VOG: USING VOLCANIC ERUPTIONS TO ESTIMATE THE HEALTH COSTS OF PARTICULATES*

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The negative consequences of long-term exposure to particulate pollution are well established but a number of studies find no effect of short-term exposure on health outcomes. The high correlation of industrial pollutants 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 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.

In this article, we use volcanic emissions to document the effect of particulate pollution on hospital admissions 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 matter on various public health outcomes and costs in a context where pollution levels are well below Environmental Protection Agency (EPA) ambient air quality standards.

Kīlauea is the most active of the five volcanoes that form the island of Hawai'i. Emissions from Kīlauea produce what is known as 'vog' (volcanic smog) pollution. Vog is essentially small particulate matter (sulphate aerosols) suspended in the air, akin to smog pollution in many 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 air quality 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 emissions 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 behaviour (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 behaviour, is thornier and has bedevilled 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 utilisation 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 utilisation (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 a specific type 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 emissions 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 O'ahu (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 winds come from the northeast there is very little particulate pollution on O'ahu, 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 the sea. Figure 3 is a satellite image showing sulphur dioxide concentrations during typical northeast wind conditions: the plume of emissions 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 O'ahu 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

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[1] For example, Künzli and Tager (1997) explain how simple OLS designs tend to underestimate the effect of air pollution on health. Goldman *et al.* (2011) and Sheppard *et al.* (2012) both suggest that the usual estimators may suffer from severe attenuation bias due to measurement error.

[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.
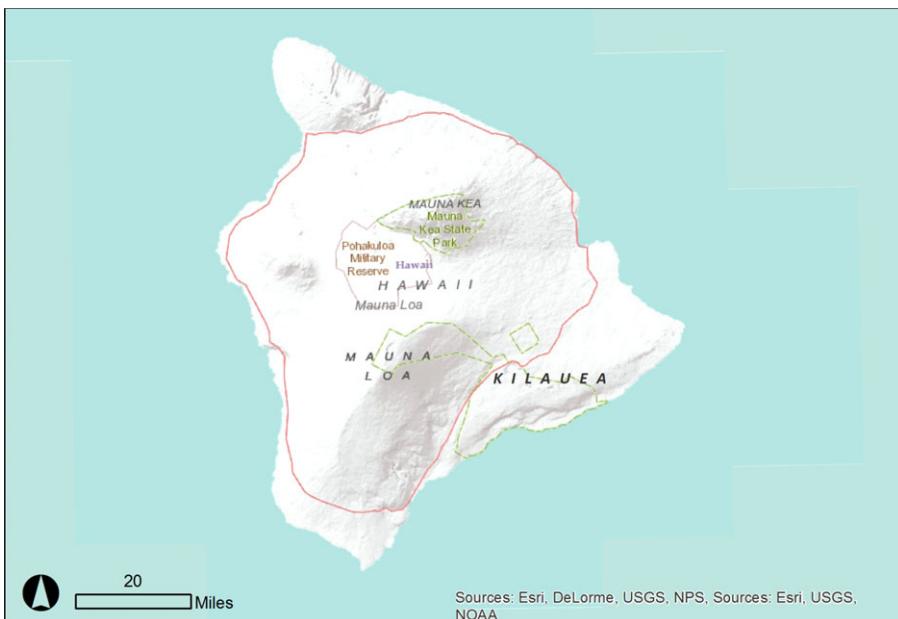
Fig. 1. *Topographical Map of the Island of Hawai'i*
*Note*. Colour figure can be viewed at wileyonlinelibrary.com.
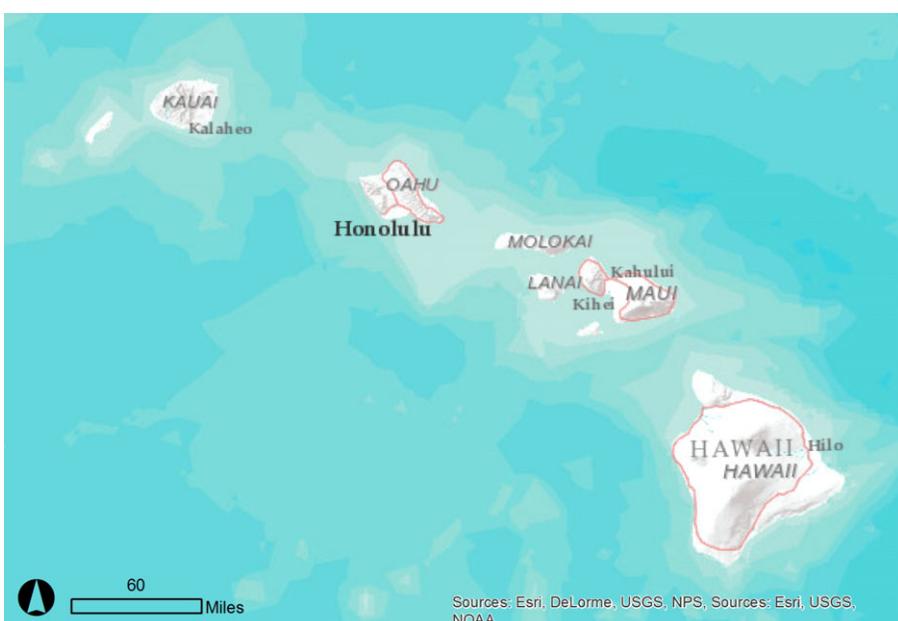
Fig. 2. *Map of the Hawaiian Islands*
Note. Colour figure can be viewed at wileyonlinelibrary.com.

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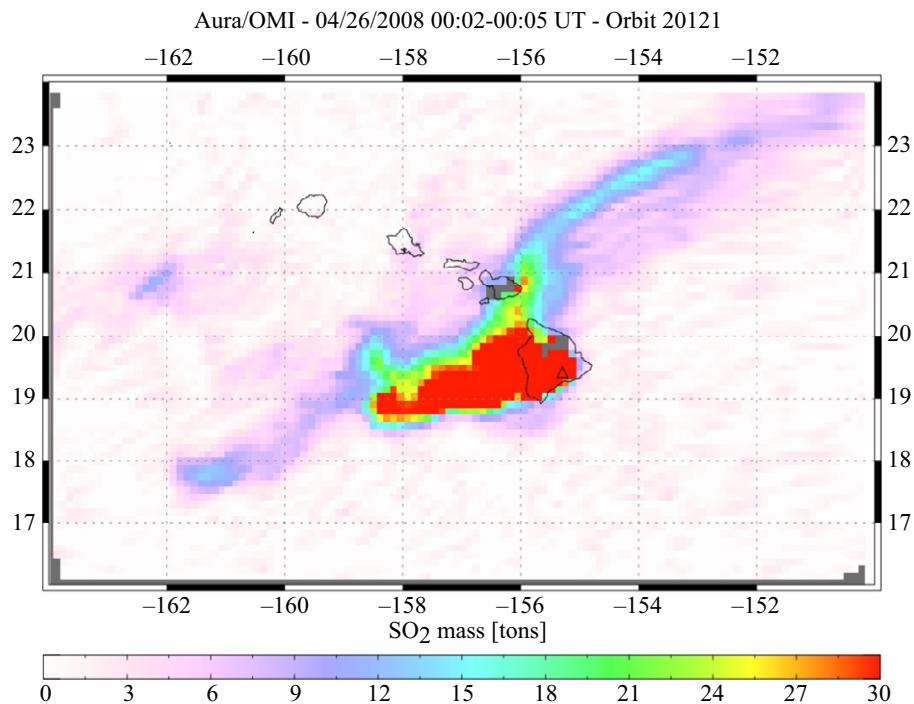
Fig. 3. *Satellite Image of Sulphur Dioxide Mass*
Note. Colour figure can be viewed at wileyonlinelibrary.com.
Source. NASA Earth Observatory.

