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

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Abstract

The negative consequences of long-term exposure to particulate pollution are well-established but many studies find no effect of short-term exposure on health outcomes. The high correlation of industrial pollutant emissions complicates the estimation of the impact of individual pollutants on health. In this study, we use emissions from Kīlauea volcano, which are uncorrelated with other pollution sources, to estimate the impact of pollutants on local emergency room (ER) admissions and a precise measure of costs. A one standard deviation increase in particulates leads to a 23-36% increase in expenditures on ER visits for pulmonary outcomes, mostly among the very young. Even in an area where air quality is well within the safety guidelines of the U.S. Environmental Protection Agency, this estimate is much larger than those in the existing literature on the short-term effects of particulates. No strong effects for cardiovascular outcomes are found.

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1 Introduction

In this paper, we use volcanic emissions to document the effect of particulate pollution on hospital admission counts and charges. Industrial and other types of anthropogenic pollution generally induce high correlation among various pollutants, possibly complicating the attribution of quantifiable effects to several different pollutants. Our pollution source, on the other hand, leads to relatively independent variation in pollutants. This variation allows us to more precisely measure the effect of particulate matters on various public health outcomes and costs in a context where variations in particulates are well below EPA ambient air quality standards.

Kīlauea is the most active of the five volcanoes that form the island of Hawai‘i. 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.

We adopt two main approaches to estimate the health impact of the pollution produced by Kīlauea. Both use high frequency data on volcanic emissions and emergency room (ER) admissions and estimate linear models. The first method estimates a parsimonious model with regional and seasonal fixed effects via Ordinary Least Squares (OLS). The second method exploits variations in wind patterns in the island chain in conjunction with information on SO_2 levels near Kīlauea to construct an instrumental variables (IV) estimator.

The OLS estimator can be justified on the grounds that the 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 and our estimates of the effects of pollution on health care utilization should be viewed as being inclusive of this adjustment margin. (We nevertheless see no effect of pollution on fractures which may be indicative of limited avoidance behaviour.) In addition, a large degree of measurement error in our pollution variables should bias our estimates downwards. Error in pollution exposure measurement may arise through imprecision in measurement instruments and misalignment between measurement and exposure locations. As such, one can reasonably view our OLS estimates as lower bounds of the true impact of vog on emergency medical care utilization (as in much of the literature).[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. 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 as well as any lingering omitted variables biases from industrial pollution or traffic congestion, we also employ an instrumental variables (IV) estimator. Our strategy employs SO_2 measurements from the south of Hawai'i island (where Kīlauea is located) in conjunction with wind direction data collected at Honolulu International Airport to instrument for particulate levels on the south shore of Oahu (a different island with high population density). Kīlauea is located on the southeast part of the island of Hawai'i which can be seen in the map in Figure 1. The basic idea is that when

[1]For example, Künzli and Tager (1997) explain how simple OLS designs tend to underestimate the effect of air pollution on health. Sheppard, Burnett, Szpiro, Kim, Jerrett, Pope III, and Brunekreer (2012) and Goldman, Mulholland, Russell, Strickland, Klein, Waller, and Tolbert (2011) both suggest that the usual estimators may suffer from severe attenuation bias due to measurement error.

winds come from the northeast there is very little particulate pollution on Oahu, which as shown in Figure 2 is to the northwest of the island of Hawai'i, because all of the emissions from Kīlauea are blown out to sea. Figure 3 is a satellite image showing sulfur dioxide concentrations during typical northeast wind conditions: the plume of sulfur dioxide coming from the volcano is blown to the southwest, away from the Hawaiian islands. On the other hand, when volcanic emissions levels are high and when the winds come from the south, particulate levels on Oahu are high.

Little 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 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. Most recently, Tam, Miike, Labrenz, Sutton, Elias, Davis, Chen, Tantisira, Dockery, and Avol (2016) show an association between vog exposure and respiratory outcomes including cough and forced expiratory volume (FEV1).

[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.

Still, it remains unclear whether increased volcanic emissions are causing health problems. In particular, selection bias (for example, respondents volunteered to answer surveys and the socio-economic characteristics of individuals who choose to live close to the volcano are quite different to the rest of the state) 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. 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 hospitalizations. Lleras-Muney (2010) uses forced changes in location due to military transfers to study the impact of pollution on children. Moretti and Neidell (2011) use boat traffic in Los Angeles; Schlenker and Walker (2016) use airport traffic in California; Knittel, Miller, and Sanders (to appear) use road traffic; and Currie and Walker (2011) use the introduction of toll roads as sources of quasi-exogenous pollution variation. Arceo-Gomez, Hanna, and Oliva (2016) use thermal inversions to measure the effect of CO and PM_{10} on infant mortality in Mexico.

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 the result of human activity (*e.g.*, from cars, airplanes, factories, or starting fires to clear forest). Second, we use

[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, p. 9). In particular, the cross-sectional nature of previous studies 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.

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 (for example, the extremely ill are less likely to volunteer to fill out surveys). Our approach is to use a regional panel that can eliminate cross-sectional confounds and we examine 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; 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 strongly correlated, making it difficult to disentangle the effects of one pollutant from another.

We find strong effects of particulate pollution on 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 2% additional ER charges when we use our OLS estimates. Our IV estimates imply a much larger effect, between 23 and 36%. We 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. 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. Following that, we discuss the relationship between volcanic emissions and pollution. 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 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 (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

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

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 O‘ahu, Hawai'i, Maui, Lāna‘i, Moloka‘i and Kaua‘i in Figure A1.

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 ($PM_{2.5}$ and PM_{10})[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/m^3). For particulates, two measures were available: an hourly and a 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

[5]To be more precise, $PM_{2.5}$ (PM_{10}) 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.

[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.

community. Table A1 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. By far, we have the most comprehensive information for $PM_{2.5}$ and, to a lesser extent, SO_2. We report summary statistics for the pollutants in Table 1.[7]

In Figures 4 through 6, 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 $PM_{2.5}$ and 150 $\mu g/m3$ for PM_{10}. We used the one-hour average of 75 ppb for SO_2.[8]

On the whole, Figures 4 through 6 indicate periods of poor air quality in particular regions. Looking at $PM_{2.5}$ in Figure 4, 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 $PM_{2.5}$ 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 PM_{10}, although this is not recorded on the island of Hawai'i. However, in Figure 6, 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.[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.

[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`.

[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.

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 (rounded to the nearest ten) with zero corresponding to the winds coming from due north. We summarize these data in the histogram in Figure 7. 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 1. An observation is an SES community/day. For all the SES communities we consider, we see that, on an average day, there were 4.01 admissions for cardiovascular reasons, 5.00 admissions for pulmonary reasons, and 1.98 admissions for fractures in a given region. Total charges for cardiovascular-related admissions are $5159.18 per day, whereas pulmonary-related admissions cost a total of $4204.16. 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 that 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:

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

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 which adjust for possible confounds due to traffic or weather patterns. 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.

