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ABSTRACT

Vog: Using Volcanic Eruptions to Estimate the Health Costs of Particulates*

The high correlation of industrial pollutant emissions complicates the estimation of the impact of industrial pollutants on health. To circumvent this, we use emissions from Kīlauea volcano, uncorrelated with other pollution sources, to estimate the impact of pollutants on local emergency room admissions and a precise measure of costs. A one standard deviation increase in particulates leads to a 20-30% increase in expenditures on ER visits for pulmonary outcomes mostly among the very young. No strong effects for SO_2 pollution or cardiovascular outcomes are found. Since 2008, the volcano has increased healthcare costs in Hawai'i by an estimated $60 million.

JEL Classification: H51, I12, Q51, Q53

Keywords: pollution, health, volcano, particulates, SO_2

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1 Introduction

Kīlauea is the most active of the five volcanoes that form the island of Hawai'i. Not only is Kīlauea the world's most active volcano, it is also the largest stationary source of sulfur dioxide (SO_2) pollution in the United States of America. Daily emissions from the volcano often exceed the annual emissions of a small coal-fired power plant. SO_2 emissions from Kīlauea produce what is known as "vog" (volcanic smog) pollution. Vog is essentially small particulate matter (sulfuric acid and other sulfate compounds) suspended in the air, akin to smog pollution in most cities. Vog represents one of the truly exogenous sources of air pollution in the United States. Based on local weather conditions (and whether or not the volcano is emitting), air quality conditions in the state of Hawai'i can change from dark, polluted skies to near-pristine conditions in a matter of hours.

Our primary approach to estimating the health impact of the pollution produced by Kīlauea is to use high frequency data and estimate linear models with regional fixed effects via Ordinary Least Squares (OLS). We claim that this variation in air quality is unrelated to human activities. The two main omitted variables that could impact our analysis are traffic congestion and avoidance behavior (*e.g.*, people avoiding the outdoors on "voggy" days). We see no compelling reason to believe that the former is systematically correlated with volcanic pollution. In addition, adjusting for a flexible pattern in seasonality will control for much of the variation in traffic congestion. The latter, avoidance behavior, is thornier and has bedeviled much of the research in this area. We are unable to control for this omitted variable, so our estimates of the effects of pollution on health care utilization should be viewed as being inclusive of this adjustment margin. In addition, a large degree of measurement error in our pollution variables should bias our estimates downwards. As such, one can reasonably view our estimates as lower bounds of the true impact of vog on emergency medical care utilization. Finally but importantly, a unique feature of our design is that we have a source of particulate pollution that is much less related to many other industrial pollutants than in other regions of the US. Consequently, we provide an estimate of the health cost of particulate pollution that is more credible than much of the extant literature.

To address the measurement error bias, we also employ an instrumental variables (IV) estimator. Our strategy employs SO_2 from South Hawai‘i where Kīlauea is located in conjunction with wind direction data collected at Honolulu International Airport to instrument for particulate levels on Oahu's south shore. The basic idea is that when winds come from the northeast there is very little particulate pollution on Oahu because all of the emissions from Kīlauea are blown out to sea. On the other hand, when emissions levels are high and when the winds come from the south, particulate levels on Oahu are high. In this sense, our IV strategy is similar to Schlenker and Walker (2011) who use weather on the East Coast of the US as an IV for pollution levels on the West Coast.

Not a lot is known about the health impacts of volcanic emissions, although a few recent studies have focused on modern eruptions.[1] In a study of Miyakejima island in Japan, Ishigami, Kikuchi, Iwasawa, Nishiwaki, Takebayashi, Tanaka, and Omae (2008) found a strong correlation between SO_2 concentrations and self-reported pulmonary effects (cough, sore throat, and breathlessness). Kīlauea itself has been the focus of a number of recent epidemiological studies. Prior to the 2008 escalation in emissions, nearby residents self-reported increased pulmonary, eye, and nasal problems relative to residents in areas unaffected by vog (Longo, Rossignol, and Green (2008); Longo (2009)). A strong correlation between vog and outpatient visits for pulmonary problems and headaches was found by Longo, Yang, Green, Crosby, and Crosby (2010). Longo (2013) uses a combination of self-reported ailments and in-person measurements (blood pressure and blood oxygen saturation) to document strong statistical correlations with exposure to vog. Half of the participants perceived that Kīlauea's intensified eruption had negatively affected their health, and

[1] In terms of historical eruptions, Durand and Grattan (2001) use health records from 1783 to document a correlation between pulmonary ailments and vog in Europe caused by the eruption of Laki volcano in Iceland.

relatively stronger magnitudes of health effects were associated with the higher exposure to vog since 2008. In a non-comparative study, Camara and Lagunzad (2011) report that patients who complain of eye irritation due to vog do have observable ocular symptoms. Still, it remains unclear whether increased volcanic emissions are causing health problems. In particular, selection bias and self-reporting errors make it difficult to infer causal evidence from previous epidemiological studies on Kīlauea.[2]

There is, of course, a much broader literature that attempts to estimate a causal relationship between industrial sources of pollutants and human health. Much of this literature has focused on the effects of SO_2 and particulate matter. Within economics, there has been an attempt to find "natural" or quasi-random sources of pollution variation in order to eliminate many of the biases present in epidemiological studies based on purely correlative evidence. Chay, Dobkin, and Greenstone (2003) use variation induced by the Clean Air Act in the 1970s to test for a link between particulate matter and adult mortality. Chay and Greenstone (2003) use the 1981-82 recession as a quasi-random source of variation in particulate matter to test for an impact on infant mortality. Neidell (2004) uses seasonal pollution variation within California to test for a link between air pollution and children's asthma hospital-

[2]The leading scholar in this literature notes that her "cross-sectional epidemiologic design was susceptible to selection bias, misclassification, and measured associations not causality" (Longo 2013). In particular, the cross-sectional nature of the study may not eliminate unobserved confounding factors. Because we exploit variation in pollution from the volcano over time within a region, our research design does a more thorough job of eliminating these confounds.

izations. Moretti and Neidell (2011) use boat traffic in Los Angeles; Schlenker and Walker (2011) use airport traffic in California; Knittel, Miller, and Sanders (2011) use road traffic; and Currie and Walker (2011) use the introduction of toll roads as sources of quasi-exogenous pollution variation. Lleras-Muney (2010) uses forced changes in location due to military transfers to study the impact of pollution on children. Finally, Ghosh and Mukherji (2014) employ micro-data from India and use regional fixed effects regressions to identify the effects of pollution on children's health.

The contributions of this study to the existing literature are as follows. First, this is one of the only studies that exploits a source of pollution that is not man-made (*e.g.*, from cars, airplanes, factories).[3] Second, we use more accurate data on the costs of hospitalization than much of the other literature, and, particularly, we do not rely on imputations to construct cost measures. Third, the variation in many of the pollution measures in our data on a day-to-day basis is much greater than in previous work. Fourth (as discussed earlier), much of the epidemiological work on the health consequences of vog relies on a single cross-section of largely self-reported data in which cross-sectional omitted variables are apt to be confounds, whereas we use a regional panel that can eliminate cross-sectional confounds and objective

[3] An exception is Jayachandran (2009) who uses forest fires.

health outcomes from a registry of hospitals in the state of Hawai‘i. Moreover, because we rely on high frequency (daily) variation in pollution within a region, any potential confound in our study would have to vary on a daily basis in lock-step with air quality within a region; few omitted variables do this. Finally, the results in this paper stem almost entirely from particulate matter and no other industrial pollutant. As such, we are quite confident that we have clean estimates of the pure effect of particulate matter. In most other studies, particulates and other pollutants are accompanied by many other industrial pollutants, so these studies have difficulty disentangling the effects of one pollutant from another.

We find strong effects of particulate pollution on emergency room (ER) admissions for pulmonary-related reasons. In particular, we find that a one standard deviation increase in particulate matter on a given day is associated with between 2 and 3% additional ER charges when we use our OLS estimates. Our IV estimates imply a much larger effect, between 20 and 30%. The OLS findings are similar to that of Ghosh and Mukherji (2014), who also find a strong association between particulates and respiratory ailments. Like Ghosh and Mukherji (2014), we also find strong effects among the very young. We do not find any effects of particulate pollution on cardiovascular-related or fracture-related admissions, of which the latter is our placebo.