in Japan, Ishigami *et al.* (2008) found a strong correlation between sulphur dioxide (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 *et al.*, 2008; Longo, 2009). A strong correlation between vog and outpatient visits for pulmonary problems and headaches was found by Longo *et al.* (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 *et al.* (2016) show an association between vog exposure and respiratory outcomes including cough and forced expiratory volume (FEV1). Still, it remains unclear whether increased volcanic emissions are causing health problems. In particular, selection bias (e.g. 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 *et al.* (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 1981–2 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 hospitalisations. 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 *et al.* (2016) use road traffic; and Currie and Walker (2011) use the introduction of toll roads as sources of quasi-exogenous pollution variation. Arceo-Gomez *et al.* (2016) use thermal inversions to measure the effect of CO and PM_{10} on infant mortality in Mexico.

There is also a corresponding medical literature on the health effects of pollution. The studies that most closely align with our own investigate the effects of particulates on respiratory hospital admissions and mortality. An early and influential study exploited the intermittent closure of a steel mill in Utah Valley to demonstrate a causal link between PM_{10} pollution and respiratory hospital admissions, particularly among pre-school age children (Pope, 1991). This study used monthly hospital admissions. A follow-up study in the same area found a significant correlation between five-day moving average PM_{10} pollution and non-accidental mortality (Pope *et al.*, 1992). Dockery *et al.* (1993), Pope *et al.* (1995), Pope *et al.* (2002) and Pope *et al.* (2009) all investigate the effects of long-term exposure to particulates and observe strong correlations with mortality in the US.

The contributions of this study to the existing literature are as follows. First, the vast majority of the studies in the economics literature exploit sources of pollution that are the result of human activity (e.g. from cars, airplanes, factories or starting fires to clear forest).[4] Second, we use more accurate data on the costs of hospitalisation 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 (e.g. the extremely ill are less likely to volunteer to fill out surveys). Our

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[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.

[4] There is a literature, predominantly in environmental science, that investigates the health effects of dust storms e.g. Chan *et al.* (2008) and Perez *et al.* (2012).

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. Fifth, given that vog is composed almost entirely of sulphate aerosols, our results shed light on the unresolved question of how the chemical composition and characteristics of particulates affect human health (Pope and Dockery, 2006). Finally, the results in this article 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 on important health outcomes. In most other studies, particulates and other pollutants are strongly correlated, making it difficult to disentangle the effects of one pollutant from another.[5]

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 2–4% 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.

The balance of this article is organised 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 summarise our results. Finally, we conclude.

1. 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 a small number again in late 2014. Other than these minor impacts, the lava flows serve mainly as a tourist attraction. The primary impact of the volcano on human activity has been intermittent but severe deteriorations in air quality. Kīlauea primarily emits water vapour, carbon dioxide and sulphur dioxide (these gases comprise 99% of total emissions), along with other minor trace gases (hydrogen, hydrogen chloride, hydrogen fluoride and carbon monoxide (CO); totalling 1% of emissions).[6] SO_2 poses a serious threat to human health and is also a common industrial pollutant.

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[5] For example, Le Tertre *et al.* (2002, p. 773) find that the effect of particulate pollution on cardiovascular disease disappears once they control for other correlated pollutants: 'The effect of PM10 was little changed by control for ozone or SO_2, but was substantially reduced (CO) or eliminated (NO_2) by control for other traffic related pollutants'.

[6] Although carbon monoxide is emitted from the volcano, it is in such small quantities that it is not a cause for concern. Carbon monoxide is not measured on Hawai'i or Maui islands or at the summit of the volcano by the United States Geological Survey (USGS). The nearest accurate measurement of carbon monoxide is in Honolulu on O'ahu where the last time the EPA's one hour standard for carbon monoxide was exceeded was on the 15 January 1973. See the USGS Kīlauea volcano website for more details: https://volcanoes.usgs.gov/observatories/hvo/hvo_gas.html.

Moreover, SO_2 turns into particulate matter which is also another harmful pollutant and the main pollution problem caused by the volcano.

There are currently two main sources of air pollution on Kīlauea: the summit itself and a hole (volcanic cone) in the 'East Rift Zone' on the side of the volcano. Since 12 March 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). Kīlauea is, not surprisingly, the largest stationary source of SO_2 pollution in the US. Depending on volcanic activity, rainfall and prevailing wind conditions, there can be vast daily differences in the actual amount of SO_2 present near the summit and surrounding areas, ranging from near pristine air quality to levels that far exceed guidelines set by the EPA.

Volcanic pollution, or vog, is composed of different gases and aerosols, and the composition typically depends on proximity to the volcano. Near Kīlauea's active vents, vog consists mostly of SO_2 gas. Over time, SO_2 gas oxidises to sulphate 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 the other Hawaiian islands), vog is essentially small particulate matter (sulphuric acid and other sulphate compounds) and no longer contains high levels of SO_2. Because this species of particulates is high in sulphuric acid, the results of this study may be more pertinent to other particulate sources that are also high in sulphate aerosols such as coal-fired power plants. In summary, the volcano has the potential to produce high levels of SO_2 pollution near the volcano and high levels of a particular species of particulate pollution anywhere in the state of Hawai'i.

We employ data from two primary 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 13 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 1 January 2000 to 31 December 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 in online Appendix A.

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 μm in diameter ($PM_{2.5}$ and PM_{10}) and SO_2.[7] All measurements for SO_2 are in parts per billion (ppb), and particulates are measured in micrograms per cubic metre (μg/m^3). For particulates, two measures were available: an hourly and a 24-hour average computed by the DOH.[8] Using the hourly measures, we computed our own 24-hour averages, which were arithmetic averages taken over 24 hourly measures. Most of the time, either the one hour or the 24-hour measure was available, but rarely were both available on the same day. When they were, we averaged the two. For our empirical results, we spliced the two time series of particulates (e.g. the 24-hour averages provided by the DOH and taken from our own calculations) together and took averages when appropriate so we could have as large of a sample as possible for our regression analysis. The measurements of SO_2 were taken on an hourly basis; to compute summary measures for a given day, we computed means for that day.

To merge the air quality data into the ER admissions data, we used the following process. First, we computed the exact longitude and latitude of the monitoring station to determine in which ZIP Code the station resided. Next, we determined the SES community in which the station's ZIP Code resided. If an SES community contained numerous monitoring stations, then we computed means for all the monitoring stations on a given day in a given SES community. Table A1 in online Appendix A 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.[9]

In Figures 4–6, 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 μg/m^3 for $PM_{2.5}$ and 150 μg/m^3 for PM_{10}. We used the older 24-hour average of 140 ppb for SO_2.[10]

On the whole, Figures 4–6 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

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[7] To be more precise, $PM_{2.5}$ (PM_{10}) is the mass per cubic metre 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) μm.