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. In particular, we have *daily* data that span the years 2000 to 2012 and, so it is a somewhat futile exercise to attempt to construct a sensible denominator for each of these days. Second, regional fixed effects will account for cross-sectional differences in the population. Third, year fixed effects account for population changes over time. Finally and most importantly, due to the presence of regional fixed effects, we are, in effect, exclusively relying on time series variation in the relationship between pollution and ER admissions. Hence, the only way that failure to use rates as opposed to levels could be problematic is if volcanic emissions were seriously impacting regional populations on a day-to-day basis which we think is implausible.[10]

OLS estimation of equation (1) has the advantage that it 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 (see footnote 1). 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

[10]To see this more formally, let A_t denote admissions on day t and POP_t denote the population on day t. Then we will have that $\log \frac{A_t}{POP_t} = \log A_t - \log POP_t$. In the absence of any effects of pollution on day-to-day population movements, the entirely of the action will stem from its impact on admission *counts*.

an instrument for particulate pollution on Oahu. Our proxy of SO_2 emissions is the measurement of SO_2 levels from the South Hawai'i monitoring stations discussed in the previous section from the Hawai'i DOH.[11] We would argue that SO_2 levels in South Hawai'i are unrelated to most causes of particulate pollution on Oahu other than, of course, vog. It is also important to say that, in unreported results, we found no direct effects of SO_2 on pulmonary outcomes and, so it appears as if the variable $SO2_t$ does not violate any exclusion restrictions. 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

$$p_{tr} = \gamma_r + \gamma_1 SO2_t + \gamma_2 NE_t + \gamma_3 SO2_t \times NE_t + e_{tr} \tag{2}$$

where p_{tr} is the particulate level (either PM_{10} or $PM_{2.5}$) in any of the regions on Oahu at time t, $SO2_t$ is the SO_2 level at time t in South Hawai'i, NE_t is a dummy variable indicating that the winds at Honolulu International Airport are coming from the northeast (*i.e.* the wind direction measurements take on values between 10 and 360 degrees: NE_t is a dummy variable for wind directions between 10 and 90 degrees[12]), and γ_r is a regional fixed effect. We do not include 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

[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).

[12] Recall that the wind direction variable is rounded to the nearest ten.

estimate

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

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.[13] 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.

[13]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.

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:

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

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.

Table 2 displays the relationship between volcanic emissions and particulate pollution (PM_{10} and $PM_{2.5}$). In column 1, we see that there is no relationship between emissions from the summit and PM_{10} during the period 2000-2007, but there is a substantial relationship for the subsequent period, 2008-2010, in column 2. Looking at emissions from the ERZ in the next two columns of the table, we see a significant relationship between air quality and emissions in both periods.

Turning to $PM_{2.5}$ in the final four columns, 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 (5) and (6), 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 $PM_{2.5}$ for 2008-2010 than for the earlier period. In the last two columns, we estimate the relationship between emissions from the ERZ and $PM_{2.5}$; we see a statistically significant relationship in both periods, although the point-estimate in column (8) is about double the estimate in column (7).

In Table 3, we estimate the impact of SO_2 emissions from Kīlauea in t/d on SO_2 levels in ppb across the state. The first four columns focus on emissions from the summit, whereas the last four columns focus on emissions from the ERZ. Since SO_2 levels should be highest near the volcano, we estimate this model only using data from 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 4. In most parts of the United States, air pollutants are highly correlated.[14] For example, in the Neidell (2004) study of California, the correlation coefficient between PM_{10} 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 PM_{10} 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 $PM_{2.5}$ is 0.85 (see Mar, Norris, Koenig, and Larson (2000)). In our sample, it is 0.0118. As evidence that SO_2, $PM_{2.5}$, and PM_{10} are being generated by the same source, the correlation coefficient between $PM_{2.5}$ and PM_{10} is 0.52, and between $PM_{2.5}$ 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).

[14] This relationship also holds in many other parts of the world, including developing countries. Ghosh and Mukherji (2014) report that the different pollutants in their sample are "highly correlated" (p. 207).

5 Results

5.1 OLS Results

First, we consider the effects of pollutants on ER admissions and charges for pulmonary-related reasons via OLS estimation of equation (1). Results are reported in Table 5. We estimate two specifications: one that only includes the contemporaneous pollution measure and another that includes contemporaneous and lagged pollution. For reasons discussed above, we report Newey-West standard errors for all estimations. Finally, we estimate the model in both levels and logs.[15]

In the first column of Table 5, we see that a one $\mu g/m^3$ increase in PM_{10} is associated with 0.015 additional admissions for a day/SES community observation. In the fifth column, we see that the effects of $PM_{2.5}$ are larger, with an estimate of 0.030 additional admissions. Both estimates are significant at the 1% level. The standard deviation of PM_{10} is 6.24 $\mu g/m^3$, indicating that a 1 standard deviation increase in PM_{10} results in an additional ER admission every 10.68 days. Similarly, the standard deviation of $PM_{2.5}$ is 3.30 $\mu g/m^3$, indicating that a 1 standard deviation increase in $PM_{2.5}$ results in one additional ER admission every 10.10 days for pulmonary-related reasons in a given region. Turning to the estimates of the effects of particulates on log admissions in columns (3) and (7), we do not see a statistically significant effect for PM_{10}, but we do see a significant effect for $PM_{2.5}$ of 0.36%.

Now looking at the effects on ER charges in the bottom panel, we see that a one $\mu g/m^3$ increase in PM_{10} is associated with \$13.67 more charges for pulmonary-related admissions. The corresponding number for $PM_{2.5}$ is \$43.61. Respectively, a 1 standard deviation increase in PM_{10} and $PM_{2.5}$ results in \$85.30 and \$143.91 additional charges in a given region on a given day. Looking at the results using the log of charges as the outcome variable, we see that a one $\mu g/m^3$ increase in $PM_{2.5}$ is associated with a 0.52% increase in charges in column (7). However, we see that the effect of PM_{10} on log charges is negative in column 3 and

[15] Because a small number of the observations were zeros, we took the log of the outcome plus one.

significant at the 10%.[16]

We report the results of the distributed lagged variant of the model in the even columns of the table. On the whole, there is mixed evidence for persistent effects of particulate pollution on pulmonary-related ER admissions. We do see evidence for persistent effects on the level of admissions for PM_{10} in column 2 and on log charges for $PM_{2.5}$ in column 6. However, the remainder of the estimations do not indicate evidence of persistent effects.

We also investigated the impact of particulates on cardiovascular-related ER admissions as well as SO_2 on both pulmonary and cardiovascular admissions. We did not uncover any effects in any of these investigations. We do not report these results, but they are available upon request.

As a placebo test, we look at the effects of PM_{10} and $PM_{2.5}$ on admissions for fractures in Table 6. We consider both the specification with only contemporaneous pollution and the distributed lag model. We see no evidence that ER admissions for fractures increase as a consequence of particulate pollution.

5.2 IV Results

We begin by discussing the first stages for PM_{10} and $PM_{2.5}$ which are reported in Table 7. For each particulate measure, we report the results from the estimation of four specifications. The first contains no seasonality controls. The second, third, and fourth include day of the week, month and year dummies in a cumulative fashion.

In columns (1)-(2) and (5)-(6), we see that winds coming from the northeast have a strong negative impact on particulate levels on Oahu for both PM_{10} and $PM_{2.5}$. Northeasterly winds are called "trade winds" and they blow the vog out to sea. Note, however, that the inclusion of month dummies in columns (3)-(4) and (7)-(8) greatly attenuates the dummy variable for northeasterly winds. The reason for this is that the trade winds display a seasonal pattern in which they are less present during the months of August through October when Oahu

[16] The effects of PM_{10} on all logged outcomes appear to be mostly insignificant and, so the negative effect on log charges may be a false negative.

residents experience what is called "Kona weather" in local parlance. As can be seen in the F-statistics reported in the bottom of the table, the net effect of this is to greatly attenuate the explanatory power of the excluded instruments since the F-statistics go from 18.46 and 17.76 in columns (1)-(2) to 8.99 and 4.28 in columns (3)-(4). We see a similar pattern for $PM_{2.5}$ with the F-statistic going from 29.54 and 28.87 in columns (5) and (6) to 13.16 and 14.64 in columns (7) and (8).

We do not believe omitting month dummies to be a serious threat to our identification. While we concede that there is monthly variation in vog levels due to seasonal patterns in the trade winds, we cannot conceive of any other omitted variables that exhibit similar monthly variation that also impact ER admissions for pulmonary-related reasons. As such, we view the main effect of inclusion of month dummies in the first stage to be weakening the instruments without controlling for important omitted variables and we thus proceed with the parsimonious specification without the seasonal controls in what follows.