Interestingly, we have not uncovered any effects for SO_2. We suspect that this is the case because the concentrations of SO_2 pollution are only in violation of EPA standards near Kīlauea in the southern and eastern part of the island of Hawai'i. The population density here is quite small and, while it is entirely reasonable to suspect that SO_2 does have pernicious effects on this island, we cannot detect any such effects in these regions perhaps due to small sample sizes and lower ER utilization in these areas.[4] For the remainder of the islands, SO_2 pollution is far below EPA standards and so it is not surprising that we do not find any effects in the more populated regions. It appears that the main effect of SO_2 on health is the particulate matter that it eventually forms.

The balance of this paper is organized as follows. In the next section, we give some further background on the volcano and describe our data. We then describe our methods. After that, we summarize our results. Finally, we conclude.

2 Background and Data

Kīlauea's current eruption period began in 1983 and occasionally disrupts life on the island of Hawai'i and across the state. Lava flows displaced some residents in 1990 and started to displace a small number of residents in late 2014. Prior to this, the

[4] These results are not reported but are available upon request.

lava flows served mainly as a tourist attraction. The primary impact of the volcano on human activity has been intermittent but severe deteriorations in air quality. Kīlauea emits water vapor, carbon dioxide, and sulfur dioxide. Sulfur dioxide or SO_2 poses a serious threat to human health and is also a common industrial pollutant. Moreover, SO_2 eventually turns into particulate matter which is also another harmful pollutant.

There are currently two main sources of air pollution on Kīlauea: the summit itself and a hole in the "East Rift Zone" on the side of the volcano. Since March 12, 2008, there has been a dramatic increase in emissions from Kīlauea: a new vent opened inside the summit, and average emissions have increased threefold, breaking all previous emissions records. Currently, emissions fluctuate on a daily basis between 500 and 1,500 tons of SO_2 per day. As a reference point, the Environmental Protection Agency's safety standard for industrial pollution is 0.25 tons of SO_2 per day from a single source (Gibson 2001). Depending on volcanic activity, rainfall, and prevailing wind conditions, there can be vast daily differences in the actual amount of SO_2 present near the summit and surrounding areas, ranging from near pristine air quality to levels that far exceed guidelines set by the EPA.

Volcanic pollution, or vog, is composed of different gases and aerosols, and the composition typically depends on proximity to the volcano. Near Kīlauea's active vents, vog consists mostly of SO_2 gas. Over time, SO_2 gas oxidizes to sulfate particles through various chemical and atmospheric processes, producing hazy conditions (particulate pollution). Thus, farther away from the volcano (along the Kona coast on the west side of Hawai'i Island and on other Hawai'ian islands), vog is essentially small particulate matter (sulfuric acid and other sulfate compounds) and no longer contains high levels of SO_2. Particulate matter is one of the most common forms of air pollution in the United States and across the world. In summary, the volcano has the potential to produce high levels of SO_2 pollution near the volcano and high levels of particulate pollution anywhere in the state of Hawai'i.

We employ data from two sources. First, we obtained data on ER admissions and charges in Hawai'i from the Hawai'i Health Information Corporation (HHIC). Second, we obtained data from the Hawai'i Department of Health (DOH) on air quality from thirteen monitoring stations in the state.

The ER data include admissions information for all cardiovascular and pulmonary diagnosis-related groups, as well as all admissions for fractures and dislocations of bones other than the pelvis, femur, or back. Fractures are designed to serve as a placebo, as they should be unaffected by air pollution. The data span the period January 1, 2000 to December 31, 2012. These data include information on the date and cause of admission as well as the total amount charged for patient care. In addition, we know the age and gender of the patient. We also have information on a broadly defined location of residence. In particular, HHIC reports the residence of location as an "SES community," which is a collection of several ZIP codes. We show the SES communities on the islands of Oʻahu, Hawaiʻi, Maui, Lānaʻi, Molokaʻi and Kauaʻi in Figure 1.

To put the data in a format suitable for regression analysis, we collapsed the data by day, cause of admission, and SES community to obtain the total number of admissions and total ER charges on a given day, in a given location, and for a given cause (*i.e.*, pulmonary, cardiovascular, or fractures). Once again, it is important to note that the location information corresponds to the patient's residence and not the location of the ER to which he or she was admitted. We did this because we believed that it would give us a more precise measure of exposure once we merged in the pollution data.

We use measurements of the following pollutants: particulates 2.5 and 10 micrometers in diameter (PM2.5 and PM10)[5] and SO_2. All measurements for SO_2 are in parts per billion (ppb), and particulates are measured in micrograms per cubic meter (μg/m3). For particulates, two measures were available: an hourly and a

[5] To be more precise, PM2.5 (PM10) is the mass per cubic meter of particles passing through the inlet of a size selective sampler with a transmission efficiency of 50% at an aerodynamic diameter of 2.5 (10) micrometers.

24-hour average computed by the DOH.[6] Using the hourly measures, we computed our own 24-hour averages, which were arithmetic averages taken over 24 hourly measures. Most of the time, either the one hour or the 24-hour measure was available, but rarely were both available on the same day. When they were, we averaged the two. For our empirical results, we spliced the two time series of particulates (*e.g.* the 24 hour averages provided by the DOH and taken from our own calculations) together and took averages when appropriate so we could have as large of a sample as possible for our regression analysis. The measurements of SO_2 were taken on an hourly basis; to compute summary measures for a given day, we computed means for that day.

To merge the air quality data into the ER admissions data, we used the following process. First, we computed the exact longitude and latitude of the monitoring station to determine in which ZIP code the station resided. Next, we determined the SES community in which the station's ZIP code resided. If an SES community contained numerous monitoring stations, then we computed means for all the monitoring stations on a given day in a given SES community. Table 1 displays the mapping between the monitoring stations and the SES communities. We did not

[6] The DOH did not simply compute an arithmetic average of hourly measurements as we did. Unfortunately, even after corresponding with the DOH, it is still not clear to us how their 24-hour averages were computed.

use data from SES communities that had no monitoring stations. In total, we used data from nine SES communities.

Unfortunately, we do not have complete time series for pollutants for all nine SES communities. By far, we have the most comprehensive information for PM2.5 and, to a lesser extent, SO_2. We report summary statistics for the pollutants in Table 2.[7]

In Figures 2 through 4, we present graphs of the time series for each of the pollutants that we consider by SES community. For each pollutant, we include a horizontal line corresponding to the National Ambient Air Quality Standards (NAAQS) for that pollutant. We use 24-hour averages of 35 $\mu g/m3$ for PM2.5 and 150 $\mu g/m3$ for PM10. We used the one-hour average of 75 ppb for SO_2.[8]

On the whole, Figures 2 through 4 indicate periods of poor air quality in particular regions. Looking at PM2.5 in Figure 2, we see violations of NAAQS in 'Aiea/Pearl City, Central Honolulu, 'Ewa, Hilo/North Hawai'i, Kona, West/Central Maui, and South Hawai'i. The noticeable spike in PM2.5 in 2007 in West/Central Maui was caused by a large brush fire. Hilo/North Hawai'i, Kona, and South Hawai'i are all on the island of Hawai'i, which generally appears to have poor air quality. We do not see any violations of NAAQS for PM10, although this is not recorded on the island of Hawai'i. However, in Figure 4, we see that SO_2 levels are very high

[7]For both the pollution and ER data, we trimmed the top and bottom 1% from the tails.
[8]For information on particulates, see http://www.epa.gov/air/criteria.html.

in Hilo/North Hawai'i, South Hawai'i and, to a lesser extent, in Kona; there are violations of NAAQS in the first two of these regions.[9] These trends make sense in that SO_2 emissions should be highest near the volcano and then dissipate with distance. SO_2 reacts with other chemicals in the air to produce particulate pollution. This mixes with other volcanic particulates to form vog, and this smog-like substance can be carried farther across the Hawai'ian islands, depending on the wind direction.

For our instrumental variables results, we employ data on wind direction collected by the National Oceanic and Atmospheric Association from their weather station at Honolulu International Airport. These data are reported in degrees with zero corresponding to the winds coming from due north. We summarize these data in the histogram in Figure 5. As can be seen, the winds primarily come from the northeast. In fact, the mean wind direction is 92.3 degrees and the median is 70 degrees. However, we do see a cluster of data between 120 and 180 which reflects that occasionally the winds do come to Oahu from the south. When this happens, the volcanic emissions from Kīlauea are blown to the island of Oahu, not out to sea.

