Northeast Hawai'i stations include Hilo, Keaau, and Mountain View stations.

second is the Mean Squared Error (MSE) for the prediction i.e. $\frac{1}{T}\sum_{t=1}^{T}\left(P_{mt}-\widehat{P_{mt}}\right)$. Note that the MSE that we compute is *not* the sum of squared residuals from the regression in which we compute the R^2 and so the usual identity will *not* hold.

In Figures A3 and A4, we display the R^2 and MSE for each station. In both of these figures, we depict the statistic in question for each group and each monitoring station in that group. We do so for $PM_{2.5}$ in the left panel and SO_2 in the right panel of each figure. Accordingly, Figures A3 and A4 each have six plots corresponding to three regional groupings and two pollutants. Each of these statistics is informative of the accuracy of the predictors but the MSE will tend to be larger when the object that is being predicted is more volatile.

Looking at the R^2 of the predictions of $PM_{2.5}$ in the left panel of Figure A3, we see considerable variation in the quality of the predictions depending on the grouping and the type of weighting (e.g. K-weights, ID-weights, or U-weights). In many cases, Kriging does not perform well for $PM_{2.5}$ which is interesting since Kriging (under appropriate conditions) delivers the BLUP. On O'ahu, we can predict roughly between 20 and 60% of the variation in $PM_{2.5}$. K-weights perform particularly poorly in Pearl City and, especially, Kapolei which are further away from the urban core of Honolulu. This might suggest that schools that are further away from monitoring stations also have poorer predictions perhaps due to abnormally small or large weights. In south Hawai‘i, our predictions are more accurate with R^2's sometimes exceeding 60% (e.g. Kona and Ocean View). On the whole, K-weights perform better on south Hawai‘i perhaps due to the nature of its geography. The predictions are the lowest in the north Hawai‘i region with R^2's between 10 and 40%. As with south Hawai‘i, K-weights perform substantially better in north Hawai‘i than they do on O'ahu. Importantly, ID-weight appear to offer little advantage over U-weights or simple local raw means.

The estimated R^2's for SO_2 predictions in Figure A3 tell a very different story than they do for $PM_{2.5}$. First, in contrast to the case of $PM_{2.5}$, K-weighted predictions perform much better for SO_2. Particularly, we see that Kriging based predictors dominate for two of three monitoring stations on south Hawai‘i and one of two monitoring stations on north Hawai‘i. Also, Kriging never performs as poorly as it did for $PM_{2.5}$ for some of the monitoring stations on O'ahu e.g. Kapolei. Second, the R^2's for the SO_2 predictions on O'ahu are zero. This reflects two factors. First, there are only two monitoring stations for SO_2 on O'ahu. Accordingly, the prediction of SO_2 levels at one station is just the level at the other station. Second, as reflected in Figure A2, the spatial correlations in SO_2 are effectively zero except when one station is to the northwest of the other station and relatively close (e.g. within 50 miles). The monitoring station at Honolulu is due east of the Kapolei station and about 15 miles separate them. Taken together, this suggests that the SO_2 predictions on O'ahu could be quite poor which should be borne in mind as we proceed. Finally, as was the case with $PM_{2.5}$, ID-weights offer no ostensible advantage to using U-weights when predicting SO_2.

The calculations of the MSEs displayed in Figure A4 reveal several interesting patterns. We still see that K-weights perform well on north Hawai'i for both $PM_{2.5}$ and SO_2 and on south Hawai'i for SO_2. However, K-weights still do not perform well on O'ahu when compared to ID- and U-weights, particularly, at the more remote stations of Kapolei and Pearl City. We also observe that all of the MSE's (i.e. for each weighting scheme) are *very* high on north Hawai'i and, especially on south Hawai'i. This is particularly the case for SO_2 levels near Kilauea. This most likely reflected the high volatility of SO_2 near Kilauea.

3.5 Estimation Equation

To identify the impact of pollution on student cognitive functioning, we employ each of our predictors of pollution exposure at a given school and estimate a linear regression via OLS of student standardized test scores onto pollution exposure while adjusting for school or individual fixed effects, seasonality, and student demographic characteristics. Specifically, we estimate the model:

$$Y_{igset} = \alpha + \beta \widehat{P}_{st} + \gamma X_{ige} + \sigma_s + \mu_m + \theta_y + \upsilon_{igset} \tag{2}$$

where Y_{igset} is the standardized test score (i.e. the raw score minus its means divided by its standard deviation) of student i enrolled in grade g at school s taking exam e (math or English) on day t. Our main variable of interest, $\widehat{P}_{st}$, is a prediction of exposure to $PM_{2.5}$ or SO_2 at school s on day t discussed above. We scale all estimates of β up by 100 in order to make the estimates more readable by providing more significant figures. This and the fact that the dependent variable is a z-score implies that the interpretation of β is that a one unit increase in the pollutant increases test scores by β % of a standard deviation. The vector X_{ige} contains time-varying student characteristics such as indicators for economic disadvantage status and recipiency of English language services, time-invariant student characteristics such as indicators for gender and ethnicity, and an indicator for the student's grade and the type of exam.[21] We include school fixed effects, denoted by σ_s, in order to control for variation at the school level. The terms, μ_m and θ_y, are month and academic year fixed effects respectively and υ_{igset} is the error term. Standard errors are clustered by school. Identification of β in equation (2) comes from plausibly exogenous variation in $\widehat{P}_{st}$ *within* schools, across time.[22]

We conclude with a few remarks about the calculation of standard errors in the presence of a generated regressor ($\widehat{P}_{st}$ in our case). With a generated regressor, standard errors should account for sampling uncertainty in $\widehat{P}_{st}$. In a standard situation in which the regressor is generated from the same sample that is used in the second stage estimation, bootstrapping the generated regressor and then bootstrapping the second stage coefficient estimates provides a common solution.

However, two points make this solution less viable in our scenario. First, the Kriging procedure that is used to generate the regressor takes 20-30 minutes (depending on the pollutant) on a fast machine. This implies that a single standard error with 100 replications could over a day to compute using standard bootstrapping procedures.[23] Second, as is common in the literature on the impacts of pollution, the generated regressor comes from a seperate sample with a separate sampling scheme than the primary estimation sample. Accordingly, the asymptotic distribution computed in Appendix 6A of Wooldridge (2010) for linear models with generated regressors does not apply as these calculations presume a single sample.

[21] Controlling for the economic status of each students' family is particularly important in this specification because the DOE grants geographic exceptions (GE) to students who wish to enroll in a school outside of their district of residence under several qualifying circumstances (e.g. parents are faculty at the receiving school, a program is offered at the receiving school but not at the student's district school, etc). Because of the GE, students who reside in areas with relatively lower average household incomes may attend schools in districts that have higher average household incomes and thus better education programs.

[22] As an additional robustness check, we replace all time-invariant student controls with student fixed effects, which account for all unobserved time-invariant differences across students (e.g. innate ability). Our preferred model avoids student fixed effects since the time frame of our study is limited to several years (2015 to 2018) which, therefore, creates some considerable power issues.

[23] We do note, however, that there are faster alternatives for extremum estimations that could be considered (Andrews, 2002).

4 Results

4.1 Balance Test

Though the Hawai‘i context likely provides exogenous variation for the identification of the effects of pollutants on learning outcomes, we can still test whether there are observable differences in student characteristics correlated with pollutant exposures. In Appendix Table A1, we regress our pollution measures on the full vector of student and exam characteristics using all three of our weighting schemes. Overall, we find little to no evidence of correlations between observable characteristics and pollutant levels. Excluding the estimates of the grade fixed effects in the second part of the table, the only significant coefficient in either column is for receipt of English language services which appears to predict $PM_{2.5}$ levels. However, this is the only significant variable across all columns. We do see that the grade indicators predict SO_2 levels and $PM_{2.5}$ levels for 5th grade using our inverse distance and uniform weighting schemes, but this is easily dealt with by the inclusion of grade fixed effects in the estimations. Finally, we note that an F-test that all of the covariates in the estimates are zero resoundingly fails to reject the null. All told, we suspect that this significant estimate in the table is the consequence of Type I error. Thus, we conclude that the variation in pollutants has no systematic relationships with observable confounders, and the detected statistical significance likely arises from Type I error.