We now estimate the model in equation (3) using IV and present the results in Table 8. In column 1, we see that the IV estimate of the impact of $PM_{2.5}$ on the level of pulmonary-related admissions is 0.418 and is significant at the 1% level. The corresponding OLS estimate in Table 5 was 0.015 and, so the effects are now about 28 times higher. Moving on to the corresponding effects of $PM_{2.5}$ in column 5, we see that the point estimate is 0.553, whereas the analogous OLS estimate was 0.030, which is about 18 times larger. Accordingly, a one standard deviation increase in PM_{10} results in 2.6 additional hospitalizations per day; the corresponding number for $PM_{2.5}$ is 1.82. Finally, looking at the impacts on the log of admissions in columns 3 and 7, we see that a one $\mu g/m^3$ increase in PM_{10} and $PM_{2.5}$ is associated with a 5.7% and a 7.0% increase in admissions, respectively. If we scale these numbers up by the respective standard deviations in PM_{10} and $PM_{2.5}$, we obtain that, respectively, a one standard deviation increase in particulate pollution results in a 35.6% and a 23.1% increase in admissions.

We now turn to the IV estimates with charges as the outcome which are reported in the even numbered columns. We see that a one $\mu g/m^3$ increase in PM_{10} and $PM_{2.5}$ is associated with \$331.38 and \$337.01 additional charges, respectively. So, a one standard deviation increase in PM_{10} and $PM_{2.5}$ results in \$2067.81 and \$1112.13 additional charges, respectively. Turning to the effects on log charges, we see that a one $\mu g/m^3$ increase in PM_{10} and $PM_{2.5}$ results in a, respective, 8.2% and a 6.7% increase in charges. If we, once again, scale these numbers up by their standard deviations, we obtain that a one standard deviation increase in PM_{10} and $PM_{2.5}$ results in a 51.2% and 21.1% increase in charges.

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. Furthermore, the fact that we find zero effects of pollution on fractures suggests that little avoidance behavior is taking place. If people are staying indoors on days with vog conditions, we should be observing a decrease in the rate of fractures on high pollution days. To prove this point, we report IV estimates of the effects of particulates on fracture outcomes in Table 9 and we can see that the effects are all statistically insignificant and quite small in magnitude.

Many readers may be surprised by the implications that these estimates have for the amount of measurement error in our particulate measurements. However, it is important to bear in mind how particulate pollution is measured. Specifically, $PM_{2.5}$ (PM_{10}) is the mass per cubic meter of particles passing through the inlet of a small size-selective sampler with a transmission efficiency of 50% at an aerodynamic diameter of 2.5 (10) micrometers which leaves plenty of scope for variations in measurement. The spatial misalignment between point of measurement and exposure location is also recognized as another important source of measurement error. The epidemiological literature suggests that these two factors (imprecision and spatial misalignment) may produce severe measurement error (see footnote 1). Furthermore, measurement error issues are exacerbated in fixed effects estimators.

We conclude this subsection by discussing a series of additional estimations which we report in Table 10. All estimations use pulmonary-related admissions as the dependent variable. The first row of estimates corresponds to PM_{10} and the second row corresponds to $PM_{2.5}$. To provide a point of reference, in the first column, we estimate the OLS specification from Table 5 using only observations from the island of Oahu. The estimates in this table are 0.013 and 0.037 for PM_{10} and $PM_{2.5}$, respectively. The corresponding estimates from Table 5 are 0.013 and 0.030 and, so the difference between the IV and the OLS results is not a consequence of only using Oahu for the IV estimations.

Next, in column 2, we use 36 dummy variables for each ten degree increment of the wind direction variable and their interactions with SO_2 levels from South Hawai‘i as the excluded IVs. For the sake of comparison, we restate the IV results from Table 8 where we use the more parsimonious first stage with just the dummy for trade winds, SO_2 levels from South Hawai‘i, and the interaction as excluded IV's. We see that the F-statistics in the second column are 6.24 and 6.08, whereas they are 18.46 and 29.54 in the third column, so increasing the number of instruments in the first stage weakens it. In addition, the point-estimates in the second column are 0.124 and 0.280 whereas they are 0.418 and 0.553 in the third column. This is a consequence of the problem of instrument proliferation in which increasing the number of instruments in the first stage decreases its F-statistic and drives the IV estimate closer to the OLS estimate as discussed by Roodman (2009) and Angrist (2014). The contrast between these two sets of estimates is interesting as they both use transformations of the same two variables, wind direction and SO_2 levels from the island of Hawai‘i as IVs but they differ by factors of four and two for PM_{10} and $PM_{2.5}$, respectively.

As our criterion for what first stage to use, we used the specification with the highest F-statistic which is the specification in the third column. However, this is a cautionary note for IV estimates in general as their magnitudes can vary by wide margins depending on how much granularity one has in the first stage. For this reason, we rely quite heavily on OLS in this paper as it does not rely on such discretionary calls. That said, the IV results provide some indication of where the true effects lie and what the magnitude of the measurement error is.

Finally, in the last two columns, we estimate the model from the third column but we exclude August-September in column 4 and August-October in column 5. These are the month when Kona weather is the most common. During the remaining months, the weather in the Hawaiian islands is relatively benign and so weather is much less likely to be a confound. We see in both columns that the estimates are unaffected by excluding these months.

5.3 Results by Age

Next, in Table 11, we investigate the effects of pollutants by the age of the person admitted. More precisely, we run the regressions using as outcomes the number of admissions in different age groups. 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 PM_{10} and $PM_{2.5}$. The next highest for both measures 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 5 to using alternative fixed effects that more thoroughly adjust for seasonality. 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 5 with the pulmonary outcomes on the right hand side. The results are reported in Table 12 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 $PM_{2.5}$ on admissions in Table 12 is 0.023 whereas it was 0.030 in Table 5. Similarly, the estimate for PM_{10} with the alternative fixed effects was 0.013 whereas it was 0.015 in Table 5.

In the bottom panel of the same table, we estimate the model using the NBM for admissions and the Tobit for charges. We still see that there are significant effects of $PM_{2.5}$ on pulmonary outcomes. However, while we still see effects of PM_{10} on charges, we no longer see any effects of PM_{10} on admissions.

Finally, in Table 13, we report alternative standard errors. The first row of the table is the point estimate of the effects of either PM_{10} and $PM_{2.5}$ on pulmonary outcomes. These are the same estimates as those in the first and fourth columns of Table 5. 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 PM_{10} and nine for the models that included $PM_{2.5}$.

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 to particulates (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% range and this matches with other quasi-experimental studies. For example, Schlenker and Walker (2016) find 17-30% increases in hospital counts for a one standard deviation increase in carbon monoxide (CO). 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 on the island of Oahu (total population of less than 1 million people) is $2.9 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%. Jayachandran (2009) uses data from the 2000 Indonesian census to infer the impact of particulate pollution from large-scale forest fires that occurred in 1997 on infant mortality. Jayachandran (2009) finds that pollution led to 15,600 "missing children," or 1.2 percent of the affected birth cohort. The effect size is much larger in poorer areas.

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. Those that do exist tend to find smaller effects. Ghosh and Mukherji (2014) explore the impact of air pollution on children in urban India. Their pollution measures vary fortnightly and they do not use a quasi-experimental source of pollution variation; their identification strategy relies on using month and city fixed effects along with other controls. Ghosh and Mukherji (2014) find that a 1 standard deviation increase in $PM_{2.5}$ is associated with a 6.01 probability points increase in the likelihood of a cough, and a 1 standard deviation increase in PM_{10} is associated with a 14.74 probability points increase in the probability of a cough. The study closest to our own is probably Ward (2015), which finds strong evidence for the detrimental effect of particulate pollution for the respiratory health of children in Ontario, Canada. Ward (2015) finds that a one standard deviation change in particulate pollution is correlated with a 4% increase in respiratory admissions. This occurs in an area where particulate levels are well below U.S. EPA standards.