We conclude this section by reporting summary statistics from the HHIC data for all the SES Communities for which we have air quality information in Table 3. An

[9] The state of Hawai'i's only coal-fired power plant is located in the 'Ewa SES. This is a small plant (roughly a quarter the size of the average coal plant on the mainland), and prevailing winds blow its emissions directly offshore. The plant appears to have no effect on SO_2 levels in 'Ewa.

observation is an SES community/day. For all the SES communities we consider, we see that, on an average day, there were 3.73 admissions for cardiovascular reasons, 4.62 admissions for pulmonary reasons, and 1.84 admissions for fractures in a given region. Total charges for cardiovascular-related admissions are \$4708.40 per day, whereas pulmonary-related admissions cost a total of \$3831.10. Finally, note that these amounts correspond to what the provider charged, not what it received, which, unfortunately, is not available from HHIC.

3 Methods

We employ two approaches to estimate the impact of volcanic emissions on ER utilization. The first is to simply estimate a linear regression of clinical outcomes onto our pollution measures while controlling for a flexible pattern of seasonality which we estimate via OLS. The second is an IV approach in which we leverage data on volcanic emissions and wind direction to instrument for particulate pollution. Throughout, we adopt the notation that t is the time period and r is the region. In addition, we let d denote the day of the week, m denote month, and y denote year corresponding to time period t.

First, we consider the following parsimonious empirical model:

$$outcome_{tr} = \beta_q (L) p_{tr} + \alpha_d + \alpha_m + \alpha_y + \alpha_r + \varepsilon_{tr} \quad (1)$$

where $outcome_{tr}$ is either ER admissions or charges and p_{tr} is a measure of air quality for a given day in a given region.[10] The next three terms are day, month, and year dummies. The parameter, α_r, is a region dummy. The final term is the residual. The term $\beta_q (L)$ is a lag polynomial of order q, which we will use to test for dynamic effects of pollution on health outcomes.

OLS estimation of equation (1) has the advantage that it is efficient and utilizes all the available data (our IV approach does not as the reader will see). On the other hand, OLS estimation of $\beta_q (L)$ will be biased downwards due to a large degree of measurement error in our pollution measurements. Our IV estimates will correct this and any possible lingering biases from omitted variables.

Next, for our instrumental variables regression, we use SO_2 emissions from Kīlauea as an instrument for particulate pollution on Oahu. Our proxy of SO_2 emissions is the measurement of SO_2 levels from the South Hawaii monitoring stations discussed

[10] We use the counts of total admissions and not rates as the dependent variable for several reasons. First, accurate population numbers are not available between census years. Second, regional fixed effects will account for cross-sectional differences in the population. Third, year fixed effects account for population changes over time.

in the previous section from the Hawai'i DOH.[11] We would argue that SO_2 levels in South Hawaii are unrelated to most causes of particulate pollution on Oahu other than, of course, vog. In addition, we exploit the fact that most of the time trade winds from the northeast blow the volcanic emissions out to sea and so, on days, with trade winds, there is very little vog. However, on occasion, the winds reverse direction and come from the south and this blows the vog towards the island of Oahu.

Accordingly, our IV approach works as follows. The first stage is

$$PART_{tr} = \gamma_r + \gamma_1 SO2_t + \gamma_2 WIND_t + \gamma_3 SO2_t * WIND_t + e_{tr} \tag{2}$$

where $PART_{tr}$ is the particulate level (either PM10 or PM2.5) in any of the regions on Oahu at time t, $SO2_t$ is the SO_2 level at time t in South Hawai'i, $WIND_t$ is the direction of the wind at Honolulu International Airport and γ_r is a regional fixed effect. Wind direction is measured in degrees and so takes on values between 0 and 359 with 0 corresponding to winds coming from the north. We do not include

[11] There is also data from the US Geological Survey but these data are very incomplete so we do not use them in our IV regressions. For example, the measurements of E_t are very intermittent, and thus, even if it were a valid instrument, IV estimates would lower the sample size substantially. Furthermore, sampling of volcanic emissions is endogenously determined by the US Geological Survey. During periods of elevated SO_2 emissions, the USGS tries to measure emission rates more frequently (often daily). When emissions are lower, the USGS chooses not to measure emissions every day and will often wait for weeks before taking a new measurement. Also, the device the USGS uses to measure emissions (a mini-UV spectrometer) only works when certain weather conditions exist (steady winds with little to no rain).

any seasonality controls since there are no systematic seasonal patterns in volcanic emissions that are also correlated with ER utilization and inclusion of these would greatly weaken the explanatory power of the instruments. In the second stage, we then estimate

$$outcome_{tr} = \beta \widehat{PART}_{tr} + \alpha_r + \varepsilon_{tr} \tag{3}$$

using only ER utilization data from Oahu.

There is an important caveat to our results, which is that our OLS and IV estimates include any sort of adaptation that may have taken place. If, for example, people were more likely to stay indoors on days when the air quality was poor, this most likely would dampen the estimated effects of pollution on health outcomes. In this sense, our estimates could be viewed as lower bounds on the effects of pollution on ER admissions if one were to fully control for adaptation.

To compute the standard errors, we will rely on an asymptotic distribution for large T but a fixed number of regions. For a discussion of such an estimator, we refer the reader to Arellano (2003), p.19. The main reason for this approach is that we have many more days in our data than regions. In addition, the large-T fixed effects estimator allows for arbitrary cross-sectional correlation in pollution since it does not rely on cross-sectional asymptotics at all. However, large-T asymptotics require an investigation of the time series properties of the residual, and if any serial correlation is present, Newey-West standard errors must be used for consistent estimation of the covariance matrix. We used ten lags for the Newey-West standard errors, although the standard errors with only one lag were very similar, indicating that ten lags is most likely more than adequate.[12] These standard errors allow for arbitrary correlations in residuals across the Hawaiian islands on a given day and serial correlation in the residuals for up to ten days.

4 Volcanic Emissions and Pollution

In this section, we establish a connection between SO_2 emissions as measured in tons/day (t/d) on our air quality measures. To accomplish this, we estimate a very simple regression of air quality on emissions:

$$p_{tr} = \alpha_1 + \alpha_2 E_t + e_{tr}. \tag{4}$$

[12]To choose the number of lags for the Newey-West standard errors, we estimated our models for pulmonary outcomes (which preliminary analysis revealed were the only outcomes for which we might find significant effects) and for three different pollutants. We then took the fitted residuals from these models and estimated AR(20) models. For particulates, we found that the autocorrelations were significant up to ten lags. For SO_2, we found significant autocorrelations for more than ten lags. For the coming estimations, we used ten lags for the Newey-West standard errors since preliminary work showed that there was little effect of SO_2 for any of the outcomes.

Our measure of volcanic emissions is E_t. Data on emissions come from the US Geological Survey (USGS). We employ daily measurements on SO_2 emissions in t/d from Kīlauea from two locations, the summit and the Eastern Rift Zone (ERZ), from January of 2000 to December of 2010. Note that these measurements were not taken on a daily basis, that many days have no measurements, and that many others have a measurement from only one of the locations. So, for these regressions, we only include E_t from the summit or from the ERZ. Finally, because a second vent opened in the summit during 2008, we estimate the model separately for the periods 2000-2007 and 2008-2010.

Tables 4 and 5 display the relationship between volcanic emissions and particulate pollution (PM10 and PM2.5). In Table 4, there is no relationship between emissions from the summit and PM10 during the period 2000-2007, but there is a substantial relationship for the subsequent period, 2008-2010. Looking at emissions from the ERZ in the last two columns of the table, we see a significant relationship between air quality and emissions in both periods.

Turning to PM2.5 in Table 5, we still see significant effects of volcanic emissions on air quality in all four columns. Comparing emissions from the summit in 2000-2007 and 2008-2010 in columns (1) and (2), while we do not see that the point estimate is higher for the later period, it is more tightly estimated than the estimate for the period 2000-2007 with a standard error about one-tenth of the size of the standard error in column (1). So we see a much more statistically significant relationship between emissions and PM2.5 for 2008-2010 than for the earlier period. In the last two columns, we estimate the relationship between emissions from the ERZ and PM2.5; we see a statistically significant relationship in both periods, although the point-estimate in column (4) is about double the estimate in column (3).

