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Improved asthma outcomes observed in the vicinity of coal power plant retirement, retrofit and conversion to natural gas

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Coal-fired power plants release substantial air pollution, which included over 60% of US sulfur dioxide emissions in 2014. Such air pollution may exacerbate asthma, but direct studies of the health impacts linked to power plant air pollution are rare. Here we take advantage of a natural experiment in Louisville, Kentucky, where one coal-fired power plant was retired and converted to natural gas, and three others installed SO_2 emission control systems between 2013 and 2016. Dispersion modelling indicated that exposure to SO_2 emissions from these power plants decreased after the energy transitions. We used several analysis strategies, which include difference-in-differences, first-difference and interrupted time-series modelling to show that the emissions control installations and plant retirements are associated with a reduced asthma disease burden related to hospitalizations and emergency room visits at the ZIP-code level, and to individual-level medication use as measured by digital medication sensors.

Coal-fired power plants provide a large amount of electricity worldwide. In 2015, they produced six trillion megawatt (MW) hours and 25% of the global supply[1]. Simultaneously, coal-fired power plants emit air pollution, which included 63% of the US economy-wide sulfur dioxide (SO_2) emissions in 2014[2], as well as nitrogen oxides (NO_x), $PM_{2.5}$ (particulate matter less than 2.5 µm in diameter) and PM_{10} (particulate matter between 2.5 and 10 µm in diameter), mercury, acid gases, polycyclic aromatic hydrocarbons and volatile organic compounds[3]. Such pollutants are associated with increased asthma symptoms, emergency room visits (ERVs), hospitalizations and mortality[4–8].

Among populations that live near coal-fired power plants and fossil fuel refineries, some, though not all[9,10], epidemiological studies found a relationship between higher SO_2 levels and uncontrolled asthma[11], respiratory symptoms[12–15] and respiratory-related hospitalizations[16]. Residential proximity to such facilities alone, without assessed air quality, was also identified as a risk factor for asthma exacerbation[17–19].

Prior scholarship related to asthma and coal-fired power plant exposures often consisted of observational and cross-sectional studies that considered single air pollutants (usually SO_2) and hospitalizations, pulmonary function or symptoms alone. Studies of symptoms lacked objective measures and usually relied on participant diaries. Some studies overcame a portion of these limitations; for example, Smargiassi et al.[16] used a case-crossover design to evaluate the relationship between SO_2 concentrations and ERVs and hospitalizations among young children who lived near a refinery. To build on these prior studies, we incorporate improved exposure and outcome assessment and capitalize on recent abrupt changes in coal-fired power plant emissions.

Between 2000 and 2015 in the United States, 49.5 GW of capacity from coal-fired generators retired at 146 coal-fired power plants[1,20] and many generating units installed flue-gas desulfurization systems (alternatively, SO_2 emission 'controls') to comply with regulations from the US Environmental Protection Agency (USEPA) and individual states, which include the Acid Rain Program, the Clean Air Interstate Rule and Mercury and Air Toxics Standards[2]. The discrete nature of these energy transitions and the ensuing abrupt changes in emissions present circumstances for a 'natural experiment' to study related changes in health in the time frame and population exposed to emissions from the coal-fired power plants[21,22]. The key feature is that the transition-induced change in exposure occurs for reasons unrelated to a health investigation and produce exposure changes that more closely resemble an experiment than a typical observational study. Such a natural experiment supports the study of the influence of coal-fired power plant emissions on asthma outcomes more directly, without relying on exposure–response functions estimated with different populations across time and space with varying levels of pollution exposure[23]. Previous studies framed in this manner used a steel mill closure[24], a ban on coal sales[25], the Olympic Games[26,27] and the Nitrogen Oxides Budget Program[28] to study the relationship between air pollution and respiratory-related medication expenditures, hospitalizations and death.

We used retirements and SO_2 emissions control installations at four coal-fired power plant facilities near Louisville, Kentucky, between 2013 and 2016 to frame a natural experiment, which

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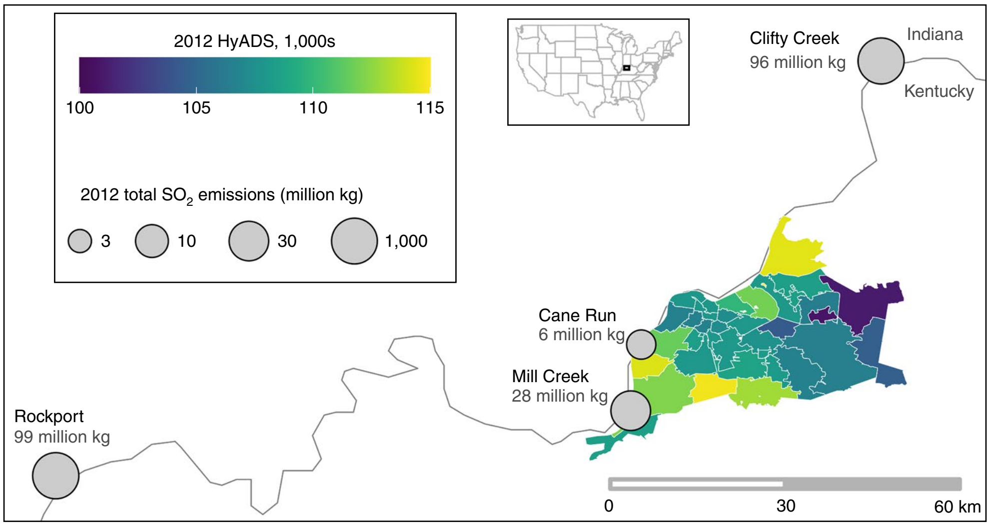