[8] 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.

[9] For both, the pollution and ER data, we trimmed the top and bottom 1% from the tails.

[10] For information on particulates, see http://www.epa.gov/air/criteria.html. Note that the current NAAQS for SO_2 is a one hour average below 75 ppb.

Table 1

Summary Statistics for Pollutant and Hospitalisation Data

	PM$_{10}$ in µg/m³	PM$_{2.5}$ in µg/m³	SO$_2$ in *ppb*	Cardiovascular		Pulmonary		Fractures	
				Admissions	Charges	Admissions	Charges	Admissions	Charges
Aiea/Pearl City	16.53	4.37	–	4.41	5,005.89	5.00	3,932.30	2.25	1,608.22
	(5.61)	(2.41)		(2.35)	(3,733.90)	(2.90)	(3,020.09)	(1.56)	(1,374.24)
Central Honolulu	13.85	4.25	0.62	4.75	6,334.18	5.42	5,043.31	2.40	1,952.71
	(4.71)	(2.32)	(0.75)	(2.51)	(4,354.10)	(2.92)	(3,624.98)	(1.61)	(1,561.85)
East Kauai	–	5.84	2.77	2.57	4,548.77	3.10	3,041.77	1.16	902.77
		(2.94)	(4.10)	(1.61)	(3,253.94)	(1.85)	(2,233.14)	(1.11)	(951.47)
Ewa	15.19	4.94	0.70	5.36	7,218.27	7.67	6,378.39	2.66	1,900.35
	(5.70)	(2.99)	(0.64)	(2.68)	(4,750.31)	(3.56)	(3,954.93)	(1.69)	(1,496.38)
Hilo/North Hawai'i	11.60	5.19	2.87	4.13	5,124.33	4.55	3,599.80	1.66	1,128.62
	(3.55)	(4.15)	(5.92)	(2.27)	(3,584.68)	(2.52)	(2,793.71)	(1.33)	(1,183.50)
Kona	–	15.98	4.96	3.08	4,366.75	4.11	3,743.41	1.94	1,600.16
		(5.88)	(4.61)	(1.90)	(3,264.70)	(2.39)	(2,671.91)	(1.43)	(1,413.31)
South Hawai'i	–	9.12	11.28	2.48	3,078.78	2.96	2,379.53	1.16	840.45
		(4.84)	(13.33)	(1.81)	(2,836.40)	(2.04)	(2,249.64)	(1.10)	(1,046.95)
West/Central Maui	20.41	6.41	–	3.11	3,992.91	3.26	2,482.01	1.73	1,494.84
	(7.54)	(5.19)		(2.01)	(3,445.52)	(2.22)	(2,235.51)	(1.41)	(1,432.09)
West Honolulu	–	7.36	–	4.74	6,125.65	7.27	6,362.04	2.21	1,736.69
		(3.70)		(2.37)	(4,084.08)	(3.45)	(3,973.84)	(1.51)	(1,442.21)
All	16.04	6.52	3.29	4.01	5,159.18	5.00	4,204.16	1.98	1,512.00
	(6.24)	(3.30)	(6.96)	(2.45)	(4,018.47)	(3.23)	(3,460.13)	(1.53)	(1,417.32)

*Note.* Reports means and standard deviations in parentheses.
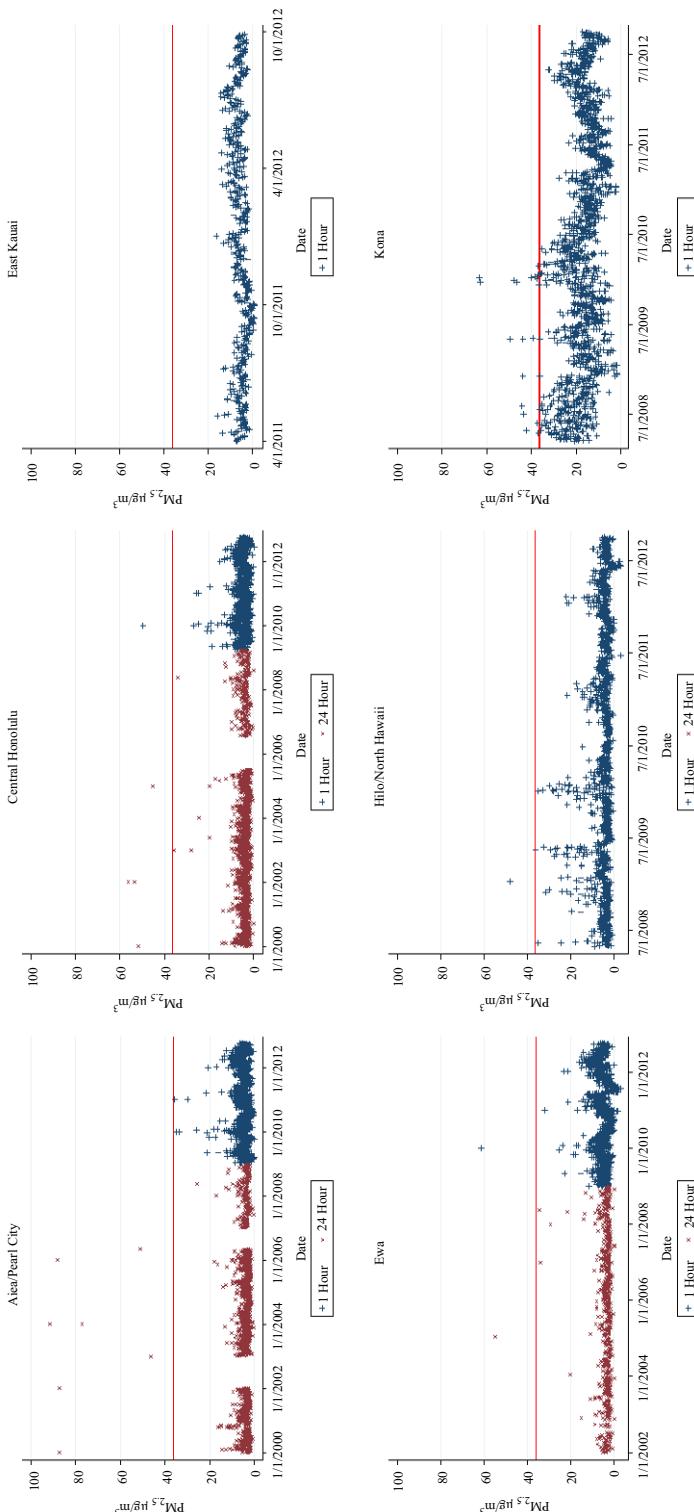
Fig. 4. $PM_{2.5}$ by SES Community

