Vog: Using Volcanic Eruptions to Estimate the Health Costs of Particulates and SO_2*

Timothy J. Halliday† John Lynham

UH - Mānoa and IZA UH - Mānoa

Áureo de Paula

UCL, São Paulo School of Economics, IFS, CeMMAP

May 6, 2015

Abstract

Kīlauea volcano is the largest stationary source of SO_2 pollution in the

*We thank Jill Miyamura of Hawai'i Health Information Corporation for the data. Chaning Jang and Jonathan Sweeney provided expert research assistance. We also thank participants at the University of Hawai Applied Micro Group for useful comments. Finally, de Paula gratefully acknowledges financial support from the European Research Council through Starting Grant 338187 and the Economic and Social Research Council through the ESRC Centre for Microdata Methods and Practice grant RES-589-28-0001.

†Corresponding Author. Address: 2424 Maile Way; 533 Saunders Hall; Honolulu, HI 96822. Tele: (808) 956 -8615. E-mail: halliday@hawaii.edu.

United States of America. Moreover, the SO_2 that the volcano emits eventually forms particulate matter, another major pollutant. We use this exogenous source of pollution variation to estimate the impact of particulate matter and SO_2 on emergency room admissions and costs in the state of Hawai'i. Importantly, our data on costs is more accurate than the measures used in much of the literature. In addition, since we use volcanic emissions as our source of variation, we have a source of particulate pollution that is much less related to many other industrial pollutants than in other regions of the US. We find strong evidence that particulate pollution increases pulmonary-related hospitalization. Specifically, a one standard deviation increase in particulate pollution leads to a 2-3% increase in expenditures on emergency room visits for pulmonary-related outcomes. However, 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. Finally, the effects of particulate pollution on pulmonary-related admissions are most concentrated among the very young. Our estimates suggest that, since the large increase in emissions that began in 2008, the volcano has increased healthcare costs in Hawai'i by approximately $6,277,204.

JEL Code: H51, I12, Q51, Q53

Keywords: Pollution, Health, Volcano, Particulates, SO_2

1 Introduction

Kīlauea is the most active of the five volcanoes that form the island of Hawai'i. 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 lava flows served mainly as a tourist attraction. The primary impact of the volcano on human activity has been intermittent, but there have been 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 industrial pollutant.

There are currently two main sources of SO_2 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 SO_2 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 (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.

SO_2 emissions from Kīlauea produce what is known as "vog" (volcanic smog). 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. SO_2 is one of the primary sources of pollution from coal-fired power plants and poses considerable health risks. 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. Therefore, 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.

Not only is Kīlauea the world's most active volcano, it is also the largest stationary source of SO_2 pollution in the United States of America. It erupts unpredictably. Based on local weather conditions, it can either pollute the air near the volcano or further away from it or, alternatively, it can produce no pollution at all. It represents one of the truly exogenous sources of air pollution in the United States and directly impacts adults who are geographically restrained in their ability to relocate (each island in this small chain has been impacted by vog at some point). In the absence of the volcano, air quality conditions in Hawai'i are ranked the highest in the United States.

Our plan in this paper is simply to use 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. We claim that this variation in air quality is unrelated to human activities, by and large. 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). However, 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. As such, one can reasonably view our estimates as lower bounds of the true impact of vog on emergency medical care utilization.[1] 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 and, consequently, we provide an estimate of the health cost of particulate pollution that is more credible than much of the extant literature.

Not a lot is known about the health impacts of volcanic emissions, although a few recent studies have focused on modern eruptions.[2] 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

[1] Instrumental variables will not save us here. For example, one might think that actual data on volcanic emissions would be a valid instrument for air quality. The problem is that avoidance behavior (which is in the residual) is correlated with air quality, which is also correlated with volcanic emissions. Therefore, volcanic emissions do not satisfy the required exclusion restriction to be a valid instrument.

[2] 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.

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 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.[3]

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

[3] 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.

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 hospitalizations. 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). 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 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; other than the examples discussed above, 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 pollution from particulates 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. This finding is 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 is the particulate matter that it eventually forms.

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

2 Data

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).

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

Second, we obtained data from the Hawaiʻi 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) 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 24-hour average computed by the DOH.[5] 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

[5] 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.