4.2 Baseline Results

We report our first set of OLS estimations in Table 4. The table contains three panels corresponding to K-weighted predictions (Panel A), ID-weight predictions (Panel B), U-weighted predictions (Panel C). Column (1) presents our results for the effect of standardized $PM_{2.5}$ levels on student test scores, as estimated in equation (2). Looking at the Kriging-based estimate in Panel A, we estimate a drop in student standardized test scores on days with higher $PM_{2.5}$

levels that is significant at the 10% level. The effect is small; a one unit increase in $PM_{2.5}$ leads to a 0.13 percent of a standard deviation drop in student test scores (recall that our pollutant effects are scaled up by a factor of 100). With a full sample standard deviation of 1.98 (see Table 2), a one standard deviation increase in $PM_{2.5}$ corresponds to a 0.26 percent drop in student test scores, on average. Our estimates using inverse distance and uniform weighting schemes in Panels B and C are larger: -0.246 and -0.253, respectively. Both estimates are significant at the 1% level. Scaling each of the estimates up by the standard deviation of $PM_{2.5}$, we estimate declines in test scores of 0.49 and 0.50 of percent a standard deviation, respectively.

In second column, we replace student controls with student fixed effects. We see that the estimate is no longer significant using the K-weights. However, the results using ID- and U-weights are robust to the inclusion of student fixed effects. In fact, both estimates barely change once student fixed effects are included. Both Panels B and C indicate that a one standard deviation increase in $PM_{2.5}$ corresponds to a 0.44 percent of a standard deviation decline in test scores. In the final two columns, we do not see any impact of SO_2 on test scores using K- and ID-weights. However, results using U-weights indicate that increases in SO_2 cause small declines in test scores that are significant at the 10% level.

The fact that the impact of $PM_{2.5}$ is robust to the inclusion of student fixed effects should assuage a large number of identification concerns. This strongly indicates that the effects of poor air quality on student performance are not driven by any differential selection out of test-taking on high pollution days.

Finally, while many of these effects are small or null, it is important to note that these weaker effects mask important underlying heterogeneity by geography, the average level of pollution, and SES within schools. We will explore each of these next.

Table 4: Effect of Pollution on Math and Reading Scores, OLS Estimates

	$PM_{2.5}$		SO_2	
	(1)	(2)	(3)	(4)
Panel A: Kriging				
Pollutant	–0.132*	–0.076	–0.212	–0.224
	(0.073)	(0.071)	(0.173)	(0.168)
R^2	0.267	0.851	0.261	0.838
Panel B: Inverse Distance				
Pollutant	–0.246**	–0.223**	–0.099	–0.073
	(0.095)	(0.103)	(0.075)	(0.067)
R^2	0.267	0.850	0.263	0.838
Panel C: Uniform Weights				
Pollutant	–0.253***	–0.223**	–0.115*	–0.123*
	(0.093)	(0.101)	(0.066)	(0.065)
R^2	0.267	0.850	0.263	0.838
Number of Schools	230	230	230	230
School FE	X	X	X	X
Month FE	X	X	X	X
Year FE	X	X	X	X
Individual FE		X		X

Notes: Standard errors are clustered by school. Control variables include gender, economically disadvantaged students, English language service recipients, exam subject, grade level and ethnicity. All estimations control for school, month and academic year fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.3 Impacts by Geographical Region

In Table 5, we estimate our model stratified by three geographical regions: O'ahu, south Hawai'i, and north Hawai'i. The important finding in this table is that we now see much larger impacts of both $PM_{2.5}$ and SO_2 in south Hawai'i while we see no impacts elsewhere. This is consistent across all three of our weighting schemes. It is also noteworthy that the estimates that use K-weighted predictions are larger than the estimates that use ID- and U-weighted predictions since Kriging performed better in south Hawai'i than the other two prediction methods. The point estimates of the effects of $PM_{2.5}$ in south Hawai'i are -0.652, -0.589, and -0.530 using Kriging, inverse distance, and uniform weights respectively. These estimates indicate that a one standard deviation increase in $PM_{2.5}$ results in test score declines ranging from 1.05 to 1.29 percent of a standard deviation. The point estimates for SO_2 indicate a 1.70 and 0.62 percent decline in test scores for every standard deviation increase in SO_2 using Kriging and uniform weights respectively. There are no significant effects of SO_2 on test scores in south Hawai'i using inverse distance weights.

We note that pollution levels are substantially higher on south Hawai'i than on O'ahu or north Hawai'i as shown in Table 3. For example, south Hawai'i has substantially worse pollution than O'ahu regardless of whether or not the trade winds are blowing. In addition, air quality in south Hawai'i is notably worse than in north Hawai'i on trade wind days but not on days in which there are no trade winds.

Thus, these effects might indicate that the effects of these pollutants are non-linear in their levels. Small exposure to either particulates or SO_2 appears to have no effects on O'ahu and, to a lesser extent, north Hawai'i. However, the effects on south Hawai'i, where air quality is notably worse, are very large.

Table 5: Effects of Pollutants on Exam Scores for Students by Region

	O'ahu		S/SW Hawai'i		N/NE Hawai'i	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Kriging						
$PM_{2.5}$	–0.070		–0.652***		0.167	
	(0.093)		(0.219)		(0.180)	
SO_2		–0.602		–0.345**		0.206
		(1.96)		(0.145)		(0.346)
R^2	0.273	0.273	0.284	0.269	0.201	0.200
Panel B: Inverse Distance						
$PM_{2.5}$	–0.0890		–0.589**		0.161	
	(0.219)		(0.201)		(0.186)	
SO_2		–2.51		–0.161		0.00397
		(1.79)		(0.110)		(0.105)
R^2	0.273	0.273	0.284	0.284	0.201	0.201
Panel C: Uniform Weights						
$PM_{2.5}$	–0.175		–0.530**		0.190	
	(0.225)		(0.185)		(0.195)	
SO_2		–2.560		–0.126**		0.136
		(1.84)		(0.0482)		(0.147)
R^2	0.273	0.273	0.284	0.284	0.201	0.201
Number of Schools	176	176	16	16	38	38

Notes: Standard errors are clustered by school. Control variables include gender, economically disadvantaged students, English language service recipients, exam subject, grade level and ethnicity. All estimations control for school, month and academic year fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