*Note.* Colour figure can be viewed at wileyonlinelibrary.com.
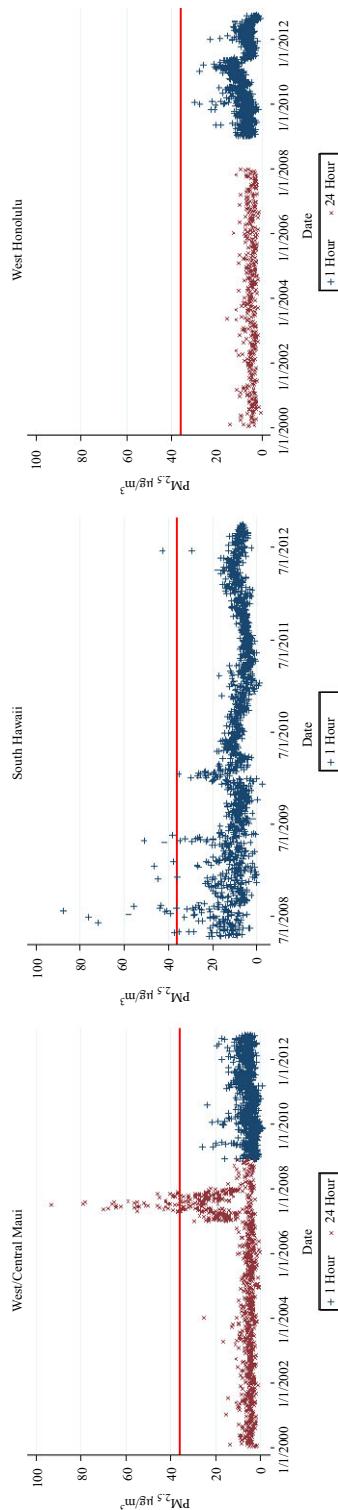
Fig. 4. (*Continued*)
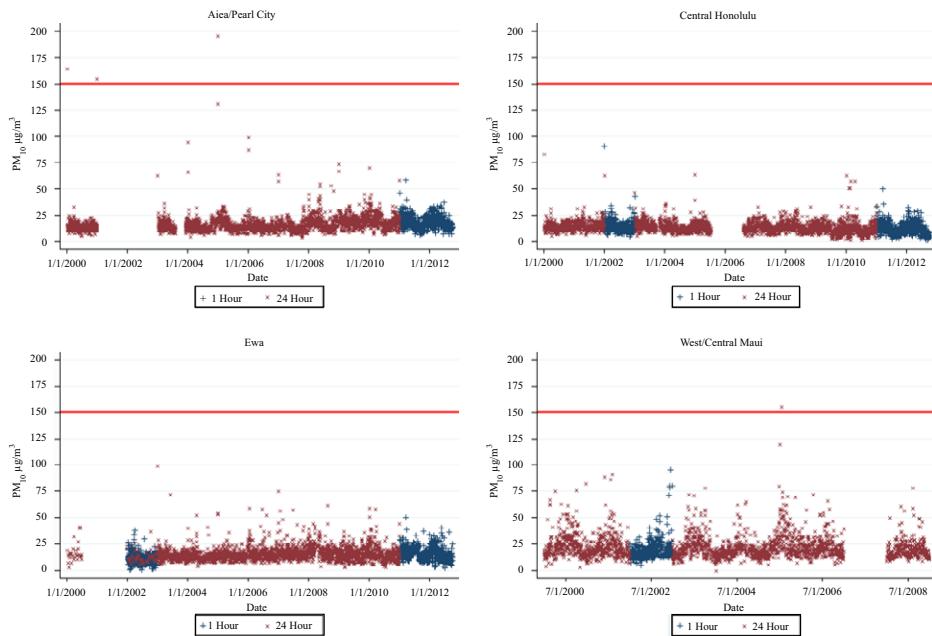
Fig. 5. *PM$_{10}$ by SES Community*
Note. Colour figure can be viewed at wileyonlinelibrary.com.

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.[11] These trends make sense in that SO$_2$ emissions is 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 Hawaiian islands, depending on the wind direction.

For our instrumental variables results, we employ data on wind direction collected by the National Oceanic and Atmospheric Association from their weather station at Honolulu International Airport. These data are reported in degrees (rounded to the nearest 10) with zero corresponding to the winds coming from due north. We summarise 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 O'ahu from the south. When this happens, the volcanic emissions from Kīlauea are blown to the island of O'ahu, not out to sea. Travel time from Kīlauea to O'ahu depends on wind strength, exact direction, and the location of the plume offshore. According

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[11] 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.
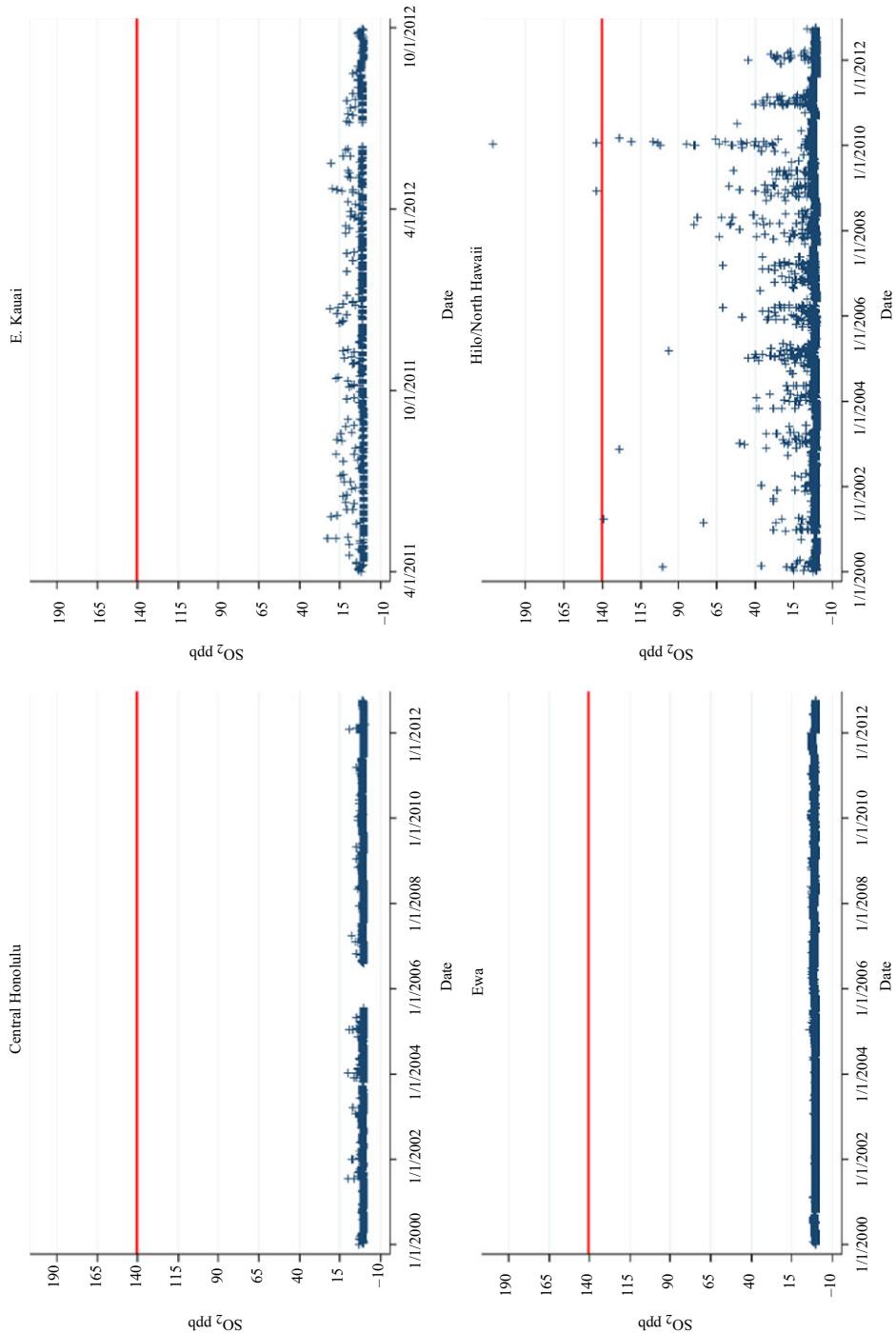
Fig. 6. *SO$_2$ by SES Community*