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 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. In addition, there may be breaks in some of these time series. 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.[6]

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.[7]

On the whole, Figures 2 through 4 indicate periods of poor air quality in particular

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

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 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.[8] 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.

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 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,

[8] 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.

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 adopt the notation that t is the time period and r is the region. In addition, we also let d denote the day of the week, m denote month, and y denote year corresponding to time period t. We consider the following parsimonious empirical model:

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

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. 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.

Our identification strategy is straight-forward. First, we control for seasonal patterns in ER admissions that may also be correlated with air quality measures through the inclusion of day, month, and year dummies. Second, to account for omitted region-specific variables that are correlated with both air quality and ER admissions, we include region dummies. Finally, conditional on these seasonal patterns and regional effects, we rely on temporal variation in SO_2 and particulate matter, which we would argue is exogenous (*i.e.*, not correlated with many confounding variables).[9]

However, there is an important caveat, which is that our estimates include any sort of adaptation that may have taken place. So, for example, if 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 of the effects of pollution on ER admissions if one were to fully control for adaptation.

To compute the standard errors of our estimate of $\beta_q(L)$, 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,

[9] 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.

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.[10] These standard errors allow for arbitrary correlations in residuals across the Hawai'ian 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

[10] 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.

simple regression of air quality on emissions:

$$p_{tr} = \alpha_1 + \alpha_2 E_t + e_{tr}. \tag{2}$$

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.

It is important to emphasize that, while these results do paint a compelling picture linking air quality in Hawai‘i to volcanic emissions from Kīlauea, we do not believe that data on volcanic emissions would be a viable instrumental variable for several reasons. The main reason is that any potential omitted variables in equation (1) that would impact the estimate of β will almost surely be correlated with E_t. For example, if one is concerned that avoidance behavior (*e.g.*, staying indoors on "voggy" days) is a confound in equation (1), then this will also be correlated with E_t for purely mechanical reasons on the basis of equation (2). Second, 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). Thus, we expect there to be a large degree of measurement error in the emissions dataset. Finally, it is important to bear in mind that the value of α_1 from equation (2) may be much larger than what we have estimated, as all of the variables in this equation contain a large amount of measurement error. On the whole, E_t would not be a good instrument.

As further evidence of the exogeneity 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

In this section, we consider the effects of pollutants on ER admissions. Results are reported in Tables 9 through 15. 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 are \$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.

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 14. 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 15, 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.

We conclude this section with a discussion of how our results compare to the existing literature. We generally find smaller effects in terms of a one standard deviation increase in measured pollution on hospital admissions. Most of our estimates are in the 2 to 3% range, whereas Schlenker and Walker (2011) find 17-30% increases in hospital counts. Moretti and Neidell (2011) observe a roughly 8% increase in hospitalizations for a one standard deviation increase in ozone (2% if avoidance behavior is not controlled for). They estimate that ozone pollution raises annual hospital costs for the entire Los Angeles region (18 million people) by $44.5 million. Neidell (2004) finds no effect of PM10 on hospitalizations for asthma among children, whereas we do find effects of PM10 on hospitalization among children under 5. He 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%. It is difficult to compare these studies directly, since they often focus on different pollutants and since background pollution levels are extremely different (especially between Hawai‘i and Los Angeles). However, many studies find no effect from PM2.5 and PM10 pollution, with most effects coming from more toxic pollutants such as carbon monoxide (CO). On the whole, our results are notable in that we find relatively strong effects for PM2.5 and PM10, perhaps because the volcano allows us to identify the causal impact of these pollutants separately from CO and ozone.

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. 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.

Specifically, a one standard deviation increase in particulate pollution leads to a 2-3% 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 μg/m3 increase in PM2.5 and, at the East Rift Zone, with a 0.00128 μg/m3 increase in PM2.5 across the state. Based on the results in Table 9, a 1 μg/m3 increase in PM2.5 raises emergency room charges by $39.11 per day per SES community. This suggests the daily cost per community of summit emissions is $62.19 and the cost of ERZ emissions is $67.40. 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 $340,498 for the summit and $369,028 for the ERZ, or a total annual cost of PM2.5 pollution from the volcano of $709,526. The equivalent number for PM10 is $187,218. Therefore, the total welfare cost of the emissions event that began on March 12, 2008 (from the standpoint of early 2015) has been $6,277,204.