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.[17] 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 PM_{10} and carbon monoxide in the Neidell (2004) sample is 0.52 and the coefficient between PM_{10} 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 (which creates ozone in the presence of sunlight).

Within the context of our finding a causal link between short-term variation in particulate pollution and ER hospitalizations, it is interesting to note that of the six main "criteria" pollutants regulated by the EPA (carbon monoxide, nitrogen dioxide, ozone, sulfur dioxide, lead, and particulate pollution), particulate pollution and lead are the only pollutants

[17] The correlation coefficient between $PM_{2.5}$ and nitrogen dioxide in the Ghosh and Mukherji (2014) study of Indian cities is 0.51.

without hourly air quality standards. In terms of temporal frequency, the standards for particulate pollution are the least restrictive (for example, the primary standard for $PM_{2.5}$ is an annual mean of 12.0 $\mu g/m^3$ whereas the primary standard for carbon monoxide is 35ppm over a one hour period). This is reflective of the conventional wisdom and the standard finding in the literature that sustained long-term exposure to particulate pollution is damaging but there is little evidence of adverse consequences due to short-term increases in particulates. Our results appear to suggest otherwise.

One important issue with extrapolating our findings to other contexts is whether or not the particulate pollution from vog is comparable to the particulate pollution found in most cities. We consulted with a number of atmospheric scientists, meteorologists, volcanologists, and medical experts to establish the main differences between vog and smog.[18] Vog and smog are similar in that both contain large amounts of sulfate aerosols. However, one of the main differences between vog and smog is that smog typically contains nitrogen oxide compounds and high ozone levels (one of the issues compounding the identification of particulate pollution in most cities) and the size of the sulfate aerosols may be different. Although the particles in vog and smog are both sulfate aerosols, it is believed that the sulfates in vog may be more acidic compared to typical smog, but this has yet to be confirmed on a consistent basis. The acidity of the sulfates depends on the degree to which they have been neutralized by ammonium gas. Ammonium gas typically comes from human and animal activity (such as breathing) and from the use of fertilizers. EPA guidelines for particulate pollution are calculated for sulfate aerosols post-neutralization with ammonium, which may explain why we are observing effects when emissions are below EPA guidelines but this is complicated by the fact that the EPA standard is based on long-term exposure. Overall, smog and vog aerosols are largely comparable because they are both primarily ammonium sulfate aerosols, although vog aerosols may be more acidic depending on the degree to which they have been neutralized by ammonium.

[18] The information in this paragraph is based on personal communication with Andre Pattantyus, John Porter, Steven Businger, Steven Howell, and Elizabeth Tam.

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 Kīlauea 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 23-36% 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, the day 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 2, a 1 ton increase in SO_2 at the summit is correlated with a 0.00195 $\mu g/m3$ increase in $PM_{2.5}$ and, at the East Rift Zone, with a 0.00128 $\mu g/m3$ increase in $PM_{2.5}$ across the state. Based on the results in Table 8, a 1 $\mu g/m3$ increase in $PM_{2.5}$ raises emergency room charges by \$337.01 per day on Oahu. This suggests the daily cost of summit emissions is \$536 and the cost of ERZ emissions is \$581 on Oahu. Multiplying these numbers by 365 (days in the year) and 4 (total number of SES communities in our IV regression) gives an annual cost of \$782,416 for the summit and \$847,975 for the ERZ, or a total annual cost of $PM_{2.5}$ pollution from the volcano of \$1,630,391. The equivalent number for PM_{10} is \$1,281,492. Therefore, the annual welfare cost is \$2.9 million and the total welfare cost of the emissions event that began on March 12, 2008 (from the standpoint of early 2016) has been \$23,295,065.

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 $PM_{2.5}$ 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.[19] 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 large.

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

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Table 1: Summary Statistics for Pollutant and Hospitalization Data

	PM_{10}	$PM_{2.5}$	SO_2	Cardiovascular		Pulmonary		Fractures	
	in $\mu g/m^3$	in $\mu g/m^3$	in ppb	Admissions	Charges	Admissions	Charges	Admissions	Charges
Aiea/Pearl City	16.53	4.37	–	4.41	5005.89	5.00	3932.30	2.25	1608.22
	(5.61)	(2.41)		(2.35)	(3733.90)	(2.90)	(3020.09)	(1.56)	(1374.24)
Central Honolulu	13.85	4.25	0.62	4.75	6334.18	5.42	5043.31	2.40	1952.71
	(4.71)	(2.32)	(0.75)	(2.51)	(4354.10)	(2.92)	(3624.98)	(1.61)	(1561.85)
East Kauai	–	5.84	2.77	2.57	4548.77	3.10	3041.77	1.16	902.77
	–	(2.94)	(4.10)	(1.61)	(3253.94)	(1.85)	(2233.14)	(1.11)	(951.47)
Ewa	15.19	4.94	0.70	5.36	7218.27	7.67	6378.39	2.66	1900.35
	(5.70)	(2.99)	(0.64)	(2.68)	(4750.31)	(3.56)	(3954.93)	(1.69)	(1496.38)
Hilo/North Hawai'i	11.60	5.19	2.87	4.13	5124.33	4.55	3599.80	1.66	1128.62
	(3.55)	(4.15)	(5.92)	(2.27)	(3584.68)	(2.52)	(2793.71)	(1.33)	(1183.50)
Kona	–	15.98	4.96	3.08	4366.75	4.11	3743.41	1.94	1600.16
		(5.88)	(4.61)	(1.90)	(3264.70)	(2.39)	(2671.91)	(1.43)	(1413.31)
South Hawai'i	–	9.12	11.28	2.48	3078.78	2.96	2379.53	1.16	840.45
		(4.84)	(13.33)	(1.81)	(2836.40)	(2.04)	(2249.64)	(1.10)	(1046.95)
West/Central Maui	20.41	6.41	–	3.11	3992.91	3.26	2482.01	1.73	1494.84
	(7.54)	(5.19)		(2.01)	(3445.52)	(2.22)	(2235.51)	(1.41)	(1432.09)
West Honolulu	–	7.36	–	4.74	6125.65	7.27	6362.04	2.21	1736.69
		(3.70)		(2.37)	(4084.08)	(3.45)	(3973.84)	(1.51)	(1442.21)
All	16.04	6.52	3.29	4.01	5159.18	5.00	4204.16	1.98	1512.00
	(6.24)	(3.30)	(6.96)	(2.45)	(4018.47)	(3.23)	(3460.13)	(1.53)	(1417.32)

Notes: Reports means and standard deviations in parentheses.

Table 2: Effects of Volcanic Emissions of SO_2 (tons/day) on Particulate Pollution

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PM_{10}				$PM_{2.5}$			
SO_2 (tons/day)	-0.000531	0.00234***	0.00059**	0.00055*	0.01061*	0.00195***	0.00067*	0.00128***
	(0.00474)	(0.00078)	(0.00029)	(0.00028)	(0.00563)	(0.00063)	(0.00041)	(0.00039)
Source of Measurement								
–Summit	×	×			×	×		
–Eastern Rift Zone			×	×			×	×
2000-2007	×		×		×		×	
2008-2010		×		×		×		×
NT	1297	1391	1130	635	895	2636	789	1203

* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Notes: Each column corresponds to a regression of a pollutant onto measures of SO_2 emissions from Kilauea measured in tons/day. Newey-West standard errors are reported in parentheses.

Table 3: Effects of Volcanic Emissions of SO_2 (tons/day) on SO_2 Pollution

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Emissions from the Summit				Emissions from the Eastern Rift Zone			
SO_2 (tons/day)	0.00926***	0.03122**	0.00254*	0.01357***	0.00060***	0.00148**	0.00029	0.00035***
	(0.000248)	(0.01235)	(0.00135)	(0.00234)	(0.00015)	(0.00067)	(0.00051)	(0.00128)
2000-2007	×	×			×	×		
2008-2010			×	×			×	×
Restricted to S. Hawai'i		×		×		×		×
NT	1608	187	2145	366	1457	180	976	162

* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Notes: Per Table 3.