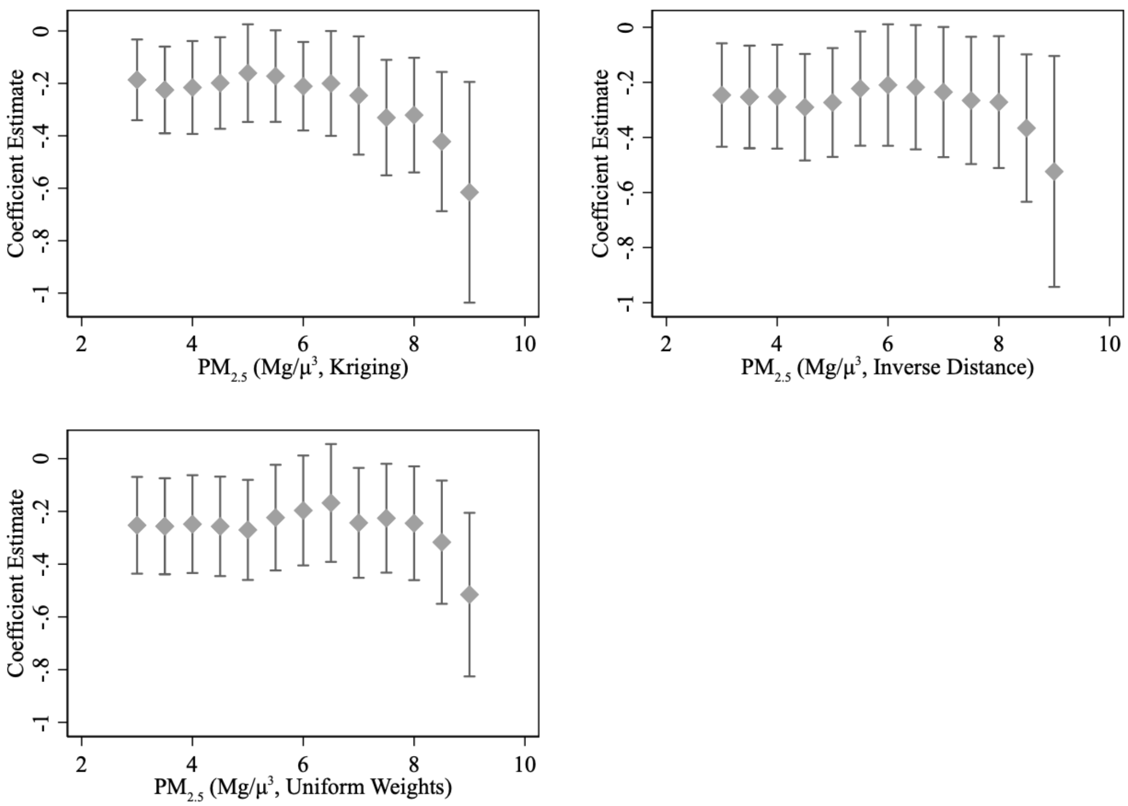
4.4 Impacts by Average Pollutant Levels

Are the effects of $PM_{2.5}$ on student cognitive performance in fact larger when mean exposure is higher? A key advantage of the Hawai‘i context (as indicated by Table 3) comes from its rich variation in pollution levels across schools stemming from their location on each island and their proximity to the Kilauea volcano. This allows us to test for possible nonlinear effects in how pollutants affect student performance, particularly across schools with lower levels of exposure on average. In Figure 4, we report coefficients across different samples by school, where each subsample progressively focuses on schools with higher average $PM_{2.5}$ levels.[24]

As we focus on schools with higher levels of pollution on average, the negative effects of pollutants sharply increase. We also ran a separate regression that restricts our sample to schools with mean pollution levels under 9 $\mu g/m^3$ (roughly the US average) and estimate that a standard deviation increase in $PM_{2.5}$ reduces test scores by 0.17 to 0.35 percent of a standard deviation depending on the weighting scheme. On the other hand, when subsetting our regression sample to schools with mean $PM_{2.5}$ levels *greater* than 9 $\mu g/m^3$, there is a precipitous drop in test score reductions ranging from 1.02 to 1.22 percent of a standard deviation with respect to a standard deviation increase in $PM_{2.5}$. Accordingly, the pernicious effects of $PM_{2.5}$ are largest when exposure is the greatest. This result is very much consistent with the results in Table 5 which show that the effects of pollutants are largest near Kilauea. Because we are see larger effects in “high pollution” schools, this could indicate that our effects are driven by long term exposure to pollution. In other words, it could be the case that students who are exposed to higher levels of pollution over longer periods of time experience worse outcomes on their tests due to a cumulative effect and not an instantaneous effect.

[24] Average $PM_{2.5}$ levels are calculated by taking the mean $PM_{2.5}$ level across the full sample of days for each school.

Figure 4: Differential Effects by Average $PM_{2.5}$ Levels



Notes: The y-axis represents the coefficient for the effect of the pollutant, $PM2.5$ on student z-scores by the mean level of exposure to $PM_{2.5}$ within each school. The x-axis represents the threshold at which each school's mean exposure is greater than a given level of $PM_{2.5}$. Standard errors are clustered by school. Control variables include female, economically disadvantaged families, non-native English speaking, math exam, grade level and ethnicity. All estimations control for school, month and academic year fixed effects.

4.5 Heterogeneity by Economic Disadvantage Status

Does poor air quality have larger effects on the most disadvantaged pupils within a school? Case et al. (2002) show that children from poorer backgrounds are at higher risk of developing a host of health problems than better off children. This suggests that more well off children will be in better health which could confer more resiliency when combating the pernicious effects of air pollution. In this sense, air pollution could exacerbate pre-existing inequities within schools.

To investigate this, in Table 6, we estimate a variation of equation (2) while including an interaction term between the pollutant level and an indicator for whether the pupil was eligible for the free and reduced school lunch program - a proxy for student economic disadvantage. In Panel A of the table, we display the estimates of the effects of particulates and we observe drastically different effects by economic status. For example, using K-weighted predctors in the first column, the interaction between $PM_{2.5}$ and the disadvantaged indicator is -0.236 whereas the direct effect is -0.008 but not significant. This implies that the the harmful effects from $PM_{2.5}$ for disadvantaged students are about 30 times the magnitude of their effects for their more advantaged counterparts. Using inverse distance and uniform weights, the effect is roughly eight and four times larger for disadvantaged students.[25] In Panel B, we find no statistically significant effects for the direct effect of SO_2 and its interaction with the disadvantage indicator.

The magnitudes of these effects on cognitive performance of disadvantaged students pupils are not trivial. Once again, using the descriptive statistics from Table 2, we calculate that a one standard deviation increase in $PM_{2.5}$ decreases test scores for disadvantaged pupils by 0.48 percent of a standard deviation using our kriging weights. A similar calculation indicates declines of 0.75 and 0.73 percent using inverse distance and uniform weights respectively.

Could these larger impacts of pollution for disadvantaged students be driven by selection? For example, there could be a potential correlation between where disadvantaged students enroll and school characteristics including the school's location, its average pollution level, or the

[25] We compared the sum of the interaction and the direct effect of particulates to the direct effect by itself.

Table 6: Effect of Pollution on Exam Scores for Economically Disadvantaged Students

	Kriging (1)	Inverse Distance (2)	Uniform Weights (3)
Panel A: $PM_{2.5}$			
Economically Disadvantaged * $PM_{2.5}$	–0.236**	–0.334**	–0.295*
	(0.106)	(0.159)	(0.164)
$PM_{2.5}$	–0.008	–0.047	–0.076
	(0.089)	(0.124)	(0.124)
Economically Disadvantaged	–29.400***	–28.685***	–28.907***
	(1.040)	(1.202)	(1.235)
R^2	0.266	0.267	0.267
Panel B: SO_2			
Economically Disadvantaged * SO_2	–0.184	–0.163	–0.085
	(0.252)	(0.155)	(0.110)
SO_2	–0.091	0.014	–0.063
	(0.246)	(0.125)	(0.101)
Economically Disadvantaged	–29.537***	–29.592***	–29.657***
	(0.957)	(0.915)	(0.929)
R^2	0.267	0.269	0.269

Notes: Standard errors are clustered by school. Control variables include gender, English language service recipients, exam subject, grade level and ethnicity. All estimations control for school, month and academic year fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

school's potential resources to combat the harmful effects of pollutants (e.g. air conditioning). We do not believe that this is the case for the simple reason that the estimates in Table 6 all include school fixed effects.

However, we can also offer an alternative test of this possibility to eliminate any lingering doubts. In Figure 5 we estimate equation (2) while focusing on subsamples of schools by the fraction of the school's students who were economically disadvantaged. The estimates in the far left of the figure correspond to schools with 20% or fewer pupils who qualify for federal programs such as free and reduced lunch whereas the far right of the figure includes all schools. As you move from the left to the right of the figure, the sample of schools becomes more disadvantaged.

Interestingly, we find little difference in how pollutants harm student learning by the school's fraction of economically disadvantaged students. This suggests that the observed disparity by student disadvantage status arises from differences across students within each school, and not due to differences across schools. In other words, disadvantaged students do not appear to be especially harmed by pollutants due to their school's location or school resources. Rather, it appears as if poorer pupils are more adversely impacted by pollution than richer pupils.