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.[11] A full accounting of the different ways that volcanic pollution affects health in Hawai'i is beyond the scope of this paper but our estimates certainly suggest that the full cost is quite large.

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

References

Arellano, M. (2003): *Panel Data Econometrics*. Oxford University Press, Oxford.

Camara, J. G., and J. K. D. Lagunzad (2011): "Ocular findings in volcanic fog induced conjunctivitis," *Hawaii medical journal*, 70(12), 262.

Chay, K., C. Dobkin, and M. Greenstone (2003): "The Clean Air Act of 1970 and adult mortality," *Journal of Risk and Uncertainty*, 27(3), 279–300.

Chay, K. Y., and M. Greenstone (2003): "The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession," *The Quarterly journal of economics*, 118(3), 1121–1167.

Currie, J., and R. Walker (2011): "Traffic Congestion and Infant Health: Evidence from E-ZPass," *American Economic Journal: Applied Economics*, 3(1), 65–90.

Durand, M., and J. Grattan (2001): "Effects of volcanic air pollution on health," *The Lancet*, 357(9251), 164.

Ghosh, A., and A. Mukherji (2014): "Air Pollution and Respiratory Ailments among Children in Urban India: Exploring Causality," *Economic Development and Cultural Change*, 63(1), 191–222.

Gibson, B. A. (2001): "A geotechniques-based exploratory investigation of vog impacts to the environmental system on Hawai'i island.," Ph.D. thesis.

Ishigami, A., Y. Kikuchi, S. Iwasawa, Y. Nishiwaki, T. Takebayashi, S. Tanaka, and K. Omae (2008): "Volcanic sulfur dioxide and acute respiratory symptoms on Miyakejima island," *Occupational and environmental medicine*, 65(10), 701–707.

Knittel, C. R., D. L. Miller, and N. J. Sanders (2011): "Caution, drivers! Children present: Traffic, pollution, and infant health," Discussion paper, National Bureau of Economic Research.

Lleras-Muney, A. (2010): "The Needs of the Army: Using Compulsory Relocation in the Military to Estimate the Effect of Air Pollutants on Children's Health," *Journal of Human Resources*, 45(3), 549–590.

Longo, B., A. Rossignol, and J. Green (2008): "Cardiorespiratory health effects associated with sulphurous volcanic air pollution," *Public health*, 122(8), 809–820.

Longo, B. M. (2009): "The Kilauea Volcano adult health study," *Nursing research*, 58(1), 23–31.

——— (2013): "Adverse Health Effects Associated with Increased Activity at Kīlauea Volcano: A Repeated Population-Based Survey," *ISRN Public Health*, 2013.

Longo, B. M., W. Yang, J. B. Green, F. L. Crosby, and V. L. Crosby (2010): "Acute health effects associated with exposure to volcanic air pollution (vog) from increased activity at Kilauea Volcano in 2008," *Journal of Toxicology and Environmental Health, Part A*, 73(20), 1370–1381.

Mar, T. F., G. A. Norris, J. Q. Koenig, and T. V. Larson (2000): "Associations between air pollution and mortality in Phoenix, 1995-1997.," *Environmental health perspectives*, 108(4), 347.

Moretti, E., and M. Neidell (2011): "Pollution, health, and avoidance behavior evidence from the ports of Los Angeles," *Journal of Human Resources*, 46(1), 154–175.

Neidell, M. J. (2004): "Air pollution, health, and socio-economic status: the effect of outdoor air quality on childhood asthma," *Journal of Health Economics*, 23(6), 1209–1236.

Schlenker, W., and W. R. Walker (2011): "Airports, air pollution, and contemporaneous health," Discussion paper, National Bureau of Economic Research.