In Tables 6 and 7, we estimate the impact of SO_2 emissions from Kīlauea in t/d on SO_2 levels in ppb across the state. Table 6 focuses on emissions from the summit. Since SO_2 levels should be highest near the volcano, we estimate this model for just South Hawai‘i, in addition to using SO_2 levels from all available monitoring stations. On the whole, both tables show a significant relationship between SO_2 emissions and SO_2 pollution levels throughout the state. Of note is that these estimates are substantially higher when we restrict the sample to South Hawai‘i, as expected.

As further evidence of the independent variation of SO_2 and particulate pollution, we present correlation coefficients between various pollutants in the state of Hawai‘i in Table 8. In most parts of the United States, air pollutants are highly correlated. For example, in Neidell (2004)'s study of California, the correlation coefficient between PM10 and the extremely harmful pollutant carbon monoxide (CO) is 0.52. In our sample, it is 0.0081. In the same Neidell study, the correlation between PM10 and

NO_2 is 0.7, whereas in our sample it is 0.0267. In the city of Phoenix, Arizona, the correlation coefficient between CO and PM2.5 is 0.85 (Mar, Norris, Koenig, and Larson 2000). In our sample, it is 0.0118. As evidence that SO_2, PM2.5, and PM10 are being generated by the same source, the correlation coefficient between PM2.5 and PM10 is 0.52, and between PM2.5 and SO_2 it is 0.4. So a unique feature of our design is that we have a source of particulate pollution that is unrelated to many other industrial pollutants (other than, of course, SO_2).

5 Results

5.1 OLS Results

First, we consider the effects of pollutants on ER admissions via OLS estimation of equation (1). Results are reported in Tables 9 through 16. For each pollutant/cause-of-admission combination, we estimate three separate specifications: one that only includes the contemporaneous pollution measure and two others that include one and two lags, respectively. For reasons discussed above, we report Newey-West standard errors for all estimations.

In Table 9, we consider the effects of particulates on pulmonary-related admissions. In the first column, we see that a 1 μg/m3 increase in PM10 is associated with 0.013 additional admissions for a day/SES community observation. In the fourth column, we see that the effects of PM2.5 are larger, with an estimate of 0.025 additional admissions. Both estimates are significant at the 1% level. The standard deviation of PM10 is 6.24, indicating that a 1 standard deviation increase in PM10 results in an additional ER admission every 12.32 days (which is a 2% increase in admissions). Similarly, the standard deviation of PM2.5 is 3.30, indicating that a 1 standard deviation increase in PM2.5 results in one additional ER admission every 12.12 days for pulmonary-related reasons in a given region (a 2% increase in admissions).

Turning to the effects on ER costs in the bottom panel, we see that a 1 μg/m3 increase in PM10 is associated with \$12.91 more charges for pulmonary causes. The corresponding number for PM2.5 is \$39.11. Respectively, a 1 standard deviation increase in PM10 and PM2.5 results in \$80.56 and \$129.06 additional charges in a given region on a given day. Looking back at Table 3, we see that the average pulmonary-related ER charges is \$3831.10 for a day/SES community, so a 1 standard deviation increase in either PM10 or PM2.5 can increase charges by 2.10% and 3.36%, respectively. The specifications that include lagged pollution variables indicate that there are persistent effects, as all the p-values on the tests of joint significance are close to zero for both admissions and charges.

In Table 10, we report the effects of SO_2 on pulmonary-related admissions. We do not see any effects of SO_2 on pulmonary outcomes.

Tables 11 and 12 report the effects of pollutants on cardiovascular-related outcomes. In Table 11, there is weak evidence of an effect of PM2.5 on costs but not admissions. However, there are no other significant estimates in the table. Turning to the effects of SO_2 in Table 12, once again, we see none.

As a placebo test, we look at the effects of pollutants on admissions for factures in Table 13. We consider the same three specifications for PM2.5 and PM10. We see no evidence that ER admissions for fractures increase as a consequence of particulate pollution.

5.2 IV Results

We now estimate the first stage of the two stage least squares model in equation (2). The results are reported in columns 1 and 4 of Table 14. First, we see that SO_2 levels in South Hawai‘i by themselves do not predict particulate levels. However, we do see that higher values of the wind direction variable are associated with more particulate pollution. Essentially, this means that when winds are coming from the south (*i.e.* there are no trade winds) that air quality gets worse.[13] Finally, the interaction

[13]Note that almost 90% of our observations for wind direction are between 0 and 180 degrees indicating that the winds are mostly coming from the northeast or the southeast but rarely from

between the wind direction and SO_2 is highly predictive of particulate pollution. This indicates that when SO_2 levels are high and the wind reverses direction then particulate levels on Oahu are very high.

Next, we move to the estimation of the second stage regression in equation (3). These results are reported in columns 2 and 3 for PM10 and columns 5 and 6 for PM2.5. Comparing these results to the analogous results in Table 9, we see that they are an order of magnitude larger. For example, the estimate of the impact of PM10 on ER admissions for pulmonary related reasons in column 2 is 0.320 whereas it was 0.013 when we used OLS and, so the estimate is about 25 times larger. Similarly, the esimate in column 3 of Table 14 is 226.92, whereas the corresponding OLS estimate was 12.91 which means that the IV estimate is 17 times larger. We also see much larger results for PM2.5 when we use IV. For example, the impact on admissions in column 5 is 0.456 whereas the OLS estimate was 0.025 indicating that IV is about 17 times larger. Looking at charges in column 6, we see an estimate of 242.76 whereas the OLS estimate was 27.50 and so, IV is larger by a factor of 8.

To get a sense of how much larger these estimates are than OLS, a one standard deviation increase in PM10 levels on a given day will result in a \$1415.98 increase in charges from ER admissions for pulmonary related reasons. This represents a 37%

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the west. Thus, higher values indicate winds coming from the south.

increase in expenditures on emergency room admissions. Similarly, a one standard deviation increase in PM2.5 levels will result in a $801.11 increase in charges (21% increase). The corresponding numbers from the OLS estimates were $80.56 and $129.06.

Our suspicion is that the substantially larger estimates that we obtain using IV are due to the presence of measurement error in our pollution variables. The only plausible omitted variable that could bias OLS downwards is avoidance behavior. However, using volcanic emissions (or a proxy of it in our case) does not correct for this bias since avoidance behavior is a direct consequence of the vog that is produced by Kīlauea which clearly violates the exclusion restriction required for IV. Moreover, even if it were a viable instrument, the discrepancy between the OLS and IV results implies an implausible degree of avoidance. This leaves us with measurement error as the only source of a downward bias in the OLS estimates, although it does suggest that there is lot of measurement error in our pollution variables.

5.3 Other Results

We now consider a "kitchen sink" regression, where we regress each of our outcomes on all of the pollution measures (*e.g.*, PM10, PM 2.5, and SO_2). The results are reported in Table 15. Looking at pulmonary-related admissions, we see no indication that SO_2 poses any health threats, and it is only when it becomes particulate matter that it poses risks according to our data. However, we do not see consistent evidence that PM10 or PM2.5 is more dangerous; we see larger effects for PM2.5 for admissions but larger effects for charges. Finally, we do not see a strong relationship for cardiovascular outcomes or fractures.

Next, in Table 16, we investigate the effects of pollutants by the age of the person admitted. We chose these age groupings primarily because we wanted to group similar people together. For example, infants are very different than everybody else, so we grouped 0-1 together; adolescents are similar, so we grouped 11-18 together; etc. The idea is to see whether there are disproportionate effects for vulnerable populations such as the very young and the very old. Because the different bins contain different numbers of ages, these estimates will vary, in part, for purely mechanical reasons. So, to gain a better idea of whether the effects of pollution are higher for a given group, we report

$$\frac{\text{Effect}}{\#\text{ of ages in bin}} \times 1000$$

to adjust for this. Higher numbers indicate larger effects.

We see that younger people are indeed disproportionately affected by particulate pollution. The adjusted estimates are the largest for the 0-1 age bin for both PM10 and PM2.5. The next highest for both PM10 and PM2.5 is for the 2-5 bin. So, it appears that it is the very young who are the most vulnerable to particulate pollution.