Note. Colour figure can be viewed at wileyonlinelibrary.com.
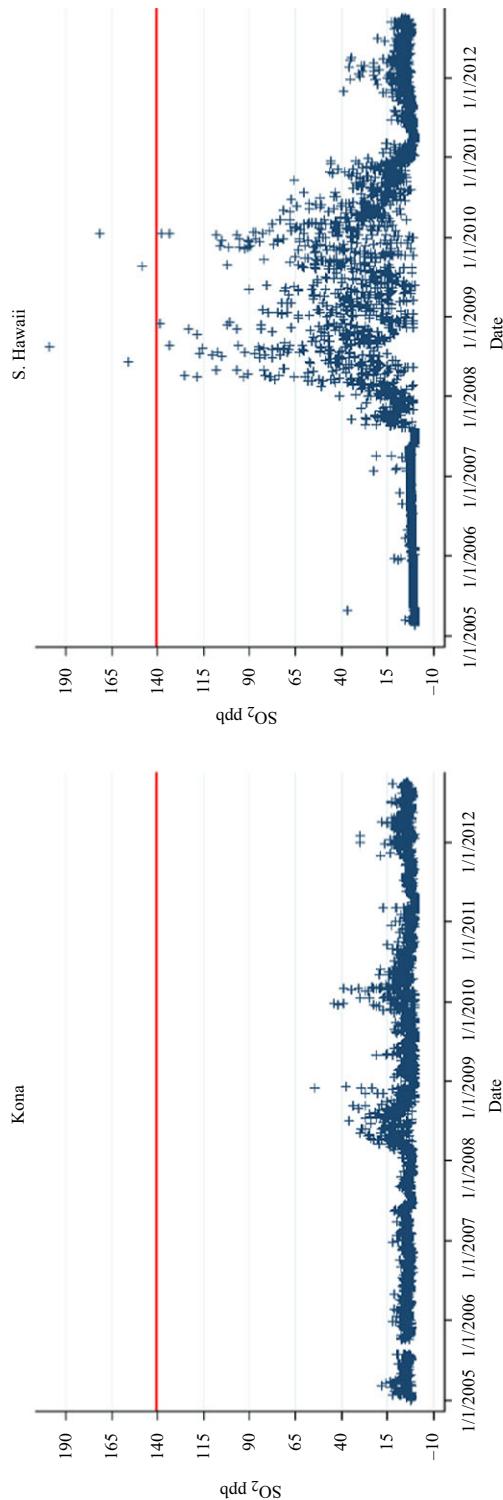
Fig. 6. (*Continued*)
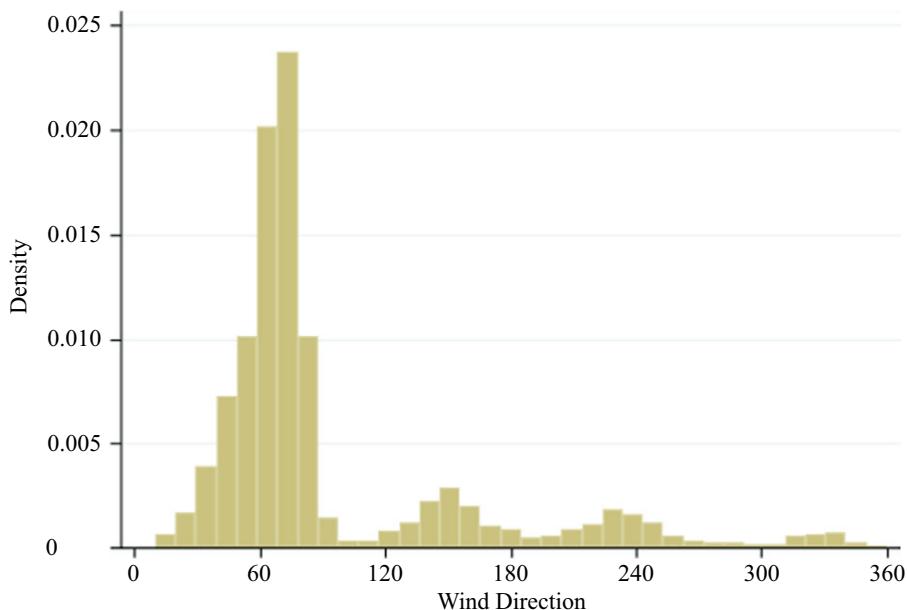
Fig. 7. *Histogram for Wind Direction Data*
Note. Colour figure can be viewed at wileyonlinelibrary.com.

to Tofte *et al.* (2017, p. 1166): 'The straight-line distance from the vents to Honolulu is about 350 kilometres. A typical wind speed between 4 and 10 m/s would give the vog plume 10–24 hour to reach Honolulu'. This travel time could be shorter if the plume is sitting offshore directly south of Oʻahu due to recent northeast winds (as depicted in Figure 3).

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 $5,159.18 per day, whereas pulmonary-related admissions cost a total of $4,204.16. Finally, note that these amounts correspond to what the provider charged, not what it received, which, unfortunately, is not available from HHIC. While some may view this as a data limitation, there may be some positive aspects to this as well if the amount charged is a better measure of the actual cost of the health service. Often, the amount paid (as opposed to charged) reflects factors other than the cost of the service such as the monopsony power of the payer.

2. Methods

We employ two approaches to estimate the impact of volcanic emissions on ER utilisation. The first is to simply estimate a linear regression of clinical outcomes onto

our pollution measures while controlling for a flexible pattern of seasonality 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 of the year 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 2000–12 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. In addition, we also employ region-specific trends in some robustness checks. 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.[12]

Ordinary least squares estimation of (1) has the advantage that it utilises 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 an instrument for particulate pollution on Oʻahu. Our proxy of SO_2 emissions is the measurement of SO_2 levels from the South Hawaiʻi monitoring stations discussed in the previous Section from the Hawaiʻi DOH. There are four monitoring stations in South Hawaiʻi that essentially surround the volcano. Mountain View station is located to the northeast of the volcano, Ocean View station is located to the southwest, Pahala station is located to the west and Puna station is located to the east. On each day, our measure of SO_2 is the maximum SO_2 level recorded at any one of these stations. Thus,

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[12] 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 $\log A_t/POP_t = \log A_t - \log POP_t$. In the absence of any effects of pollution on day-to-day population movements, the entirety of the action will stem from its impact on admission counts.

wind direction should have a negligible impact on the actual measurement of SO_2 within close proximity to the volcano, since no matter which direction the wind blows, there is a weather station that should be intercepting the emissions.[13]

We would argue that SO_2 levels in South Hawai'i are unrelated to most causes of particulate pollution on O'ahu other than, of course, vog. It is also important to say that, in unreported results, we found no direct effects of local SO_2 on pulmonary outcomes and, so, it appears as if using SO_2 levels from South Hawai'i as an IV 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 O'ahu.