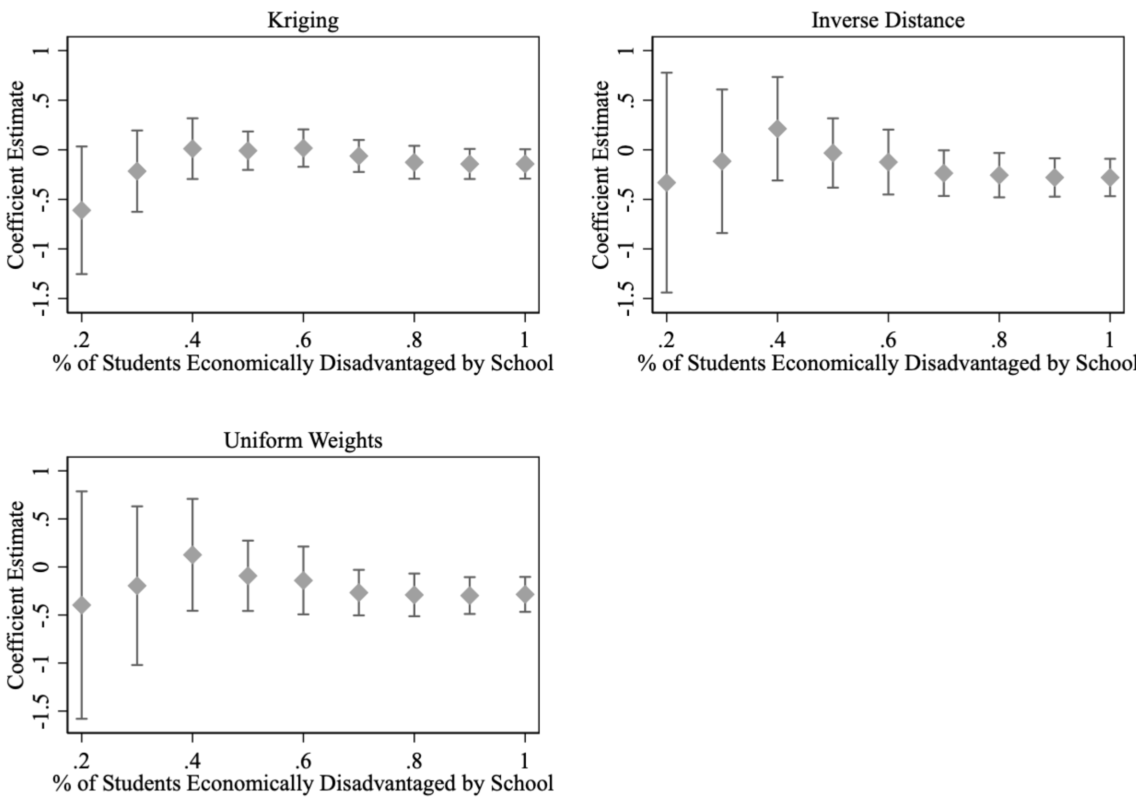
5 Robustness Checks

In this section, we explore the robustness of our findings to two factors. First, we investigate the role that delayed test dates play in potentially biasing our estimates. Second, we examine the robustness of our findings to temperature. This second exercise is important as Park et al. (2020) show that temperature can be an important factor determining learning outcomes and, so this may be a potentially important omitted variable.

5.1 Test Date Delays

One potential threat to the validity of our results is that although schools dictate test dates, students might stay home from school on high pollution days, taking their make-up exam on a later day when the air quality is better. Importantly, this mechanism would suggest a *positive* bias as pupils ostensibly should be performing better on the delayed date with lower pollution levels. As such, this vignette does not pose much of a threat to our findings as it suggest that we are underestimating the true effect of pollution on test scores.

Figure 5: Differential Effects by % of Economically Disadvantaged Students Within Each School



Notes: The y-axis represents the coefficient for the effect of the pollutant, $PM2.5$ on student z-scores by the percentage of students who are economically disadvantaged within each school. The x-axis represents the threshold at which each school has less than a given percentage of economically disadvantaged students. Standard errors are clustered by school. Control variables include female, economically disadvantaged families, non-native English speaking, math exam, grade level and ethnicity. All estimations control for school, month and academic year fixed effects.

In Figure A5, we present histograms of test dates for a sample of six schools. We note that there are 230 schools in our sample spanning seven grades. With the exception of one school (Robert Louis Stevenson Middle), the distribution of test dates tends to be concentrated around a single mode. James B Campbell High School (in the top left of the figure) does show slightly more dispersion but it is the largest school in the State of Hawaii with over 3000 pupils.

In Table A2, we estimate the same models as in Table 4 but include a binary control variable for the student delaying their test date. Throughout, we only employ school fixed effects. This indicator variable is turned on when the pupil's test date is either above the modal test date (odd columns) or the median test date (even columns). The modes and medians were computed within the school/grade/exam (math or english).

The estimates in Table A2 are larger in magnitude than those in Table 4. Prima facie, this appears to lend credence to the story in which students delay their exams on high pollution days and this enables them to obtain higher scores when they do take their exams. However, the indicator for delayed exam is *negative* and significant. This most likely reflects that students who are absent from school more often tend to perform worse - a negative selection effect. Accordingly, in order to obtain a positive bias from the delayed test indicator, it must be the case that students are more likely to delay their test when pollution is lower (not higher).[26] All told, delaying tests in the face of poor air quality is neither a plausible nor even possible explanation for our finding that poorer air quality causes students to perform worse on standardized tests.

5.2 Including Temperature Controls

Park et al. (2020) show that heat directly impacts student learning. In Table A3, we include temperature as an additional control. The estimations are otherwise identical to those in Table 4. All told, the results in Table A3 indicate that our core estimates from Table 4 are robust to tem-

[26] We do not report these results, but this is indeed the case. We do not have student absenteeism data at the daily level, so we cannot make statements about the effects of pollution on absenteeism on the day of the exam.

perature controls on the whole.[27] However, in contrast to Table 4, none of coefficient estimates for SO_2 are significant (although the results were weaker for SO_2 in that table). Consistent with the literature, we obtain that higher temperatures are associated with lower test scores when we only include school fixed effects. However, temperature is no longer significant once we include individual fixed effects but that is likely due to low power.

6 Conclusion

Using variation in air quality in the Hawaiian islands due to volcanic activity, we estimate the impacts of $PM_{2.5}$ and SO_2 on student performance. Because of the state's normally pristine air quality conditions, variation in pollutants are primarily determined by wind direction and volcanic emissions from Kilauea volcano on the island of Hawai‘i. Exploiting this variation in pollution across the state, we find that worsening air quality decreases student exam scores. Specifically, we find that a standard deviation increase in $PM_{2.5}$ decreases test scores by about 0.26 to 0.50 percent of a standard deviation on average.

We also find that schools with higher average pollution levels tend to see worse effects of air quality on student performance. Specifically, when we focus on schools with less than 9 $\mu g/m^3$ of $PM_{2.5}$ on average, we see reductions in test scores of about 0.17 to 0.35 percent of a standard deviation with respect to a one standard deviation increase in $PM_{2.5}$. However, schools with average $PM_{2.5}$ exposure above 9 $\mu g/m^3$ see reductions in test scores of 1.02 to 1.22 percent of a standard deviation at the same margin. We also observe these nonlinear effects when estimating our main specification by geographic region. The negative, statistically significant effects of pollution on test scores are concentrated within south Hawai‘i, which has notably higher levels of pollution than in other areas across the state. These results might reflect the possibility that pupils in schools with higher mean levels of exposure have had more long-term exposure to

[27] For our three regions (Oahu, S/SE Hawaii, N/NE Hawaii), we used average daily temperature information from the largest airports in those regions: Daniel K. Inouye International Airport (HNL), Ellison Onizuka Kona International Airport (KOA), and Hilo International Airport (ITO).