Table 4: Pollution Correlation Matrix

	$PM_{2.5}$	PM_{10}	SO_2	CO	NO_2
$PM_{2.5}$	1				
PM_{10}	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 5: Effects of Particulates on Pulmonary Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PM_{10} (in levels)				$PM_{2.5}$ (in levels)			
	Levels		Logs		Levels		Logs	
	Admissions							
t	0.015***	0.012**	0.0006	0.0002	0.030***	0.025***	0.0036***	0.0038***
	(0.004)	(0.005)	(0.0007)	(0.0009)	(0.006)	(0.007)	(0.0010)	(0.0013)
$t-1$		0.009**		0.0008		0.007		0.0000
		(0.005)		(0.0008)		(0.007)		(0.0013)
F-Test		[0.000]		[0.2205]		[0.000]		[0.0043]
NT	13902	12933	13902	12933	17831	14844	17831	14844
	Charges							
t	13.67***	11.89**	-0.0045*	-0.0058*	43.61***	28.11***	0.0052***	0.0040
	(4.03)	(4.74)	(0.0025)	(0.0032)	(6.40)	(8.13)	(0.0026)	(0.0037)
$t-1$		6.34		0.0014		13.68*		0.0002
		(4.62)		(0.0030)		(8.08)		(0.0036)
F-Test		[0.000]		[0.1187]		[0.000]		[0.2072]
NT	13869	12899	13869	12899	17745	14751	17745	14751

* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Notes: All estimations include region, day, month, and year dummies. Newey-West standard errors are reported in parentheses. The F-test is a test that the sum of the contemporaneous and lagged pollution variable sum to zero and its p-value is reported in brackets. The dependent variable is ER admissions or charges either in levels or logs.

Table 6: Placebo Tests: Effects of Particulates on Admissions for Fractures

	(1)	(2)	(3)	(4)
	PM_{10}		$PM_{2.5}$	
t	0.003	0.001	0.002	0.000
	(0.002)	(0.003)	(0.003)	(0.004)
$t-1$		0.003		0.003
		(0.003)		(0.004)
F-Test		[0.435]		[0.677]
NT	14004	13036	17965	14982

* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level
Notes: Per Table 5.

Table 7: IV Results: First Stages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PM_{10}				$PM_{2.5}$			
NE (Northeasterly winds)	-1.23***	-1.21***	-0.12	-0.12	-1.02***	-1.02***	-0.46**	-0.58***
	(0.30)	(0.29)	(0.28)	(0.27)	(0.20)	(0.20)	(0.20)	(0.19)
SO_2	0.06***	0.06***	0.06***	0.05***	0.04***	0.04***	0.04***	0.03**
	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
$SO_2 \times$ NE	-0.03*	-0.03*	-0.03***	-0.03**	-0.03**	-0.03**	-0.03**	-0.03**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Day of Week Dummies	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Month Dummies	No	No	Yes	Yes	No	No	Yes	Yes
Year Dummies	No	No	No	Yes	No	No	No	Yes
F-Test	18.46	17.76	8.99	4.28	29.54	28.87	13.16	14.64
NT	6814	6814	6814	6814	6195	6195	6195	6195

* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Notes: All estimations include region dummies. Newey-West standard errors are reported in parentheses. The F-Test is a test of the joint significance of the excluded exogenous variables.

Table 8: IV Results: The Impact of Particulates on Pulmonary Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Admissions	Charges	Admissions	Charges	Admissions	Charges	Admissions	Charges
	Levels		Logs		Levels		Logs	
PM_{10}	0.418***	331.38***	0.057***	0.082***	-	-	-	-
	(0.073)	(72.53)	(0.010)	(0.015)				
$PM_{2.5}$	-	-	-	-	0.553***	337.01***	0.070***	0.067***
					(0.087)	(77.25)	(0.011)	(0.015)
F-Test		18.46					29.54	
NT	6814	6779	6814	6779	6195	6115	6195	6115

* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Notes: All estimations include region dummies. Newey-West standard errors are reported in parentheses. The F-Test is a test of the joint significance of the excluded exogenous variables. We only report the F-statistics from the first stages using admissions; the F-statistics from the regressions using charges are similar.

Table 9: IV Results: The Impact of Particulates on Fracture Outcomes (in levels)

	Admissions	Charges
PM_{10}	0.003	6.11
	(0.026)	(25.92)
$PM_{2.5}$	-0.03	-39.68
	(0.036)	(36.22)

Notes: Each cell corresponds to a separate estimate from the same specifications reported in Table 8. Newey-West standard errors are reported in parentheses.

Table 10: Additional IV Results: Pulmonary-Related Admissions

	(1)	(2)	(3)	(4)	(5)
PM_{10}	0.013**	0.124***	0.418***	0.424***	0.443***
	(0.006)	(0.030)	(0.073)	(0.084)	(0.096)
F-Test		6.24	18.46	14.32	12.00
$PM_{2.5}$	0.037***	0.280***	0.553***	0.526***	0.583***
	(0.013)	(0.054)	(0.087)	(0.100)	(0.117)
F-Test		6.08	29.54	22.24	17.50
Excluded Months	None	None	None	Aug-Sep	Aug-Oct
Estimation Method	OLS	IV	IV	IV	IV

* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

Notes: All estimations only use observations from the island of Oahu. Each cell corresponds to a separate regression. The OLS regressions in column (1) have the same specification as the regressions in Table 5. Newey-West standard errors are reported in parentheses. The F-Test is a test of the joint significance of the excluded exogenous variables. The specification in column (2) uses 36 dummy variables for the wind direction variable and their interactions with SO_2 as excluded IV's.

Table 11: Effects of Particulates on Pulmonary Admissions by Age of the Patient

	PM_{10}	$\frac{\text{Effect}}{\text{\# of ages in bin}}$X1000	$PM_{2.5}$	$\frac{\text{Effect}}{\text{\# of ages in bin}}$X1000
0-1	0.005***	2.50	0.007***	3.50
	(0.002)		(0.002)	
2-5	0.003**	0.75	0.007***	1.75
	(0.001)		(0.002)	
6-10	0.001	0.20	0.000	0.00
	(0.001)		(0.001)	
11-18	0.001	0.13	0.004***	0.50
	(0.001)		(0.001)	
19-50	0.006***	0.19	0.011***	0.34
	(0.002)		(0.003)	
51-65	0.000	0.00	0.006***	0.40
	(0.001)		(0.002)	
65+	0.002	-	0.006***	-
	(0.001)		(0.002)	

* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level
Notes: All estimates come from a separate OLS regression that includes region, month, and year dummies. Newey-West standard errors are reported in parentheses. Each cell corresponds to a separate regression.

Table 12: Robustness Checks

	Admissions		Charges	
	Alternative Fixed Effects			
PM_{10}	0.013***	-	10.04**	-
	(0.004)		(4.03)	
$PM_{2.5}$	-	0.023***	-	34.38***
		(0.006)		(6.19)
	NBM		Tobit	
PM_{10}	0.004	-	12.17***	-
	(0.004)		(3.86)	
$PM_{2.5}$	-	0.020***	-	43.53***
		(0.005)		(5.82)

* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level
Notes: Standard errors are in parentheses. The alternative fixed effects in the firsty panel are for year/month interactions, day of the week, and region. For the negative binomial and Tobit models, we include month, year, day of the week, and region fixed effects and report the marginal effects.