5.4 Robustness Checks

In this section, we conduct a series of robustness checks. First, we explore the robustness of the results in Table 9 to using alternative fixed effects. Second, we estimate the model in equation (1) using the negative binomial model (NBM). Third, we compute the robust and clustered standard errors of the model and compare these to the Newey-West standard errors that we have already computed.

The alternative fixed effects that we consider are month/year interactions and so we estimate the model

$$outcome_{tr} = \beta p_{tr} + \alpha_d + \alpha_{my} + \alpha_r + \varepsilon_{tr}. \tag{5}$$

We re-estimate the specifications that were estimated in Table 9 with the pulmonary outcomes on the right hand side. The results are reported in Table 17 in the top panel. First, we see that the main findings are robust to the inclusion of these alternative fixed effects. Second, we see that, while the magnitudes are similar, the point-estimates are slightly smaller. For example, the estimate of the effects of PM2.5 on admissions in Table 17 is 0.020 whereas it was 0.025 inTable 9. Similarly, the estimate for PM10 with the alternative fixed effects was 0.010 whereas it was

0.011 in Table 9.

In the bottom panel of the same table, we estimate the model using the NBM. We also use the NBM for charges to account for the prevalence of zeros in the data. We still see that there are significant effects of PM2.5 on pulmonary outcomes, but we no longer see any effects for PM10.

Finally, in Table 18, we report alternative standard errors. The first row of the table is the point estimate of the effects of either PM10 and PM2.5 on pulmonary outcomes. These are the same estimates as those in the first and fourth columns of Table 9. In the next three rows, we report three standard errors: Newey-West (NW), Eicker-White (EW), and robust standard errors clustered by SES community (C). The NW standard errors rely on large T asymptotics and are robust to arbitrary cross-sectional correlations and serial correlation up to ten lags. The EW standard errors are the most naive. They rely on large N and T asymptotics while only allowing for heteroskedasticity. The C standard errors rely on the number of clusters going to infinity and allow for serial correlation within SES communities. Note that in our data, we only had five SES communities for the estimations that included PM10 and nine for the models that included PM2.5.

As we have already argued, the NW standard errors are the appropriate standard errors. First, they are robust to spatial and serial correlation. Second, tests based on the NW covariance are more powerful as we divide by $\sqrt{T}$. On the other hand, standard errors that rely on the number of clusters tending to infinity will be needlessly large.

Looking at the table, the following findings emerge. First, as expected, the NW standard errors are smaller than the clustered standard errors (with the exception of final column). However, note that all of the point estimates are significantly different from zero even when we use the clustered standard errors. Finally, while the EW standard errors are smaller than the NW standard errors, they are remarkably close.

5.5 Comparison with the Literature

We conclude this section with a discussion of how our results compare to the existing literature. We start by comparing our results to the literature on different pollutants (carbon monoxide, nitrogen dioxide, etc.). We generally find similar effects in terms of a one standard deviation increase in measured pollution on hospital admissions. Our IV estimates are in the 20 to 30% and this matches with other quasi-experimental studies. For example, Schlenker and Walker (2011) find 17-30% increases in hospital counts. Neidell (2004) finds that a 1 standard deviation increase in CO increases asthma ER admissions for children aged 1-3 by 19%. Lleras-Muney (2010) finds that a one standard deviation increase in ozone increases respiratory hospitalizations for children by 8-23%. In terms of cost estimates, Moretti and Neidell (2011) estimate that ozone pollution raises annual hospital costs for the entire Los Angeles region (18 million people) by $44.5 million. Our corresponding estimate for the particulate pollution attributable to vog in Hawaiʻi (total population of 1.4 million people) is $4.4 million (see the next section for the exact calculation).

In terms of studies focused primarily on particulates, most quasi-experimental approaches have focused on long-term exposure to large changes in particulate pollution. By comparing similar areas located on opposite sides of the Huai river, Chen, Ebenstein, Greenstone, and Li (2013) find ambient concentrations of particulates are about 55% higher in the north and life expectancies are about 5.5 years lower due to increased cardiorespiratory mortality. A similar study examined the decision to ban the sale of coal in Dublin, Ireland in 1990. By comparing 6 years before and 6 years after the coal ban, (Clancy, Goodman, Sinclair, and Dockery 2002) found that black smoke concentrations in Dublin decreased by 70%, non-trauma deaths declined by 6%, respiratory deaths by 16%, and cardiovascular deaths by 10%.

It has proven much more difficult to estimate the effect of relatively small reductions in particulates on short-term outcomes such as illness and hospitalization. Thus, there are very few studies that we are aware of that allow us to directly compare our results. As mentioned earlier, one of the major confounding issues in identifying the short-term effect of particulates on health is that most major pollutants are highly correlated. In fact, many studies that look at the effect of particulates alongside other pollutants find that particulates have no effect on health outcomes. For example, Neidell (2004) finds no effect of particulate pollution on hospitalizations for asthma among children but other pollutants have large effects on emergency room admissions. The correlation coefficient between PM10 and carbon monoxide in the Neidell (2004) sample is 0.52 and the coefficient between PM10 and nitrogen dioxide is 0.7. The corresponding numbers in our sample are 0.0118 and 0.0267. Thus, one of the reasons we may be one of the few studies to observe both statistically and economically significant effects of particulates is that we have an instrument that affects only one pollutant. Kīlauea volcano does not emit carbon monoxide or nitrogen dioxide.

6 Conclusions

We have used variation in air quality induced by volcanic eruptions to test for the impact of SO_2 and particulate matter on emergency room admissions and costs in the state of Hawai‘i. Air quality conditions in Hawai’i are typically ranked the highest in the nation except when the largest stationary source of SO_2 pollution in the United States is erupting and winds are coming from the south. We observe a strong statistical correlation between volcanic emissions and air quality in Hawai'i. The relationship is strongest post-2008, when there has been an elevated level of daily emissions. Relying on the assumption that air quality in Hawai'i is randomly determined, we find strong evidence that particulate pollution increases pulmonary-related hospitalization.

Our IV results suggest that a one standard deviation increase in particulate pollution leads to a 20-30% increase in expenditures on emergency room visits for pulmonary-related outcomes. We do not find strong effects for pure SO_2 pollution or for cardiovascular outcomes. We also find no effect of volcanic pollution on fractures, our placebo outcome. The effects of particulate pollution on pulmonary-related admissions are the most concentrated among the very young (children under the age of five).

In terms of welfare effects, we can use our estimates to calculate the total welfare impact of the volcano on health costs in Hawai'i. Since March 12 of 2008, in which a new vent opened on Kīlauea, the summit and the East Rift Zone have produced average daily emissions of 815.47 and 1,346.81 tons of SO_2, respectively. Based on the estimates in Table 5, a 1 ton increase in SO_2 at the summit is correlated with a 0.00195 $\mu g/m3$ increase in PM2.5 and, at the East Rift Zone, with a 0.00128 $\mu g/m3$ increase in PM2.5 across the state. Based on the results in Table 14, a 1

$\mu g/m3$ increase in PM2.5 raises emergency room charges by \$242.76 per day. This suggests the daily cost of summit emissions is \$386.03 and the cost of ERZ emissions is \$418.37. Multiplying these numbers by 365 (days in the year) and 15 (total number of SES communities in the state of Hawai'i) gives an annual cost of \$2,113,506 for the summit and \$2,290,596 for the ERZ, or a total annual cost of PM2.5 pollution from the volcano of \$4,404,102. The equivalent number for PM10 is \$3,290,740. Therefore, the total welfare cost of the emissions event that began on March 12, 2008 (from the standpoint of late 2015) has been \$57,711,324.

A number of caveats need to be borne in mind when interpreting our welfare calculation and our regression estimates in general. Since the USGS only measures volcanic emissions during periods of elevated emissions, the average daily emissions estimate is likely upward biased. However, as discussed earlier, avoidance behavior likely implies that our regression estimates of the admissions and costs associated with PM2.5 are biased downwards. Furthermore, we have restricted our attention to ER admissions. Anecdotal evidence suggests that vog causes considerable health impacts that do not necessitate a trip to the emergency room.[14] A full accounting of the different ways that volcanic pollution affects health in Hawai'i is beyond the scope of this analysis but our estimates certainly suggest that the full cost is quite

[14] "Vog - volcanic smog - kills plants, casts a haze over Hawai'i", *USA Today*, May 2, 2008.

large.