$PM_{2.5}$ and SO_2.

Finally, the negative effects of pollution on student performance are much larger for poorer students. The effects of $PM_{2.5}$ on test scores for economically disadvantaged pupils are at least four times larger than they are for their more advantaged peers. These effects are not driven by school level characteristics but are instead a result of student level differences within schools. This is in line with previous literature which shows that poorer children are subject to worse health outcomes (Case et al., 2002) which may imply greater susceptibility to environmental insults.

All told, the findings from our study have implications for environmental justice. We show that poor students face additional obstacles accumulating human capital when air quality is poor relative to those who are more financially stable. This suggests that air pollution contributes to the strong persistence in socioeconomic status across generations that we observe in the United States.

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A.1 Technical Details of the Kriging Procedure

To fix ideas, we let $s \in \{1, ..., S\}$ denote the school, and $t \in \{1, ..., T\}$ denote the time periods, and $m \in N(s)$ denote the monitoring station where $N(s)$ is the neighborhood of school s. We consider three neighborhoods: the island of O'ahu, the southwestern part of Hawai'i (that is most exposed to Kilauea's emissions), and the remainder of Hawai'i. These are depicted in Figures 2 and 3. We denote the pollution measurement at a given monitoring station on a particular day as Π_{mt}. The predicted exposure is then

$$\widehat{P}_{st} = \sum_{m \in N(s)} \lambda_{sm}(NE_t)\Pi_{mt}$$

where the kriging weights are $\lambda_{sm}(NE_t) \equiv \lambda(d_{sm}, l_{sm}, NE_t)$. Once again, bear in mind that $NE_t \in \{0, 1\}$.

The weights are chosen to guarantee that the predictions are unbiased and that the prediction error has minimum variance. Unbiasedness requires that the weights sum to unity. If we let Π_{st} represent the true pollution measurement at school s, both criteria can formally be written as

$$\min_{\{\lambda_{sm}(b)\}_{m \in N(s)}} V\left(\widehat{P}_{st} - \Pi_{st}\right)$$
$$\text{subject to} \sum_{m \in N(s)} \lambda_{sm}(b) = 1$$

This minimization problem is solved twice: once for trade wind days ($b = 1$) and once for non-trade wind days ($b = 0$). This delivers two sets of weights which depend on the prevailing winds for that day.

Following Montero et al. (2015) (see p. 86) and making some local stationarity assumptions, the first order conditions that guarantee these criteria are

$$\sum_{m \in N(s)} \lambda_{sm}(b)\gamma_{nm}(b) + \alpha_b = \gamma_{ns}(d_b) \text{ for } n \in N(s) \tag{A.1}$$

$$\sum_{m \in N(s)} \lambda_{sm}(b) = 1 \tag{A.2}$$

where both conditions hold for $b \in \{0, 1\}$ and α_b is the Lagrangian multiplier on the constraint in A.2 which guarantees the unbiasedness of the prediction. The object, $\gamma_{nm}(b)$, is the semi-variogram between locations m and n when $NE_t = b$. For each school in $N(s)$, equations A.1 and A.2 constitute a set of $\#N(s) + 1$ equations in as many unknowns. So, we then have $\#N(s) \times (\#N(s) + 1)$ equations in total. If we index the monitoring stations in $N(s)$ from one to $M(s) \equiv \#N(s)$ (with some abuse of notation) and define

$$\lambda_s(b) \equiv (\lambda_{s1}(b), ..., \lambda_{sM(s)}(b), \alpha_b)'$$

then the Kriging weights are $\lambda_s(b) = \Gamma(b)^{-1}\Gamma_s(b)$ where

$$\Gamma(b) \equiv \begin{bmatrix} \gamma_{11}(b) & \dots & \gamma_{1M(s)}(b) & 1 \\ \vdots & \ddots & \vdots & \vdots \\ \gamma_{M(s)1}(b) & \dots & \gamma_{M(s)M(s)}(b) & 1 \\ 1 & \dots & 1 & 0 \end{bmatrix}$$

and

$$\Gamma_s(b) \equiv \begin{bmatrix} \gamma_{1s}(b) \\ \vdots \\ \gamma_{M(s)s}(b) \\ 1 \end{bmatrix}.$$

Hence, the task of computing the Kriging weights is reduced to computing the semivariogram for $NE_t = 1$ and $NE_t = 0$.

To compute the semivariogram, we postulate a functional form for the semivariogram. We assume that

$$\gamma_{mn}(NE_t) = 1 - \text{exp}\left(-d_{mn} \times \left(\phi NE_t + \sum_{j\in\mathcal{L}}(\delta_j 1_{mn}(j) + \beta_j \times 1_{mn}(j) \times NE_t)\right)\right) \quad \text{(A.3)}$$

where $\mathcal{L} \equiv \{NE, SE, SW, NW\}$ (which collects the relative location variables) and $1_{mn}(j)$ is an indicator for the location of n relative to m where m is held fixed. Note that distance enters multiplicatively to ensure that the semivariogram is zero when $d_{mn} = 0$ and, by construction, $\gamma_{mn}(NE_t) \in [0, 1]$. This assumption reduces the spatial covariance structure to a smaller number of parameters which allows us to make extrapolations and interpolations needed to construct $\Gamma_s(b)$. We collect these parameters in the vector θ.

We estimate these parameters using GMM. We let $\widetilde{\gamma_{mn}}(b)$ denote the *empirical* semivariogram for the monitoring station pair (m, n) for $b \in \{0, 1\}$. Similarly, $\widetilde{\Gamma(b)}$ is the matrix that collects the empirical semivariograms. Then for each pair (m, n), we can compare two collections of moment conditions

$$q_b(\theta) = \text{vec}\left(\text{lower triangle}\left(\widetilde{\Gamma(b)} - \Gamma(b; \theta)\right)\right)$$

for $b \in \{0, 1\}$. We further collect these in the $(M(s)+1)\times M(s)\times 2$ vector $q(\theta) \equiv (q_0(\theta)', q_1(\theta)')'$. We estimate θ by minimizing $q(\theta)'q(\theta)$.

Importantly, θ is easy to estimate. First, compute the empirical semivariagrams for trade wind ($NE_t = 1$) and non-trade wind days ($NE_t = 0$). Second, we re-write A.3 as

$$1 - \gamma_{mn}(NE_t) = \text{exp}\left(-d_{mn} \times \left(\phi NE_t + \sum_{j\in\mathcal{L}}(\delta_j 1_{mn}(j) + \beta_j \times 1_{mn}(j) \times NE_t)\right)\right)$$

and we then note that estimation can proceed by using a simple Poisson regression package in

Stata or R. Once θ is estimated, we can then estimate the Kriging weights $\lambda_s(b)$.

A.2 Additional Tables and Figures

Table A1: Balance Test

	Kriging		Inverse Distance		Uniform Weights	
	(1)	(2)	(3)	(4)	(5)	(6)
	$PM_{2.5}$	SO_2	$PM_{2.5}$	SO_2	$PM_{2.5}$	SO_2
Female	-0.008	-0.001	-0.003	0.001	-0.004	0.011
	(0.014)	(0.003)	(0.009)	(0.006)	(0.009)	(0.009)
Economically Disadvantaged	-0.037	0.002	-0.037	0.006	-0.029	0.007
	(0.031)	(0.007)	(0.025)	(0.013)	(0.025)	(0.017)
Received English Language Services	0.085*	-0.005	0.004	0.005	0.021	0.005
	(0.050)	(0.014)	(0.027)	(0.021)	(0.026)	(0.027)
Math Exam	-0.082	0.053	-0.119	0.121	-0.148	0.052
	(0.229)	(0.042)	(0.123)	(0.074)	(0.118)	(0.107)
Filipino	-0.017	-0.003	0.009	-0.011	0.003	-0.000
	(0.026)	(0.005)	(0.014)	(0.009)	(0.013)	(0.012)
Native Hawaiian	0.026	0.000	0.009	0.013	0.004	0.015
	(0.030)	(0.007)	(0.021)	(0.012)	(0.021)	(0.015)
Pacfic Islander	-0.020	-0.006	0.010	-0.020	0.007	-0.011
	(0.033)	(0.007)	(0.022)	(0.018)	(0.021)	(0.016)
White	-0.007	-0.009	0.019	-0.005	0.017	0.003
	(0.024)	(0.006)	(0.016)	(0.012)	(0.016)	(0.013)
Other Ethnicity	-0.027	-0.012	0.008	-0.008	0.004	-0.012
	(0.031)	(0.008)	(0.021)	(0.012)	(0.021)	(0.014)

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

Notes: Standard errors clustered by school. Regressors include female, economically disadvantaged families, non-native English speaking, math exam, grade level and ethnicity. All estimations control for school, month and academic year fixed effects. The F-test tests for whether the covariates in each model are jointly equal to zero.