We restrict the IV estimations to the island of O'ahu since one of the aims of this work is the estimate the health consequences of particulate pollution without being contaminated by other pollutants. Using SO_2 pollution from the island of Hawai'i (in conjunction with wind direction) as an instrument for particulate pollution on O'ahu provides us with a clean way of doing this. Inclusion of regions on Maui or Hawai'i in the estimations may have compromised this because these regions may have had higher SO_2 concentrations due to their proximity to the volcanic eruptions.

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 O'ahu 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) and γ_r is a regional fixed effect. We do not include any seasonality controls since there are no apparent systematic seasonal patterns in volcanic emissions that are also correlated with ER utilisation and inclusion of these would greatly weaken the explanatory power of the instruments. In the second stage, we then estimate:

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

using only ER utilisation data from O'ahu.

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 (Neidell, 2009; Zivin

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[13] 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 volcanic emissions are very intermittent and thus, 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).

and Neidell, 2009; Moretti and Neidell, 2011).[14] 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). 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 10 lags for the Newey–West standard errors, although the standard errors with only one lag were very similar, indicating that 10 lags is most likely more than adequate.[15] These standard errors allow for arbitrary correlations in residuals across the Hawaiian islands on a given day and serial correlation in the residuals for up to 10 days. In the online Appendix, we also report alternative standard errors as well.

3. 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. We do this to establish that SO_2 emissions from Kīlauea are the source of the particulate pollution that we consider in this article. In addition, the results in this Section provide some insights into how volcanic emissions affect pollution in the state over time. Finally, some of the estimations in which we restrict the sample to south Hawai'i establish a clear connection between the volcanic emissions and SO_2 levels near Kīlauea which is a precursor to the first stage of the IV estimation that we report in the next Section.

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 edge of the crater at the summit and Pu'u 'Ō'ō volcanic cone within the Eastern Rift Zone (ERZ), from January of 2000 to December of 2010. The two locations are about 11.5 miles apart. Note that these measurements were not taken on a daily basis, that many days have no measurements, and that many

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[14] For example, the State of Hawai'i encourages citizens to stay indoors during heavy vog conditions: http://ltgov.hawaii.gov/emergency-information/important-information-about-vog/. It should also be noted that there could be behavioural responses that work in the opposite direction: a pre-existing sore throat might become more salient when there is vog in the air.

[15] 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 10 lags. For SO_2, we found significant autocorrelations for more than 10 lags. For the coming estimations, we used 10 lags for the Newey–West standard errors since preliminary work showed that there was little effect of SO_2 for any of the outcomes.

others have a measurement from only one of the locations. The measurements are taken by USGS staff using vehicle-based spectrometers. Due to staffing and other logistical constraints, it is not always possible to take a measurement at both locations everyday of the year. 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 2000–7 and 2008–10. Emissions from the summit increased threefold starting on 12 March 2008.

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 2000–7, but there is a substantial relationship for the subsequent period, 2008–10, 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. In fact, the estimated coefficients are almost identical (0.00059 compared to 0.00055). This is reassuring given that the level of emissions from the ERZ has been relatively constant over the two-time periods. It is only the summit source of emissions that has experienced a very large increase since 2008.

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 2000–7 and 2008–10 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 2000–7 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 2008–10 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-estimates are not as close as we observed for PM_{10}.

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 US, air pollutants are highly correlated.[16] 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 (Mar *et al.*, 2000). In our sample, it is 0.0118.

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

Table 2

Effects of Volcanic Emissions of SO₂ (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			×	×		×	×	×
2000–7		×	×				×	
2008–10	×			×	×	×		×
NT	1,297	1,391	1,130	635	895	2,636	789	1,203

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

Table 3

Effects of Volcanic Emissions of SO₂ (tons/day) on SO₂ 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)
2000–7	×		×		×		×	
2008–10		×		×		×		×
Restricted to S. Hawai'i			×	×			×	×
NT	1,608	187	2,145	366	1,457	180	976	162

Notes. Per Table 3. *Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level.

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

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, between $PM_{2.5}$ and SO_2 it is 0.4 and between PM_{10} and SO_2 it is 0.1.[17] 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).

4. Results

4.1. *OLS Results*

First, we consider the effects of pollutants on ER admissions and charges for pulmonary-related reasons via OLS estimation of (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.[18]

In the first column of Table 5, we see that a 1 μg/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 μg/m^3, indicating that a one 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 μg/m^3, indicating that a one 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 1 μg/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 one 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 1 μg/m^3 increase in $PM_{2.5}$ is associated with a

[17] It is important to note that $PM_{2.5}$ is a component of PM_{10}.
[18] Because a small number of the observations were zeros, we took the log of the outcome plus one.

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	13,902	12,933	13,902	12,933	17,831	14,844	17,831	14,844
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	13,869	12,899	13,869	12,899	17,745	14,751	17,745	14,751

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

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 significant at the 10%.[19]

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.

An important point is that the effects of PM$_{2.5}$ are systematically larger than the effects of PM$_{10}$ in Table 5. This is consistent with the medical consensus since PM$_{2.5}$, due to their small size, can travel deeply into lungs making them particularly dangerous. Note that PM$_{10}$ does contain PM$_{2.5}$. Because of this and because the smaller particulates are more dangerous, one can view PM$_{10}$ as a noisy proxy for PM$_{2.5}$ where the measurement error due to the addition of coarser particulates between 2.5 and 10 $\mu g/m^3$ is not mean zero but classical otherwise. As we have witnessed in Table 5, this would suggest that the estimates of the effects estimated using PM$_{10}$ should be attenuated. We provide a formal explanation of this in the online Appendix.

[19] The effects of PM$_{10}$ on all logged outcomes appear to be mostly insignificant and, so the negative effect on log charges may be spurious.

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	14,004	13,036	17,965	14,982

Note. Per Table 5.

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.

Finally, in the online Appendix we conduct a number of robustness tests. First, we investigate robustness to region-specific trends. We show that there are still significant effects with the regional trends, but they are somewhat attenuated. Second, we explore the robustness of the results in Table 5 to using alternative fixed effects that more thoroughly adjust for seasonality and, once again, the results are robust to their inclusion. Third, we estimate the model in (1) using the negative binomial model (NBM) and Tobit. Most of the results are still significant with the NBM and Tobit. Fourth, we compute alternative standard errors of the model and compare these to the Newey–West standard errors that we have already computed. Generally, we find that the Newey–West standard error lies between the Eicker–White robust standard error and the standard error clustered on SES regions.