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Table 1: Mapping between Monitoring Stations and SES Communities

Monitoring Station	SES Community
Honolulu	Central Honolulu
Kapolei	Ewa
Pearl City	Pearl City - Aiea
Sand Island	West Honolulu
West Beach	Ewa
Kihei	West and Central Maui
Hilo	Hilo/North Hawai'i
Kona	Kona
Mt View	South Hawai'i
Ocean View	South Hawai'i
Pahala	South Hawai'i
Puna	South Hawai'i
Niumalu	East Kauai

Table 2: Summary Statistics for Pollutant Data

	PM10	PM2.5	SO_2
Aiea/Pearl City	16.53	4.37	-
	(5.61)	(2.41)	
Cen. Honolulu	13.85	4.25	0.62
	(4.71)	(2.32)	(0.75)
E.Kauai	-	5.84	2.77
		(2.94)	(4.10)
Ewa	15.19	4.94	0.70
	(5.70)	(2.99)	(0.64)
Hilo/N. Hawai'i	11.60	5.19	2.87
	(3.55)	(4.15)	(5.92)
Kona	-	15.98	4.96
		(5.88)	(4.61)
S. Hawai'i	-	9.12	11.28
		(4.84)	(13.33)
W./Cen. Maui	20.41	6.41	-
	(7.54)	(5.19)	
W. Honolulu	-	7.36	-
		(3.70)	
All	16.04	6.52	3.29
	(6.24)	(3.30)	(6.96)

Notes: We report means and standard deviations in parentheses. An observation is an SES community/day. Particulate data are in $\mu g/m3$ and SO_2 is in ppb.

Table 3: Summary Statistics for ER Data

	Cardiovascular		Pulmonary		Fractures	
	Admissions	Charges	Admissions	Charges	Admissions	Charges
Aiea/Pearl City	4.33	4859.24	4.87	3808.29	2.17	1556.76
	(2.35)	(3685.16)	(2.82)	(2992.58)	(1.48)	(1334.40)
Cen. Honolulu	4.83	6372.87	5.48	5047.71	2.36	1929.77
	(2.52)	(4259.62)	(2.88)	(3499.99)	(1.53)	(1498.98)
E.Kauai	1.97	2423.14	2.67	1857.65	1.00	602.61
	(1.55)	(2573.41)	(1.82)	(1740.02)	(1.03)	(742.80)
Ewa	5.40	7067.09	7.42	6248.51	2.57	1880.76
	(2.69)	(4547.10)	(3.29)	(3767.64)	(1.59)	(1450.55)
Hilo/N. Hawai'i	4.15	5137.23	4.55	3614.37	1.65	1118.96
	(2.28)	(3546.39)	(2.49)	(2760.43)	(1.29)	(1146.56)
Kona	2.57	3362.35	3.50	2890.59	1.77	1296.73
	(1.84)	(3048.58)	(2.29)	(2498.04)	(1.36)	(1261.27)
S. Hawai'i	2.50	3108.90	2.98	2411.51	1.16	838.10
	(1.82)	(2831.94)	(2.04)	(2271.67)	(1.10)	(1020.49)
W./Cen. Maui	3.14	4003.13	3.29	2508.75	1.73	1481.99
	(2.02)	(3399.64)	(2.23)	(2244.42)	(1.39)	(1394.43)
W. Honolulu	4.82	6238.87	7.18	6389.57	2.22	1763.79
	(2.37)	(4009.55)	(3.20)	(3776.24)	(1.48)	(1424.57)
All	3.73	4708.40	4.62	3831.10	1.84	1382.12
	(2.47)	(3897.75)	(3.07)	(3301.57)	(1.46)	(1344.96)

Notes: We report means and standard deviations in parentheses. An observation is an SES community/day. Charges are in 2000 US dollars.

Table 4: Effects of Volcanic Emissions of SO2 (tons/day) on Pollution (PM10)

	(1)	(2)	(3)	(4)
SO_2 (t/d)	-0.00531	0.00234^{***}	0.00059^{**}	0.00055^{*}
	(0.00474)	(0.00078)	(0.00029)	(0.00028)
Source of Measurement				
-Summit	X	X		
-ERZ			X	X
2000-2007	X		X	
2008-2010		X		X
Number of Obs.	1297	1391	1130	635

* sig at 10% level;**sig at 5% level; ***sig. at 1% level

Note: Each column corresponds to a regression of a pollutant on measures of SO_2 emissions from Kīlauea measured in tons/day. Newey-West standard errors are in parentheses. The two sources of measurement are the summit and the Eastern Rift Zone (ERZ).

Table 5: Effects of Volcanic Emissions of SO2 (tons/day) on Pollution (PM2.5)

	(1)	(2)	(3)	(4)
SO_2 (t/d)	0.01061^{*}	0.00195^{***}	0.00067^{*}	0.00128^{***}
	(0.00563)	(0.00063)	(0.00041)	(0.00039)
Source of Measurement				
-Summit	X	X		
-ERZ			X	X
2000-2007	X		X	
2008-2010		X		X
Number of Obs.	895	2636	789	1203

* sig at 10% level;**sig at 5% level; ***sig. at 1% level

Note: Per Table 4.

Table 6: Effects of Volcanic Emissions of SO2 (tons/day) from the Summit on Pollution (SO2)

	(1)	(2)	(3)	(4)
SO_2 (t/d)	0.00926***	0.03122**	0.00254*	0.01357***
	(0.00248)	(0.01235)	(0.00135)	(0.00234)
2000-2007	X	X		
2008-2010			X	X
Restricted to S. Hawai'i		X		X
Number of Obs.	1608	187	2145	366

* sig at 10% level;**sig at 5% level; ***sig. at 1% level

Note: Per Table 4.

Table 7: Effects of Volcanic Emissions of SO2 (tons/day) from the ERZ on Pollution (SO2)

	(1)	(2)	(3)	(4)
SO_2 (t/d)	0.00060***	0.00148**	0.00029	0.00347***
	(0.00015)	(0.00067)	(0.00051)	(0.00128)
2000-2007	X	X		
2008-2010			X	X
Restricted to S. Hawai'i		X		X
Number of Obs.	1457	180	976	162

* sig at 10% level;**sig at 5% level; ***sig. at 1% level

Note: Per Table 4.

Table 8: Pollution Correlation Matrix

	PM2.5	PM10	SO_2	CO	NO_2
PM2.5	1				
PM10	0.5247	1			
SO_2	0.4047	0.0937	1		
CO	0.0118	0.0081	0.0560	1	
NO_2	0.0798	0.0267	0.2032	-0.0346	1

Table 9: Effects of Particulates on Pulmonary Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
				Admissions		
		PM10			PM2.5	
t	0.013***	0.009**	0.009**	0.025***	0.023***	0.024**
	(0.004)	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)
$t-1$	-	0.008*	0.005	-	0.004	0.007
		(0.004)	(0.005)		(0.007)	(0.008)
$t-2$	-	-	0.005	-	-	-0.006
			(0.004)			(0.007)
F-test[1]	-	7.33	4.54	-	7.81	5.49
		[0.000]	[0.035]		[0.000]	[0.001]
Number of Obs	13719	12755	12128	17601	14643	14207
				Charges		
t	12.91***	10.61**	11.49**	39.11***	27.57***	27.50***
	(3.88)	(4.56)	(4.75)	(6.21)	(8.04)	(8.40)
$t-1$	-	6.92	4.25	-	9.99	16.52*
		(4.48)	(5.12)		(7.84)	(9.09)
$t-2$	-	-	3.82	-	-	-11.13
			(4.53)			(8.13)
F-test[1]	-	6.86	4.66	-	11.23	8.03
		[0.001]	[0.003]		[0.000]	[0.000]
Number of Obs	13751	12783	12157	17562	14578	14145

* sig at 10% level;**sig at 5% level; ***sig. at 1% level

Notes: All estimations include region, day, month and year dummies. Newey-West standard errors in parentheses.

[1]This is a test of joint significance of pollution variables. p-values in brackets.