Table A1: Balance Test Continued

	Kriging		Inverse Distance		Uniform Weights	
	(1)	(2)	(3)	(4)	(5)	(6)
	$PM_{2.5}$	SO_2	$PM_{2.5}$	SO_2	$PM_{2.5}$	SO_2
4th Grade	0.155	-0.055	-0.050	-0.088	-0.043	-0.196**
	(0.186)	(0.034)	(0.090)	(0.070)	(0.089)	(0.098)
5th Grade	-0.051	-0.030	-0.179***	-0.060	-0.172**	0.004
	(0.160)	(0.032)	(0.068)	(0.050)	(0.067)	(0.067)
6th Grade	0.027	-0.066**	-0.048	-0.282***	-0.051	-0.298***
	(0.208)	(0.031)	(0.088)	(0.095)	(0.089)	(0.096)
7th Grade	-0.220	-0.137**	-0.056	-0.382***	-0.020	-0.423***
	(0.237)	(0.055)	(0.134)	(0.110)	(0.127)	(0.159)
8th Grade	-0.027	-0.148***	-0.064	-0.407***	-0.023	-0.393**
	(0.233)	(0.055)	(0.125)	(0.118)	(0.125)	(0.157)
11th Grade	-0.355	-0.011	-0.385*	-0.680	-0.408	-0.392
	(0.316)	(0.129)	(0.230)	(0.505)	(0.255)	(0.366)
Month FE	X	X	X	X	X	X
Academic Year FE	X	X	X	X	X	X
School FE	X	X	X	X	X	X
R^2	0.315	0.672	0.398	0.545	0.377	0.623
F-test	1.019	1.159	1.043	1.249	1.103	1.222
p-value	0.498	0.814	0.354	0.596	0.766	0.470

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

Notes: Standard errors clustered by school. Regressors include female, economically disadvantaged families, non-native English speaking, math exam, grade level and ethnicity. All estimations control for school, month and academic year fixed effects. The F-test tests for whether the covariates in each model are jointly equal to zero.

Table A2: OLS Estimates With Delayed Test Date Control

	$PM_{2.5}$		SO_2	
	Modal Date (1)	Median Date (2)	Modal Date (3)	Median Date (4)
Panel A: Kriging				
Pollutant	–0.152**	–0.158**	–0.193	–0.202
	(0.076)	(0.076)	(0.166)	(0.167)
Delayed Test	–10.889***	–10.184***	–9.531***	–8.899***
	(1.040)	(1.321)	(1.131)	(1.229)
R^2	0.269	0.263	0.262	0.262
Panel B: Inverse Distance				
Pollutant	–0.310***	–0.312***	–0.103	–0.109
	(0.091)	(0.093)	(0.073)	(0.074)
Delayed Test	–10.925***	–10.270***	–9.608***	–8.983***
	(1.091)	(1.323)	(1.125)	(1.221)
R^2	0.269	0.263	0.264	0.264
Panel C: Uniform Weights				
Pollutant	–0.325***	–0.325***	–0.107*	–0.112*
	(0.091)	(0.092)	(0.064)	(0.064)
Delayed Test	–10.940***	–10.281***	–9.600***	–8.974***
	(1.091)	(1.322)	(1.125)	(1.221)
R^2	0.269	0.263	0.264	0.264
Number of Schools	230	230	230	230
School FE	X	X	X	X
Month FE	X	X	X	X
Year FE	X	X	X	X

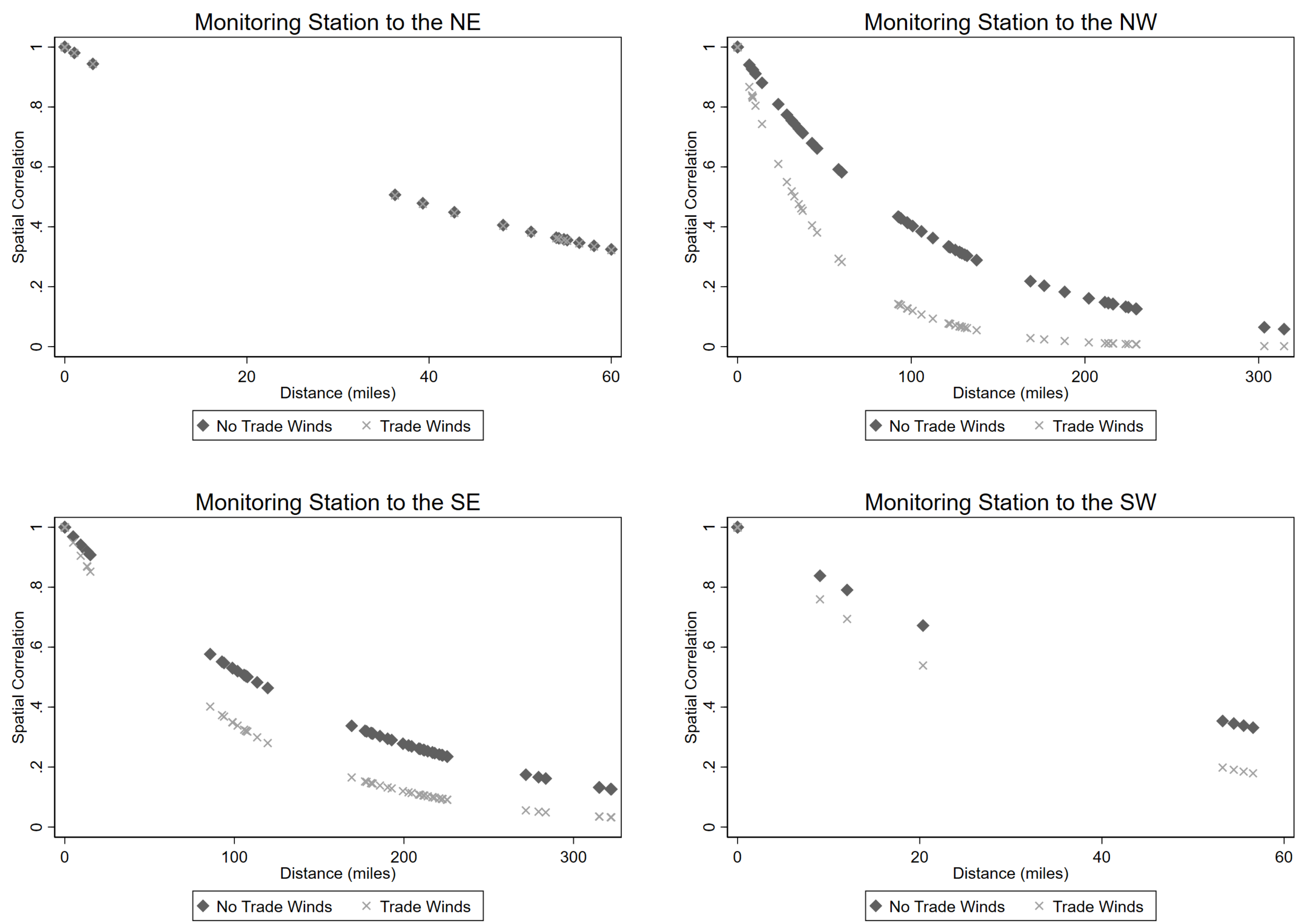
Notes: Standard errors are clustered by school. Control variables include a dummy equal to 1 if a student has a delayed exam date and 0 otherwise, gender, economically disadvantaged students, English language service recipients, exam subject, grade level and ethnicity. All estimations control for school, month and academic year fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: OLS Estimates With Air Temperature Control