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 (5.61)	4.37 (2.41)	-
Cen. Honolulu	13.85 (4.71)	4.25 (2.32)	0.62 (0.75)
E.Kauai	-	5.84 (2.94)	2.77 (4.10)
Ewa	15.19 (5.70)	4.94 (2.99)	0.70 (0.64)
Hilo/N. Hawai'i	11.60 (3.55)	5.19 (4.15)	2.87 (5.92)
Kona	-	15.98 (5.88)	4.96 (4.61)
S. Hawai'i	-	9.12 (4.84)	11.28 (13.33)
W./Cen. Maui	20.41 (7.54)	6.41 (5.19)	-
W. Honolulu	-	7.36 (3.70)	-
All	16.04 (6.24)	6.52 (3.30)	3.29 (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^{***} (0.004)	0.009^{**} (0.005)	0.009^{**} (0.005)	0.025^{***} (0.006)	0.023^{***} (0.007)	0.024^{**} (0.007)
$t-1$	-	0.008^{*} (0.004)	0.005 (0.005)	-	0.004 (0.007)	0.007 (0.008)
$t-2$	-	-	0.005 (0.004)	-	-	-0.006 (0.007)
F-test[1]	-	7.33 [0.000]	4.54 [0.035]	-	7.81 [0.000]	5.49 [0.001]
Number of Obs	13719	12755	12128	17601	14643	14207
			Charges			
t	12.91^{***} (3.88)	10.61^{**} (4.56)	11.49^{**} (4.75)	39.11^{***} (6.21)	27.57^{***} (8.04)	27.50^{***} (8.40)
$t-1$	-	6.92 (4.48)	4.25 (5.12)	-	9.99 (7.84)	16.52^{*} (9.09)
$t-2$	-	-	3.82 (4.53)	-	-	-11.13 (8.13)
F-test[1]	-	6.86 [0.001]	4.66 [0.003]	-	11.23 [0.000]	8.03 [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 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	0.004
	(0.003)	(0.004)	(0.004)
$t-1$	-	-0.004	-0.001
		(0.004)	(0.004)
$t-2$	-	-	-0.006
			(0.004)
F-test[1]	-	0.77	1.21
		[0.4649]	[0.3045]
Number of Obs	18759	18555	18378
		Charges	
t	-4.89	-3.29	-3.32
	(3.44)	(4.23)	(4.30)
$t-1$	-	-2.76	0.65
		(3.92)	(4.48)
$t-2$	-	-	-5.24
			(4.19)
F-test[1]	-	1.17	1.21
		[0.3096]	[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 (0.003)	-0.000 (0.004)	-0.000 (0.004)	0.003 (0.004)	0.001 (0.006)	0.000 (0.006)
$t-1$	-	-0.003 (0.004)	-0.002 (0.004)	-	-0.004 (0.006)	-0.005 (0.007)
$t-2$	-	-	0.001 (0.004)	-	-	0.003 (0.006)
F-test[1]	-	0.59 [0.5527]	0.15 [0.9283]	-	0.25 [0.7823]	0.17 [0.9163]
Number of Obs	13857	12896	12271	17791	14821	14386
			Charges			
t	-2.10 (4.76)	2.20 (5.77)	1.69 (6.04)	20.77^{***} (7.50)	9.83 (10.69)	111.09 (10.98)
$t-1$	-	-6.15 (5.67)	-4.03 (6.42)	-	6.25 (10.21)	-1.11 (12.21)
$t-2$	-	-	0.29 (5.88)	-	-	8.16 (10.47)
F-test[1]	-	0.60 [0.5476]	0.14 [0.9319]	-	1.47 [0.2431]	1.10 [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 (0.002)	0.000 (0.003)	0.000 (0.003)	0.003 (0.003)	0.001 (0.004)	0.002 (0.004)
$t-1$	-	0.003 (0.003)	0.005 (0.003)	-	0.002 (0.004)	0.001 (0.005)
$t-2$	-	-	-0.000 (0.003)	-	-	0.000 (0.004)
F-test[1]	-	1.46 [0.2325]	1.29 [0.2774]	-	0.49 [0.6110]	0.24 [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: 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