Table 13: Alternative Standard Errors

	(1)	(2)	(3)	(4)
	Admissions		Charges	
	PM_{10}	$PM_{2.5}$	PM_{10}	$PM_{2.5}$
Point Estimate	0.0153	0.0300	13.67	43.61
NW Standard Error	0.0040	0.0060	4.03	6.40
Robust Standard Error	0.0037	0.0052	3.71	5.75
Clustered Standard Error	0.0055	0.0064	6.97	6.04

Notes: We computed the effects of particulates on pulmonary outcomes while computing the standards errors three different ways. The clustered standard errors clustered by SES community.

Table A1: 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

Figure 1: Topographical Map of the Island of Hawai'i

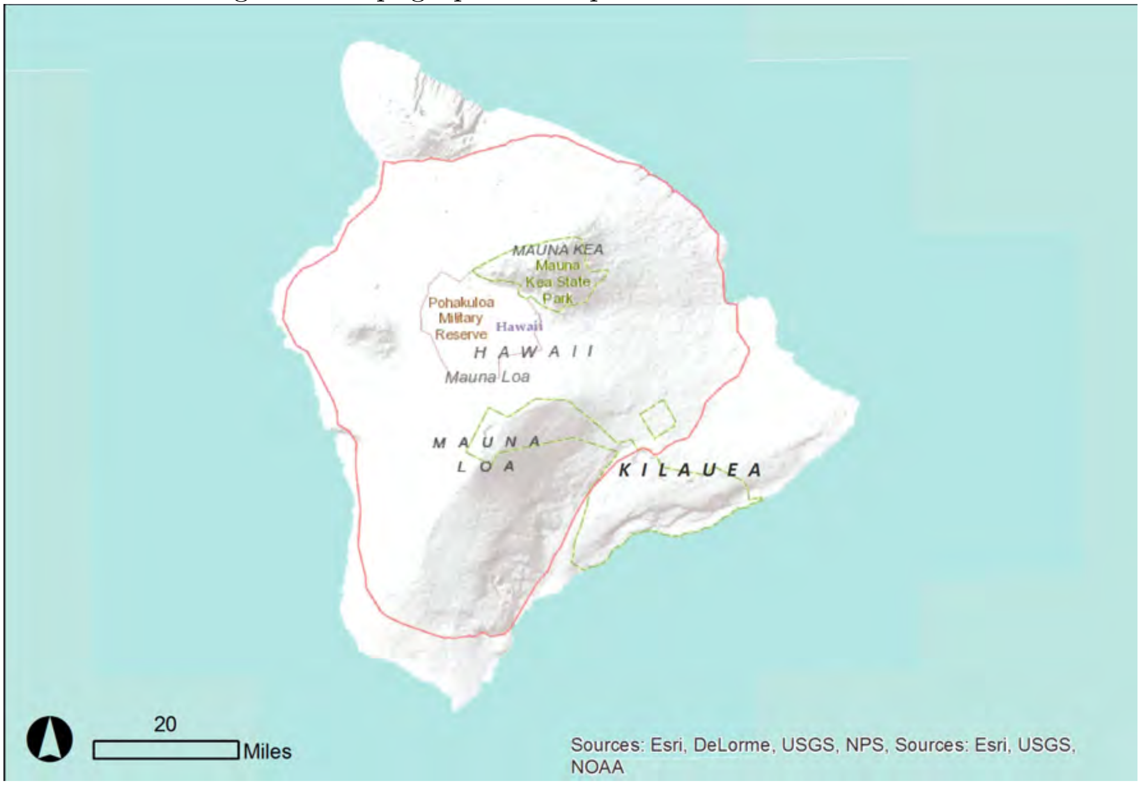


Figure 2: Map of the Hawai'ian Islands

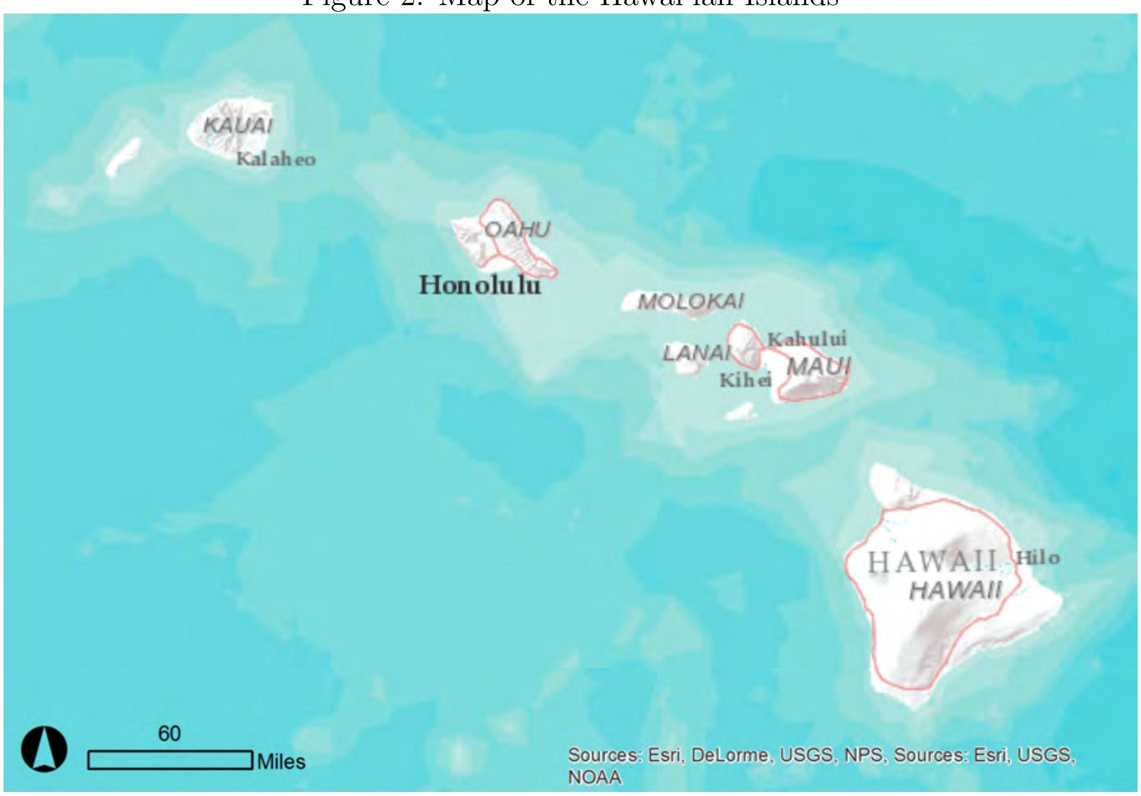
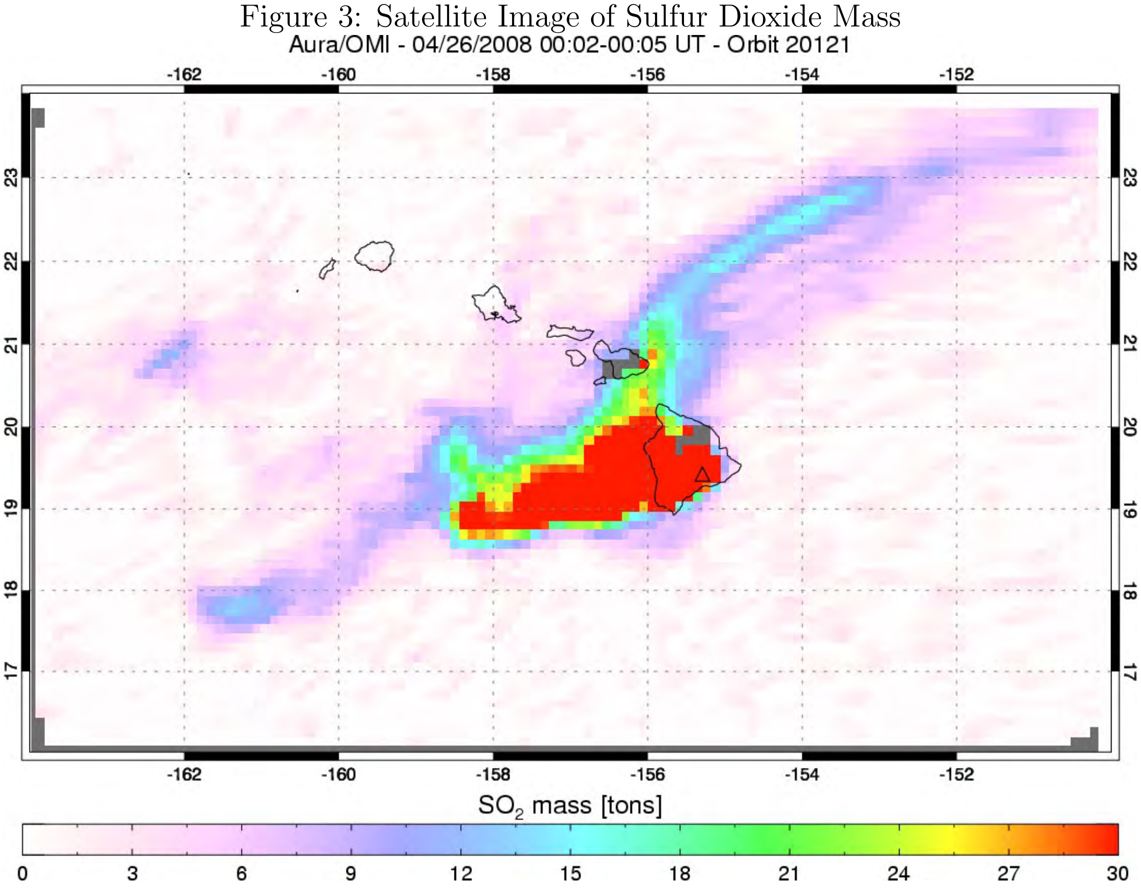