	$PM_{2.5}$		SO_2	
	(1)	(2)	(3)	(4)
Panel A: Kriging				
Pollutant	–0.160**	–0.081	–0.187	–0.070
	(0.073)	(0.073)	(0.186)	(0.190)
Air Temperature	–0.469**	–0.079	–0.388*	–0.035
	(0.208)	(0.207)	(0.206)	(0.197)
R^2	0.267	0.851	0.260	0.850
Panel B: Inverse Distance				
Pollutant	–0.271***	–0.227**	–0.072	–0.025
	(0.093)	(0.103)	(0.072)	(0.071)
Air Temperature	–0.442**	–0.080	–0.395*	–0.046
	(0.204)	(0.195)	(0.205)	(0.198)
R^2	0.268	0.850	0.262	0.850
Panel C: Uniform Weights				
Pollutant	–0.278***	–0.227**	–0.065	–0.063
	(0.091)	(0.101)	(0.068)	(0.065)
Air Temperature	–0.441**	–0.078	–0.393*	–0.039
	(0.204)	(0.195)	(0.205)	(0.197)
R^2	0.268	0.850	0.262	0.850
Number of Schools	230	230	230	230
School FE	X	X	X	X
Month FE	X	X	X	X
Year FE	X	X	X	X
Individual FE		X		X

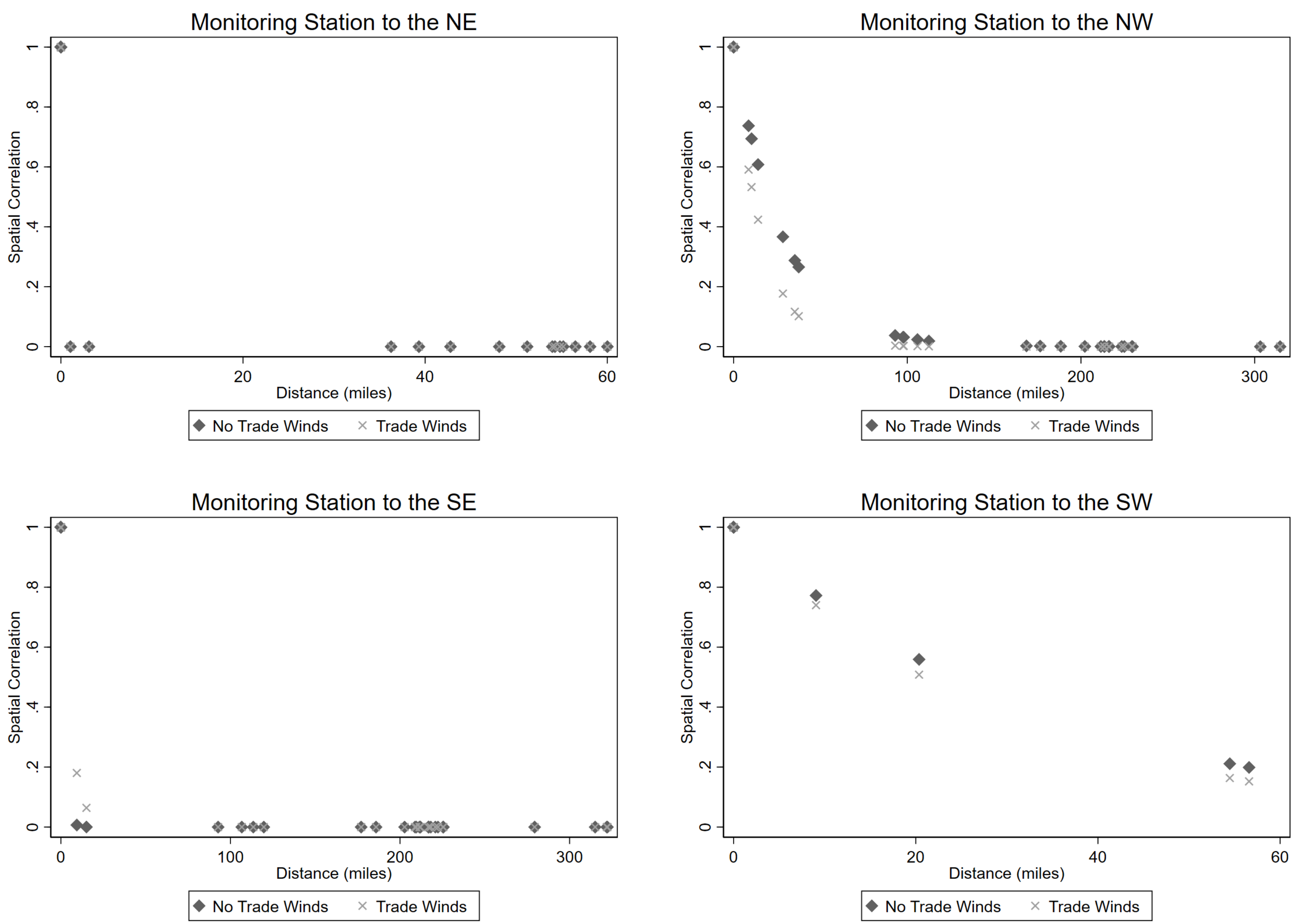
Notes: Standard errors are clustered by school. Control variables include air temperature, gender, economically disadvantaged students, English language service recipients, exam subject, grade level and ethnicity. All estimations control for school, month and academic year fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A1: Covariograms for $PM_{2.5}$



Notes: Displays estimated covariograms by the relative locations of the monitoring stations and by the direction of the trade winds.