Table 10: Effects of SO_2 on Pulmonary Outcomes

	(1)	(2)	(3)
		Admissions	
t	-0.000 (0.003)	0.003 (0.004)	0.004 (0.004)
$t-1$	-	-0.004 (0.004)	-0.001 (0.004)
$t-2$	-	-	-0.006 (0.004)
F-test[1]	-	0.77 [0.4649]	1.21 [0.3045]
Number of Obs	18759	18555	18378
		Charges	
t	-4.89 (3.44)	-3.29 (4.23)	-3.32 (4.30)
$t-1$	-	-2.76 (3.92)	0.65 (4.48)
$t-2$	-	-	-5.24 (4.19)
F-test[1]	-	1.17 [0.3096]	1.21 [0.3028]
Number of Obs	18790	18586	18407

* sig at 10% level;**sig at 5% level; ***sig. at 1% level

Notes: Per Table 9.

Table 11: Effects of Particulates on Cardiovascular Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
			Admissions			
		PM10			PM2.5	
t	-0.003	-0.000	-0.000	0.003	0.001	0.000
	(0.003)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)
$t-1$	-	-0.003	-0.002	-	-0.004	-0.005
		(0.004)	(0.004)		(0.006)	(0.007)
$t-2$	-	-	0.001	-	-	0.003
			(0.004)			(0.006)
F-test[1]	-	0.59	0.15	-	0.25	0.17
		[0.5527]	[0.9283]		[0.7823]	[0.9163]
Number of Obs	13857	12896	12271	17791	14821	14386
			Charges			
t	-2.10	2.20	1.69	20.77***	9.83	111.09
	(4.76)	(5.77)	(6.04)	(7.50)	(10.69)	(10.98)
$t-1$	-	-6.15	-4.03	-	6.25	-1.11
		(5.67)	(6.42)		(10.21)	(12.21)
$t-2$	-	-	0.29	-	-	8.16
			(5.88)			(10.47)
F-test[1]	-	0.60	0.14	-	1.47	1.10
		[0.5476]	[0.9319]		[0.2431]	[0.3589]
Number of Obs	13736	12776	12156	17622	14662	14232

* sig at 10% level; **sig at 5% level; ***sig. at 1% level

Notes: Per Table 9.

Table 12: Effects of SO_2 on Cardiovascular Outcomes

	(1)	(2)	(3)
		Admissions	
t	-0.001	-0.001	-0.008
	(0.002)	(0.003)	(0.004)
$t-1$	-	-0.000	-0.002
		(0.004)	(0.004)
$t-2$	-	-	0.003
			(0.004)
F-test[1]	-	0.12	0.18
		[0.6388]	[0.9089]
Number of Obs	18895	18691	18513
		Charges	
t	-5.75	-4.16	-5.76
	(3.78)	(5.26)	(5.60)
$t-1$	-	-2.92	-8.28
		(5.52)	(6.19)
$t-2$	-	-	11.15
			(5.58)
F-test[1]	-	1.30	2.08
		[0.2730]	[0.1011]
Number of Obs	18746	18544	18366

* sig at 10% level;**sig at 5% level; ***sig. at 1% level

Notes: Per Table 9.

Table 13: Placebo Tests: Effects of Particulates on ER Admissions for Fractures

	(1)	(2)	(3)	(4)	(5)	(6)
			Admissions			
		PM10			PM2.5	
t	0.003	0.000	0.000	0.003	0.001	0.002
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
$t-1$	-	0.003	0.005	-	0.002	0.001
		(0.003)	(0.003)		(0.004)	(0.005)
$t-2$	-	-	-0.000	-	-	0.000
			(0.003)			(0.004)
F-test[1]	-	1.46	1.29	-	0.49	0.24
		[0.2325]	[0.2774]		[0.6110]	[0.8706]
Number of Obs	13817	12857	12232	17797	14840	14405

* sig at 10% level;**sig at 5% level; ***sig. at 1% level

Notes: Per Table 9.

Table 14: IV Results: The Impact of Particulate Pollution on Pulmonary Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	PM10	Admissions	Charges	PM2.5	Admissions	Charges
SO_2	0.015 (0.011)	-	-	-0.004 (0.006)	-	-
Wind Direction	0.008*** (0.017)	-	-	0.006*** (0.002)	-	-
SO_2∗Wind	0.0002** (0.000)	-	-	0.0002** (0.000)	-	-
PM10	-	0.320*** (0.054)	226.92*** (55.931)	-	-	-
PM2.5	-	-	-	-	0.456*** (0.081)	242.76*** (77.852)
F-Test[1]	24.01 [0.000]	-	-	29.13 [0.000]	-	-
Number of Obs.	7000	6658	6666	6400	5999	5956

*sig at 10% level;**sig at 5% level;***sig at 1% level

Notes: All estimations include region dummies. Newey-West standard errors are in parentheses.

[1]This is a test of joint significance of the excluded variables. p-values in brackets.

Table 15: Kitchen Sink Regressions

	Pulmonary		Cardiovascular		Fractures	
	Admissions	Charges	Admissions	Charges	Admissions	Charges
SO_2	0.004	−43.61	0.039	112.28	0.034	5.13
	(0.059)	(62.47)	(0.048)	(76.98)	(0.031)	(34.25)
PM10	0.017*	29.76***	−0.006	−10.24	0.001	−1.04
	(0.010)	(11.01)	(0.008)	(12.70)	(0.005)	(5.33)
PM2.5	0.045**	23.85	0.007	12.88	0.010	18.12*
	(0.021)	(25.61)	(0.017)	(27.89)	(0.011)	(10.83)
Number of Obs	4874	4846	4963	4863	4982	4976

* sig at 10% level;**sig at 5% level; ***sig. at 1% level

Notes: Per Table 9.

Table 16: Effects of Particulates on Pulmonary Admissions by Age of Patient

	PM10	$\frac{\text{Effect}}{\text{\# of ages in bin}}$ X 1000	PM2.5	$\frac{\text{Effect}}{\text{\# of ages in bin}}$ X 1000
0-1	0.005*** (0.002)	2.5	0.007*** (0.002)	3.5
2-5	0.003** (0.001)	0.75	0.007*** (0.002)	1.75
6-10	0.001 (0.001)	0.2	0.000 (0.001)	0.00
11-18	0.001 (0.001)	0.13	0.004** (0.001)	0.5
19-50	0.006** (0.002)	0.19	0.011*** (0.003)	0.34
51-65	0.000 (0.001)	0.00	0.006*** (0.002)	0.4
66+	0.002 (0.001)	–	0.006*** (0.002)	–

* sig at 10% level;**sig at 5% level; ***sig. at 1% level

Note: All estimations include region, day, month and year dummies. Newey-West standard errors in parentheses. Each cell corresponds to an estimate from a separate regression.

Table 17: Robustness Checks

	(1)	(2)	(3)	(4)
	Admissions		Charges	
	Alternative Fixed Effects			
PM10	0.010^{***} (0.004)	-	9.567^{***} (3.882)	-
PM2.5	-	0.020^{***} (0.005)	-	31.496^{***} (6.073)
	Negative Binomial Model			
PM10	0.000 (0.001)	-	-0.001 (0.001)	-
PM2.5	-	0.003^{***} (0.001)	-	0.005^{***} (0.001)

* sig at 10% level;**sig at 5% level; ***sig. at 1% level

Notes: Standard errors in parentheses. The alternative fixed effects in the first panel are for year/month interactions, day of the week and region. For the NBM, we include month, year, day of the week and region fixed effects.