Figure 3: Satellite Image of Sulfur Dioxide Mass



Source: NASA Earth Observatory

Figure 4: $PM_{2.5}$ by SES Community

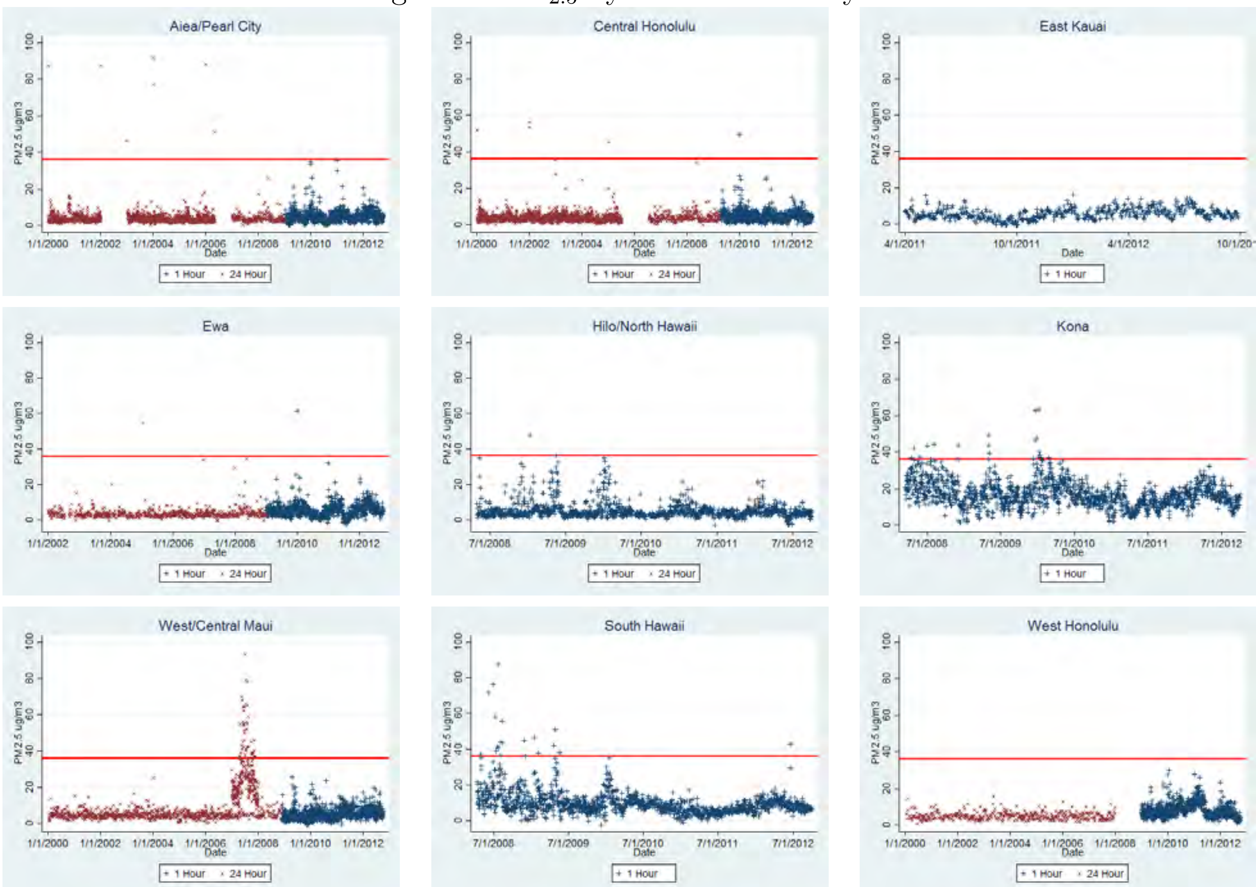


Figure 5: PM_{10} by SES Community

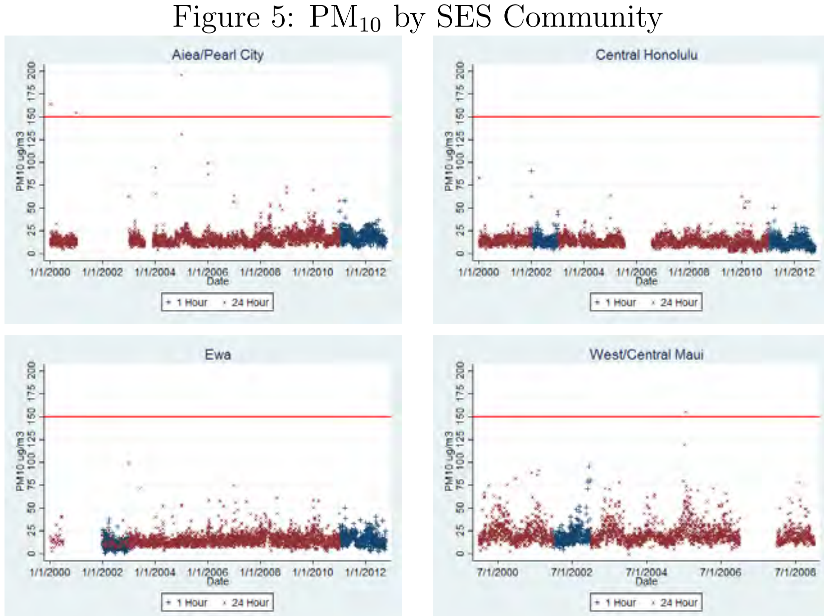


Figure 6: SO_2 by SES Community