4.2. *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 O'ahu for both PM$_{10}$ and PM$_{2.5}$. As we discussed, 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 strong seasonal patterns, which includes a period in which they are less present during the months of August to October when O'ahu residents

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	6,814	6,814	6,814	6,814	6,195	6,195	6,195	6,195

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

experience what is called 'Kona weather' in local parlance. This seasonality is depicted in Figure 8.[20] 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. Also and importantly, the OLS specifications that we estimate include a comprehensive set of controls for seasonality including one specification with month/year dummies whose results are reported in Table A3 in the online Appendix. Our OLS estimates are robust to comprehensive controls for seasonality. Because of measurement error, those estimates provide a lower bound on the relation. 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 confounded omitted variables and we thus proceed with the parsimonious specification without the seasonal controls in what follows.
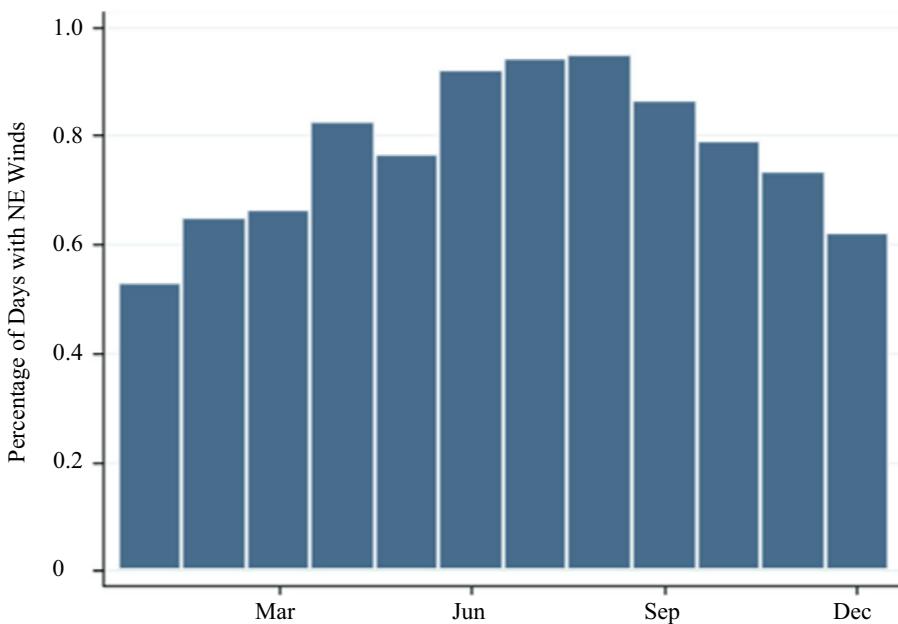

Fig. 8. *Seasonality in NE Winds*
Note. Colour figure can be viewed at wileyonlinelibrary.com.

[20] Note that the figure shows that northeasterly winds are actually least prevalent during the winter months. Nevertheless, our main point remains, which is that there are seasonal patterns in winds.

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	6,814	6,779	6,814	6,779	6,195	6,115	6,195	6,115

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

We now estimate the model in (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 hospitalisations 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 1 μg/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.

Importantly, the results from Table 8 are robust to the inclusion of quarterly dummies (as well as day of the week and year dummies) in the second stage, although the estimates are attenuated by this. For example, the estimate of the impact of PM_{10} on pulmonary related admissions in the first column of 0.418 becomes 0.211 (p < 0.10) when quarterly dummies are included. Similarly, the corresponding estimate for $PM_{2.5}$ of 0.553 in the fifth column becomes 0.282 (p < 0.01) when the quarterly dummies are included. These results are not reported but are available upon request.

We now turn to the IV estimates with charges (per day) as the outcome which are reported in the even numbered columns. We see that a 1 μg/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 $2,067.81 and $1,112.13 additional charges, respectively. Turning to the effects on log charges, we see that a 1 μg/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 behaviour. However, using volcanic emissions (or a proxy of it in our case) does not correct for this bias since avoidance behaviour 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. However, in the online Appendix, we show that we find zero effects of pollution on fractures suggesting that little avoidance behaviour is taking place.

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 $2.5(10)\mu m$ which leaves plenty of scope for variations in measurement. The spatial misalignment between point of measurement and exposure location is also recognised as another important source of measurement error. The epidemiological literature suggests that these two factors (imprecision and spatial misalignment) may produce severe measurement errors (see footnote 1). Furthermore, measurement error issues are exacerbated in fixed effects estimators.

Finally, in the online Appendix, we conduct a series of additional exercises, using our IV estimator. First, we estimate the impact of particulates on our placebo outcome, fractures. We do not find evidence of any effects. Next, we estimate the IV model using a more granular first stage. We show that using a more granular first stage moves the estimates towards the OLS estimates because the proliferation of instruments raises the first stage R^2. Finally, we estimate the model excluding months in which Kona weather is most common. The results are robust to this further suggesting that our IV results are not simply picking up a possible effect of Kona weather on ER admissions.

4.3. *Mechanisms*

The IV results just presented seem to indicate that there is a direct effect of particulate pollution on pulmonary-related health outcomes in the short term. While this result cannot be driven by omitted variables stemming from industrial pollution or traffic, one possible confounder is SO_2 pollution on the island of Oʻahu that is correlated with either PM_{10} or $PM_{2.5}$. In Tables 9 and 10, we conduct a series of exercises to investigate if our estimates of the effects of particulates on ER admissions are contaminated by SO_2 that has migrated from the island of Hawaiʻi to Oʻahu.

In Table 9, we estimate a version of the first stage in (2) except that in lieu of either $PM_{2.5}$ or PM_{10}, we use SO_2 levels on Oʻahu as the dependent variable. Whereas the estimation of the first stage in Table 7 demonstrates the degree to which volcanic

Table 9

OLS Estimates of the Effects of SO$_2$ from the Island of Hawai'i on SO$_2$ on O'ahu

	(1)	(2)	(3)	(4)
NE (Northeasterly winds)	−0.305***	−0.304***	−0.243***	−0.260***
	(0.047)	(0.047)	(0.048)	(0.046)
SO$_2$	−0.002	−0.002	−0.002	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)
SO$_2$ × NE	0.004*	0.004*	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Day of week dummies	No	Yes	Yes	Yes
Month dummies	No	No	Yes	Yes
Year dummies	No	No	No	Yes
F-test	1.62	1.61	1.11	1.01
	[0.1989]	[0.1997]	[0.3298]	[0.3655]
NT	4,633	4,633	4,633	4,633

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 SO$_2$ and its interaction with the wind variable. Its p-value is reported in brackets. *Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level.