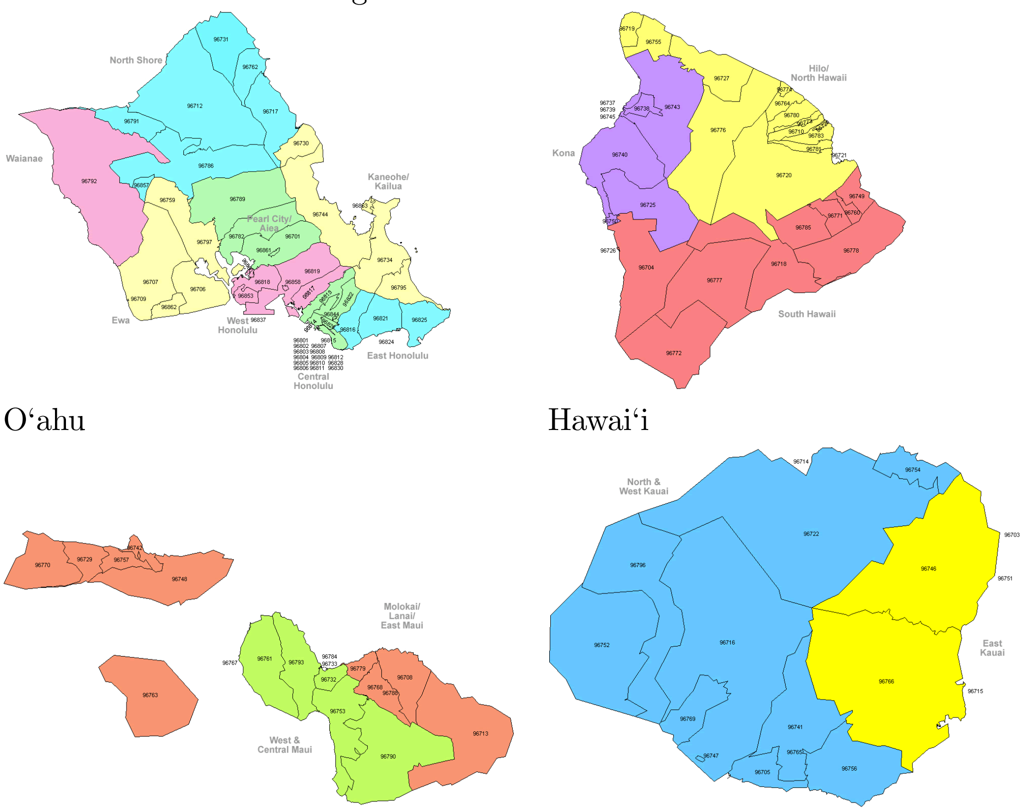
Notes: Per Table 9.

Table 15: 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 day, month and year dummies.
Newey-West standard errors in parentheses. Each cell corresponds
to an estimate from a separate regression.