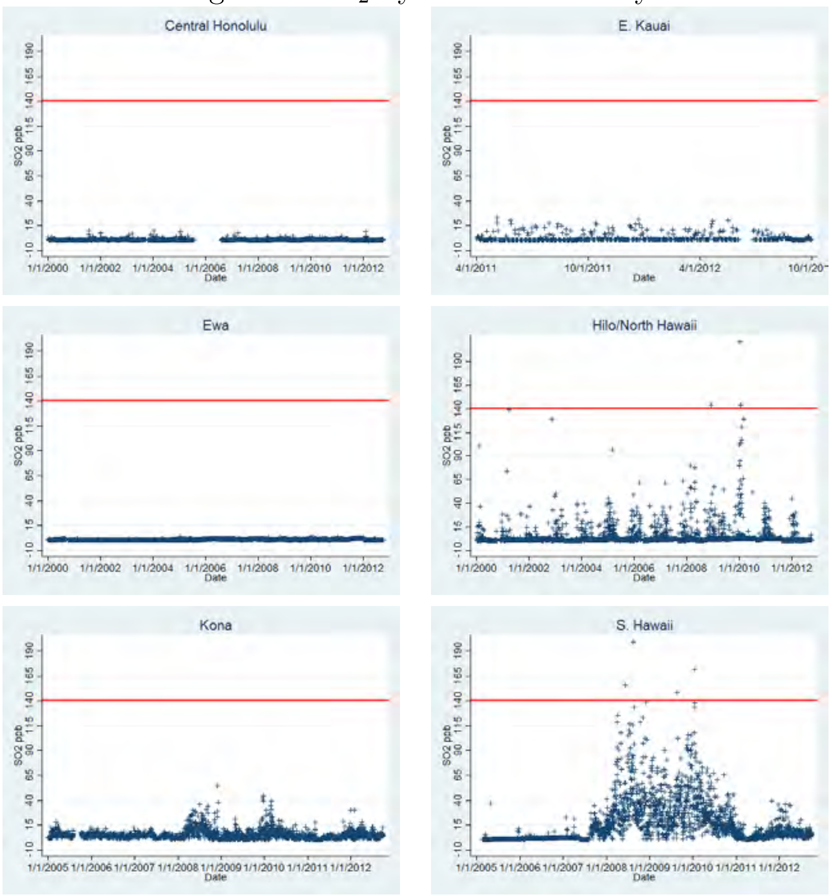


Figure 7: Histogram for Wind Direction Data

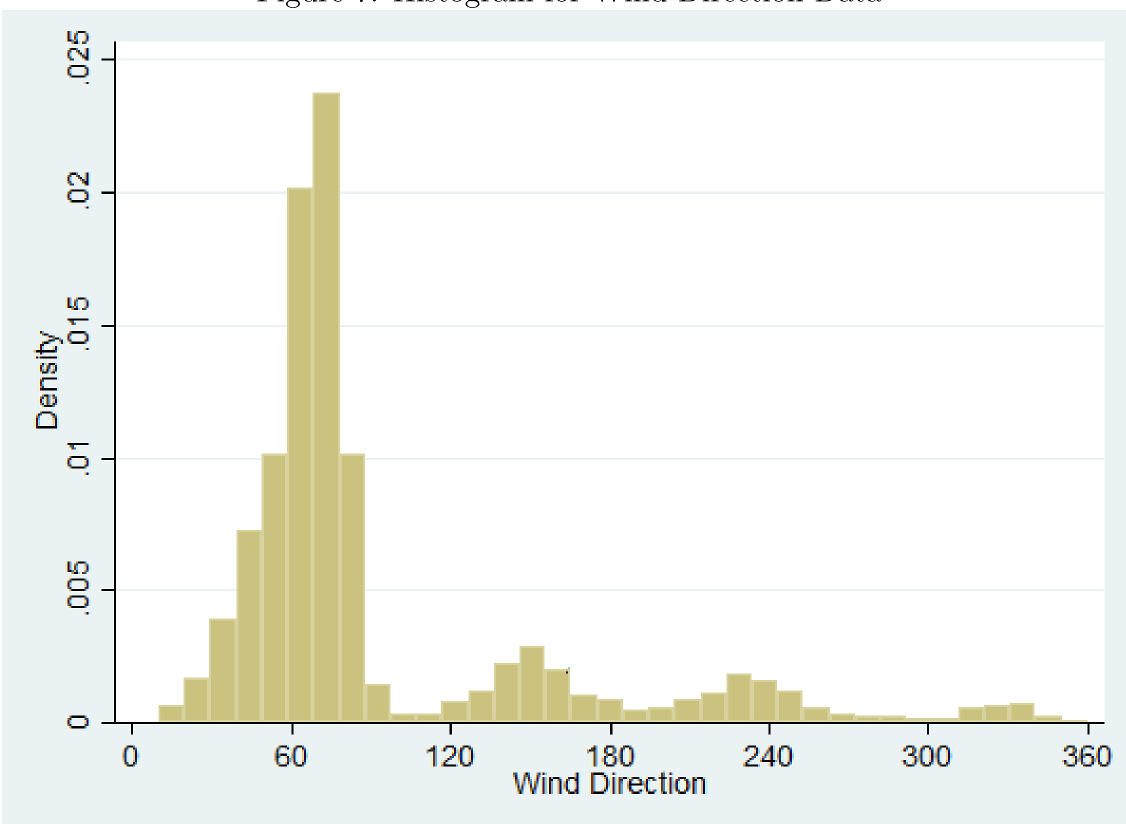
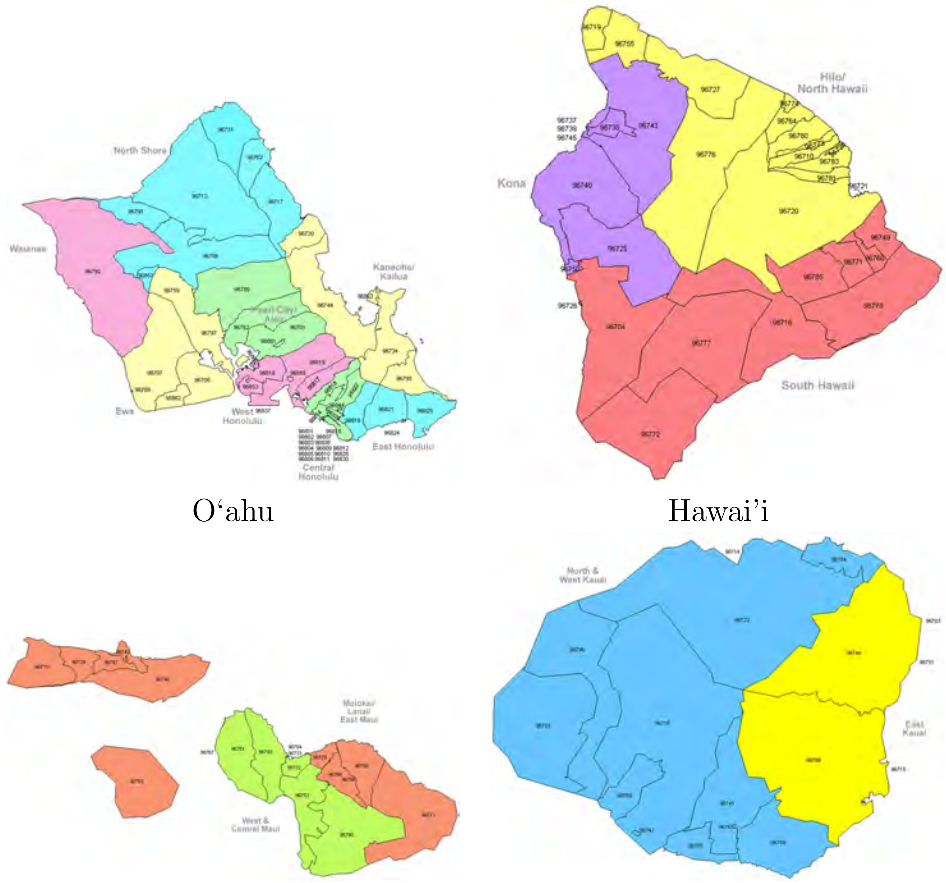


Figure A1: SES Communities



O‘ahu

Hawai’i

Maui/Lana‘i/Moloka‘i

Kaua‘i