Table 10

Kitchen Sink OLS Regression on O'ahu

	Pulmonary outcomes	
	Admissions	Charges
SO$_2$	0.028	−47.61
	(0.060)	(64.99)
PM$_{10}$	0.018*	31.97***
	(0.011)	(11.60)
PM$_{2.5}$	0.050**	35.29
	(0.023)	(27.13)
F-test	9.63	9.70
	[0.0001]	[0.0001]
NT	4,684	4,941

Notes. All estimations include region, day, month and year dummies. Newey–West standard errors are reported in parentheses. The F-test is a test of the joint significance of PM$_{10}$ and PM$_{2.5}$. Its p-value is reported in brackets. *Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level.

emissions creates particulate pollution on O'ahu, Table 9 indicates the degree to which the volcanic emission on the island of Hawai'i (as proxied by SO$_2$ levels on south Hawai'i) are associated with SO$_2$ levels on O'ahu. The basic idea of this exercise is to test if it really is volcanic emission of SO$_2$ on the island of Hawai'i that get converted to particulates on O'ahu that is driving our results.

We estimate all four specifications from Table 9 and we do not find evidence that the volcanic emissions from Kīlauea are raising SO$_2$ levels on O'ahu. The coefficient on SO$_2$ is never significant and always has the incorrect sign. In contrast, the coefficient estimates on SO$_2$ in Table 7 are all positive and highly significant indicating a strong relationship between volcanic emissions from Kīlauea and particulate levels on O'ahu. Next, the interactions between wind direction and SO$_2$ are marginally significant in the first two columns. However, as shown by the estimates of the coefficient on *NE*, this is

likely driven by the fact that wind direction is strongly associated with SO_2 levels. Finally, the F-test of joint significance of the coefficients on SO_2 and the interaction term all fail to reject the null that the terms involving SO_2 are zero.

In Table 10, we estimate 'kitchen sink' regressions restricted to the island of O'ahu via OLS. Specifically, we regress pulmonary admissions and charges onto a vector that includes PM_{10}, $PM_{2.5}$ and SO_2. In both estimations, SO_2 is never significant, whereas both particulate measures significantly impact admissions in the first column and PM_{10} has a highly significant impact on charges in the second column. Finally, the F-test of the joint significance of the two particulate measures resoundingly rejects the null that both coefficients are zero.

4.4. *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. 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:

$$(\text{Effect})/(\text{No. of ages in bin}) \times 1,000,$$

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.

Table 11

Effects of Particulates on Pulmonary Admissions by Age of the Patient

	PM_{10}	$\frac{\text{Effect}}{\text{No. of ages in bin}} \times 1,000$	$PM_{2.5}$	$\frac{\text{Effect}}{\text{No. of ages in bin}} \times 1,000$
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)	
11–8	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)	

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

4.5. *Comparison with the Literature*

We conclude this Section with a discussion of how our results compare to the existing literature. 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 *et al.* (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 six years before and six years after the coal ban, Clancy *et al.* (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% 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 hospitalisation. Thus, there are very few studies that we are aware of that allow us to directly compare our results.[21] 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 one 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 US 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.[22] 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 hospitalisations for asthma among children but other pollutants have large effects on emergency room

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[21] Chang *et al.* (2016) explore short-term variation in particulate matter at levels below EPA standards but focus on worker productivity and not health outcomes.

[22] The correlation coefficient between $PM_{2.5}$ and nitrogen dioxide in the Ghosh and Mukherji (2014) study of Indian cities is 0.51. In the words of Pope and Dockery (2006, p. 730): 'Highly related to understanding the role of various characteristics and constituents of PM is understanding the relative importance of various sources and related co-pollutants. For example, PM exposure to pollution from the burning of coal typically includes substantial secondary sulphates and co-exposure to SO_2. PM exposure to pollution from traffic sources often includes substantial secondary nitrates and co-exposure to nitrogen dioxide and CO'.

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. As another example, the correlation between carbon monoxide and particulate matter in Bharadwaj *et al.* (2017, p. 507) typically exceeds 0.9 and, in their own words: 'It is worth mentioning that an important caveat here is that while we estimate the impacts of carbon monoxide exposure, CO is emitted along with other pollutants and we are unable to separately identify the impacts of CO *versus* PM10 *versus* PM2.5, etc'. 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 hospitalisations, it is interesting to note that of the six main 'criteria' pollutants regulated by the EPA (carbon monoxide, nitrogen dioxide, ozone, sulphur dioxide, lead and particulate pollution), particulate pollution and lead are the only pollutants without hourly air quality standards. In terms of temporal frequency, the standards for particulate pollution are the least restrictive (e.g. the primary standard for $PM_{2.5}$ is an annual mean of 12.0 μg/m^3 whereas the primary standard for carbon monoxide is 35 ppm 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 vog from Kīlauea 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 from Kīlauea and smog.[23] Vog should not be confused with volcanic ash (fragments of rock and minerals created during volcanic eruptions). Vog from Kīlauea and smog are similar in that both contain large amounts of sulphate aerosols. One of the main differences between Kīlauea 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 sulphate aerosols may be different. Although the particles in Kīlauea vog and smog are both sulphate aerosols, it is believed that the sulphates in the vog may be more acidic compared to typical smog, but this has yet to be confirmed on a consistent basis. The acidity of the sulphates depends on the degree to which they have been neutralised by ammonium gas. Ammonium gas typically comes from human and animal activity (such as breathing) and from the use of fertilisers. EPA guidelines for particulate pollution are calculated for sulphate aerosols post-neutralisation with ammonium, which may

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[23] The information in this paragraph and the next is based on personal communication with Steven Businger, Steven Howell, Andre Pattantyus, C. Arden Pope III, John Porter and Elizabeth Tam, as well on research published in Mather *et al.* (2012) and Businger *et al.* (2015).

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 that is primarily composed of sulphate aerosols (such as that found near coal-fired power plants) is very similar to Kīlauea vog. That said, this does not mean that vog in Hawai'i can be directly compared to smog in the coal regions of eastern Pennsylvania, for example. There are differences based on particle size, shape, chemistry and absorption of co-pollutants. However, this caveat applies to any study of smog pollution; the smog in Pennsylvania cannot be directly compared to smog in New York or California. There are differences in the physical and chemical properties of particulate pollution across regions and sources. At this point in time, we do not know how these differences affect health outcomes. In a comprehensive review, Pope and Dockery (2006, pp. 730–731) state that, 'One of the biggest gaps in our knowledge relates to what specific air pollutants, combination of pollutants, sources of pollutants, and characteristics of pollutants are most responsible for the observed health effects. Although the literature provides little evidence that a single major or trace component of PM is responsible for the observed health effects, various general characteristics may affect the relative toxicity of PM pollution'. Thus, in terms of external validity, we feel most confident extrapolating our results to settings where smog is primarily composed of sulphate aerosols (e.g. areas near coal-fired power plants in eastern Pennsylvania) but less so to settings where smog is primarily ozone or other pollutants (e.g. Los Angeles). In fact, our results reinforce the call by Pope and Dockery to focus on the characteristics of pollutants. Major advances in public health could be made if we can correctly identify what are the most dangerous forms of particulate pollution.

5. 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 hospitalisation.

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).

A number of caveats need to be borne in mind when interpreting our regression estimates from a welfare perspective. As discussed earlier, avoidance behaviour 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.[24] 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.

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Additional Supporting Information may be found in the online version of this article:

Appendix A. Attenuation Bias.
Appendix B. Robustness Checks.
Appendix C. Additional IV Results.
Data S1.

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