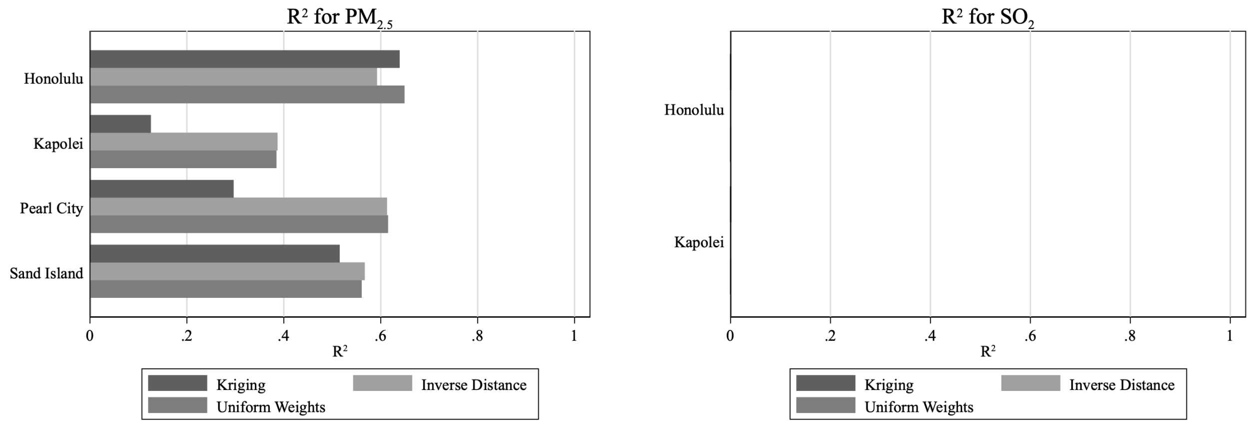
Figure A2: Covariograms for SO_2



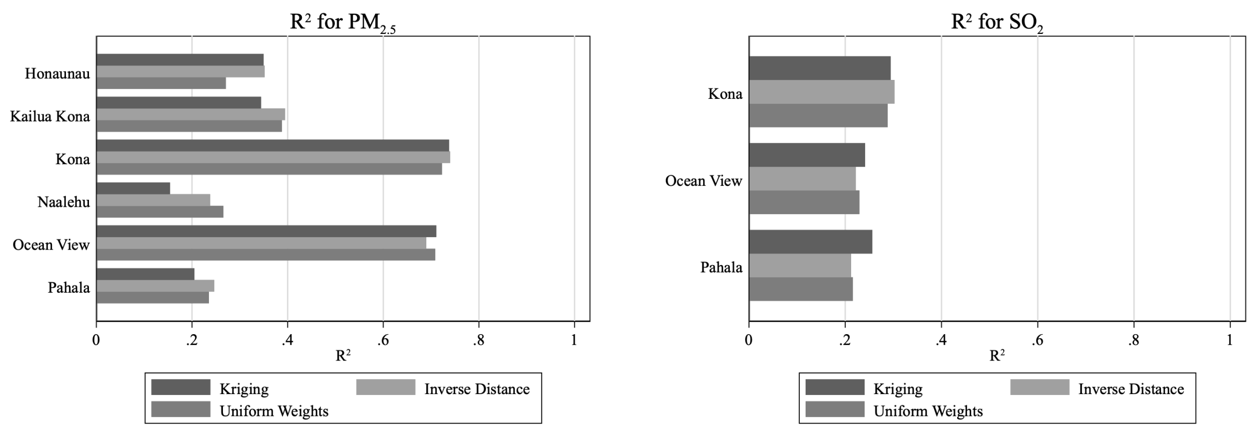
Notes: Per Figure A1

Figure A3: Cross-Validation: R^2 of Predictions

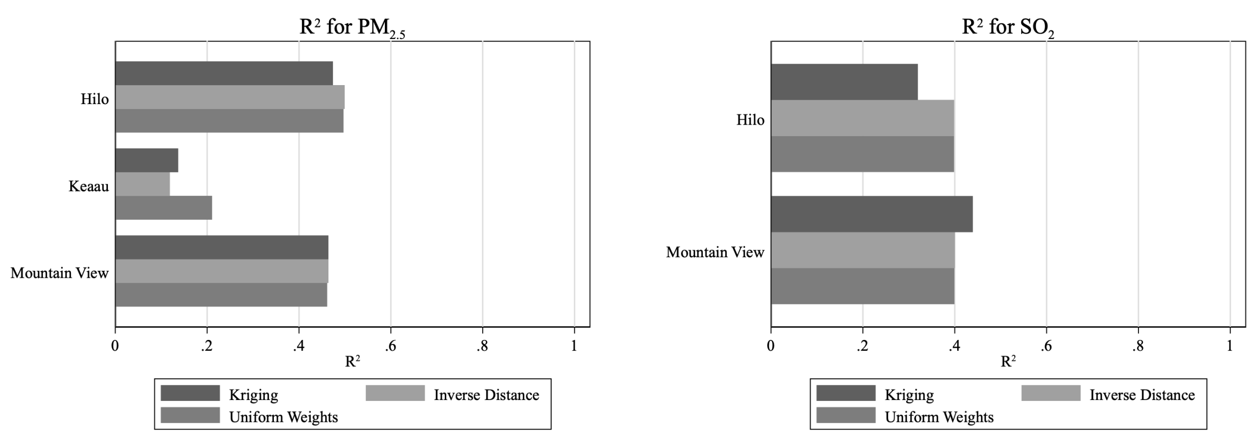
O'ahu



South Hawai'i

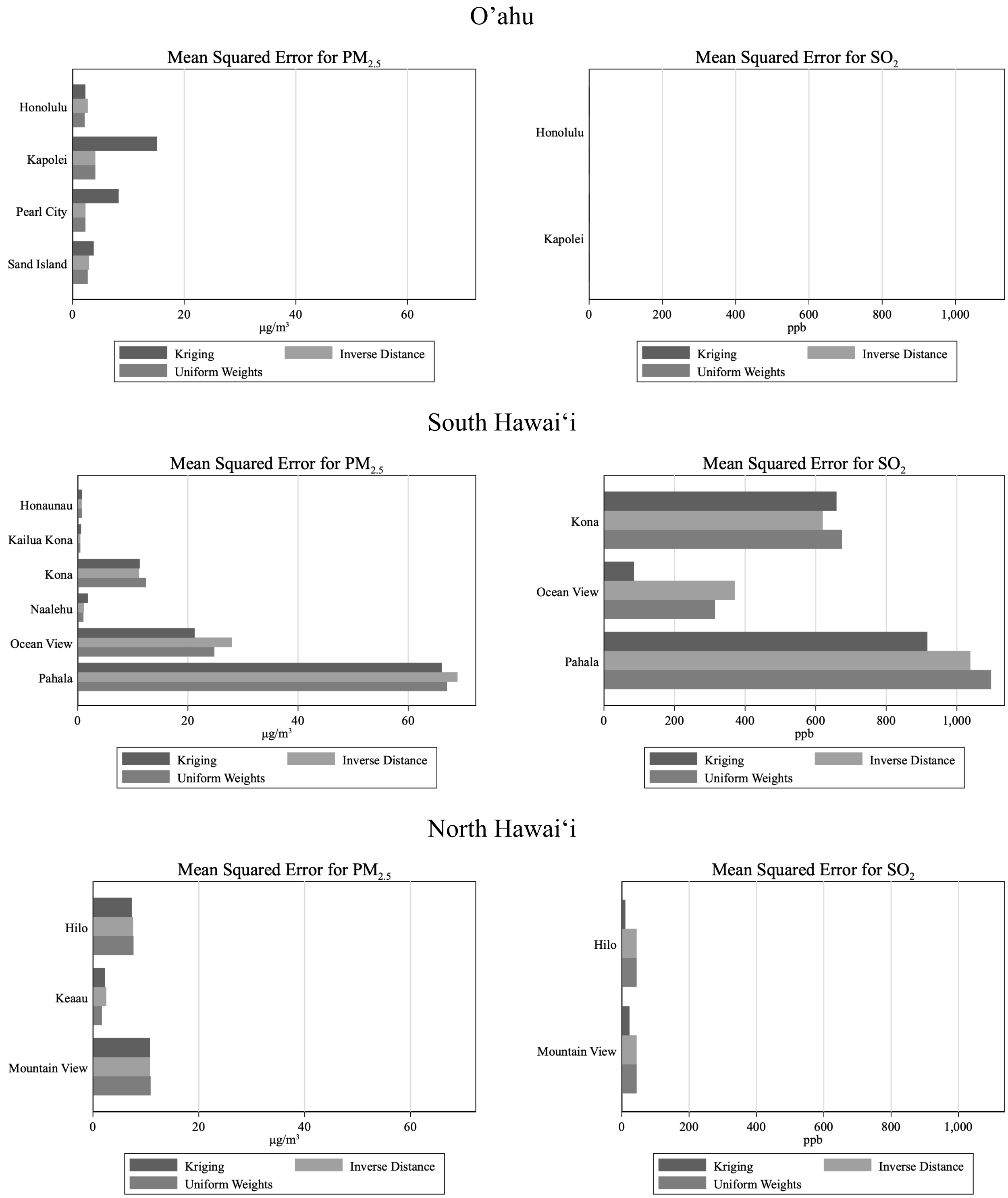


North Hawai'i



Notes: This figure displays the R^2 of regressions of pollution measures at a given monitoring in a given group onto its prediction when the monitoring station in question is excluded from the prediction.

Figure A4: Cross-Validation: Mean-Squared Error of Predictions



Notes: This figure displays the Mean-Squared Errors of pollution predictions from the cross-validation exercise.

Figure A5: Math SBA Exam Dates by School, 2015