Figure 1: SES Communities



O‘ahu

Hawai‘i

Maui/Lāna‘i/Moloka‘i

Kaua‘i

Figure 2: PM2.5 by SES Community

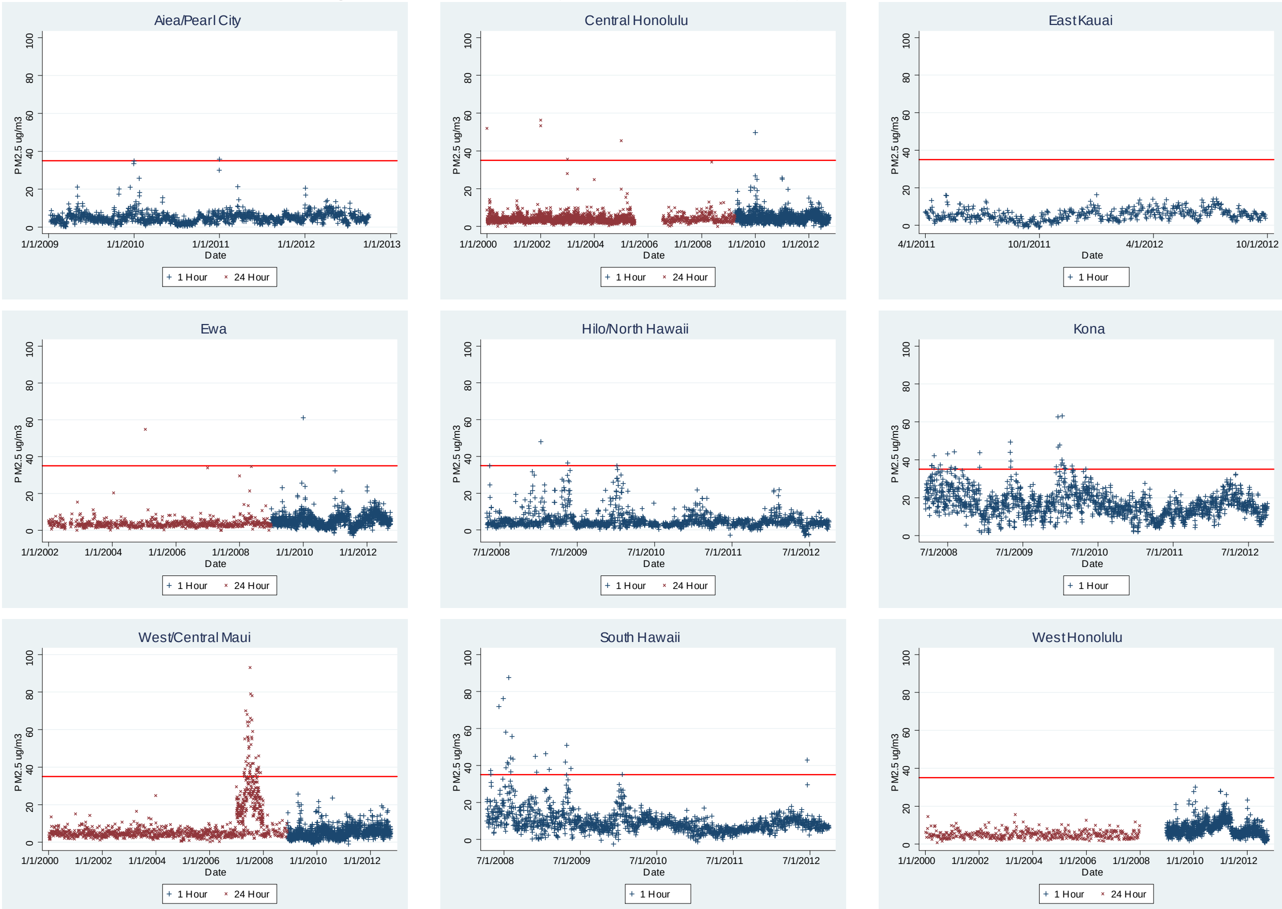


Figure 3: PM10 by SES Community

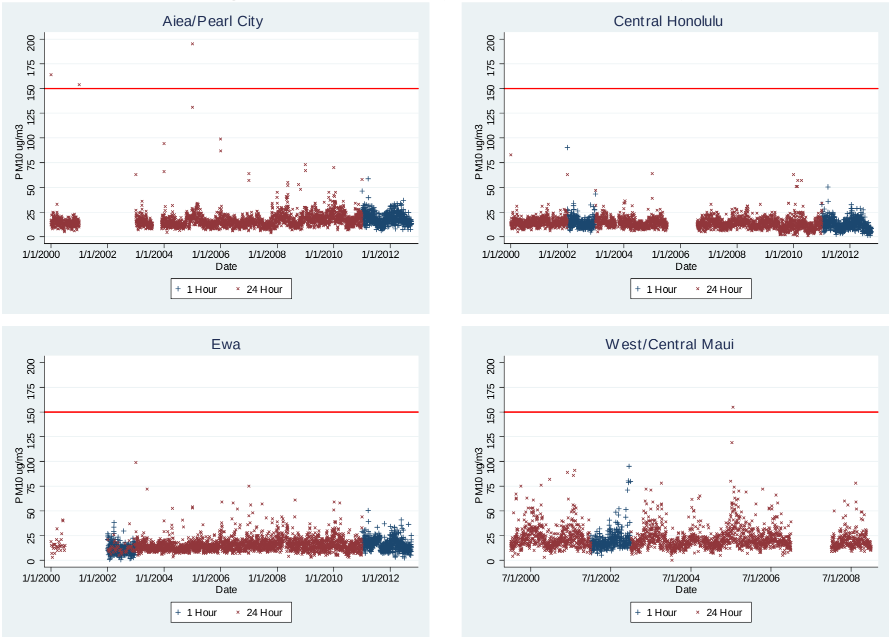


Figure 4: SO2 by SES Community