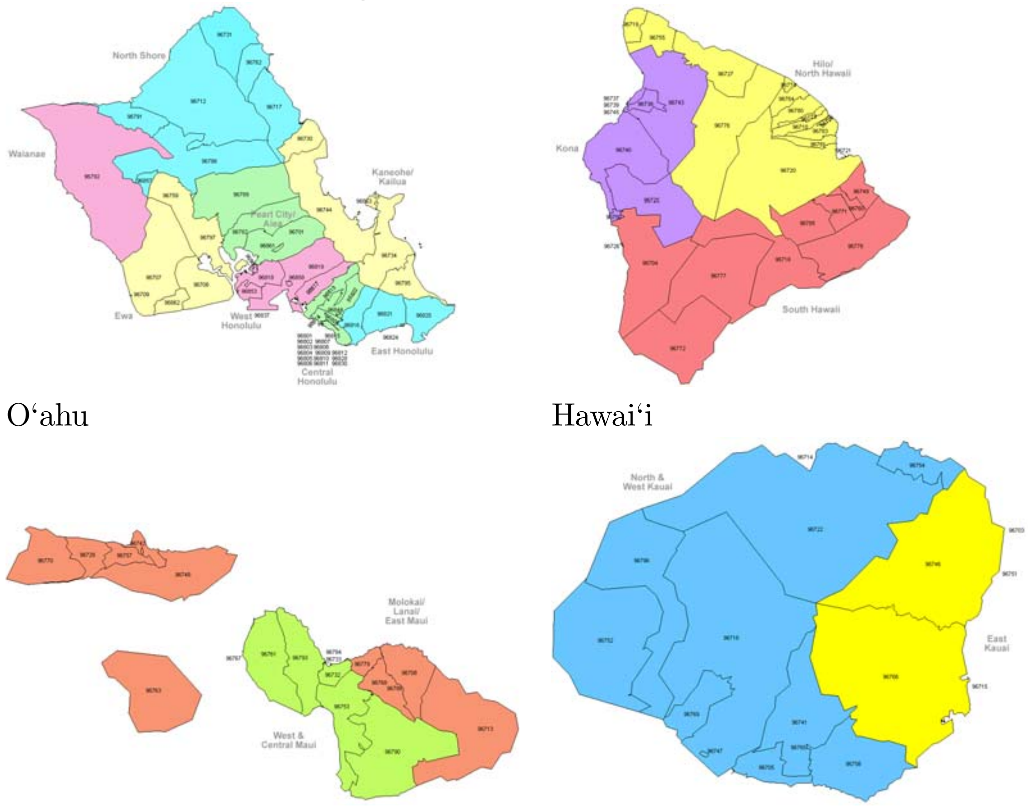
Table 18: Alternative Standard Errors

	(1)	(2)	(3)	(4)
	Admissions		Charges	
	PM10	PM2.5	PM10	PM2.5
Point Estimate	0.0128	0.0249	12.915	39.111
NW Std Error	0.0038	0.0055	3.883	6.216
Robust Std Error	0.0036	0.0050	3.582	5.624
Clustered Std Error[1]	0.0055	0.0066	5.697	5.581

Notes: We estimated the effects of PM10 and PM2.5 on pulmonary outcomes while computing the standard errors three different ways.

[1]We clustered the standard errors by SES community.

Figure 1: SES Communities



O‘ahu Hawai‘i

Maui/Lāna‘i/Moloka‘i Kaua‘i

Figure 2: PM2.5 by SES Community

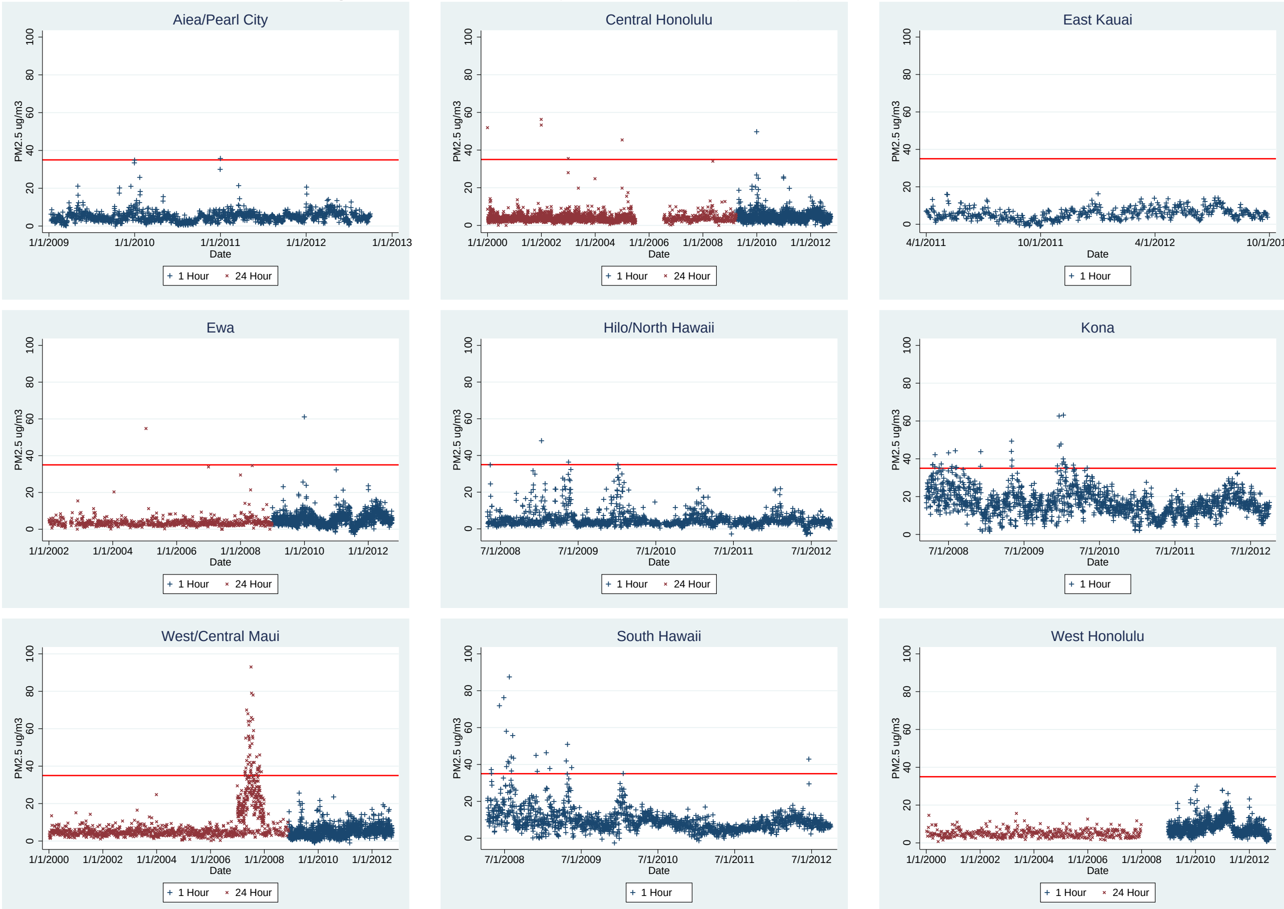


Figure 3: PM10 by SES Community

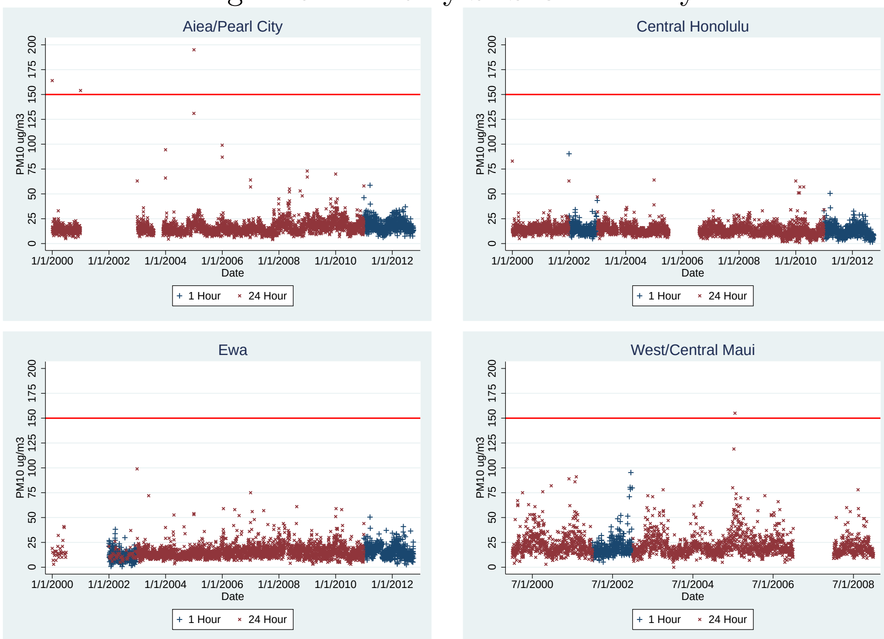


Figure 4: SO2 by SES Community

Figure 5: Histogram for Wind Direction Data