Fig. 1 | Power plant locations, emissions and exposure. The locations of the four coal-fired power plant facilities, their total SO_2 emissions (larger grey circles indicate higher emissions) and their total HyADS exposures at the ZCTA level within Jefferson County in 2012. Unit and facility data downloaded from the USEPA Air Markets Program[50].

generated abrupt changes in air pollution exposures that varied in extent across the Louisville area. The circumstances of these energy transitions and their resemblance to an experiment that (approximately) randomizes exposure changes motivates a variety of analysis approaches that each mitigate some of the common threats to observational studies. Our approaches include comparing asthma-related end-points in areas more and less exposed to changes in air pollution and individuals before and after the discrete transition events to evaluate impacts on the asthma-related end-points. Kentucky has historically ranked among the top five in the United States for SO_2, NO_2 and PM_{10} emissions from power generation[29]. We confirmed air-quality improvements after the power plant energy transitions using a longitudinal coal-fired power plant emission exposure model[30]. Analyses that leveraged different elements of spatial and temporal variability in exposure demonstrated that the coal-fired power plant energy transitions were associated with reductions in asthma-related hospitalizations and ERVs at the ZIP-code level and asthma symptoms measured at the individual level using digital medication sensors within the Louisville metropolitan area.

Impact of retirement, retrofit and conversion on emissions

Four coal-fired power plants—Cane Run, Clifty Creek, Mill Creek and Rockport—with emissions that impacted air quality in Jefferson County, Kentucky (which fully contains Louisville), either retired or installed SO_2 controls between 2012 and 2016 (Fig. 1). We quantified monthly ZIP-code variability in SO_2 emissions exposure from these plants using the HYSPLIT Average Dispersion (HyADS) model, which aggregates the results from 146,000 HYSPLIT runs per power plant[30]. During the study period, the quarterly median unitless HyADS exposure was 6,553 (interquartile range (IQR), 2,283 and 9,702; maximum, 31,781). Power plant energy transitions resulted in declining levels over time (Fig. 2 and Supplementary Figs. 1 and 2). Data from the Louisville Metro Air Pollution Control District confirmed that retirements at Cane Run and scrubbers at Mill Creek reduced the annual SO_2 emissions by 9.6 and 12.9 million kg, respectively (Supplementary Fig. 3). Comparing years pre- and post-control installations, SO_2 emissions also declined at Clifty Creek (−90%) and Rockport (–50%). These four facilities contributed 36, 30 and 16% of the total average ZIP-code HyADS exposure in Louisville in 2012, 2014 and 2016, respectively. The transitions at the four facilities contributed to an overall decline in coal-fired power plant emissions exposures in Jefferson County.

HyADS emissions exposures peaked annually during the third quarter (April–June, Fig. 2). In a companion analysis, we found that meteorological variability contributed more than emissions reductions to changing HyADS in 2012, 2013 and 2014[31]. Table 1 shows that, accounting for seasonality and meteorological factors, the average level of HyADS exposure decreased substantially after three of the four energy transitions, with a 55% decline from baseline after the second quarter of 2015 (Q2-2015).

Observed changes in ZIP-code-level asthma outcomes

The median (IQR) quarterly asthma hospitalizations/ERV counts across the 35 ZIP codes in Jefferson County between 2012 and 2016 was 16 (range 9–31), and the counts declined county-wide over time (Fig. 3 and Supplementary Table 1). Between 2012 and 2016 the rates of uninsured and unemployed individuals also fell. Quarter 4 typically exhibited hospitalization and ERV values higher than those of other quarters after adjusting for ZIP code and annual specific means.

Three of the four energy transitions were associated with reductions in ZIP-code-level asthma hospitalizations and ERVs (Table 2), which correspond to the three transitions associated with reduced HyADS (Table 1). The largest reduction in risk came after the Q2-2015 transitions, relative risk (RR) = 0.81; 95% confidence interval (CI), 0.70, 0.92. We therefore focused the next stage of analysis on the Q2-2015 transitions at Cane Run, Mill Creek and Rockport. During the time surrounding the Q2-2015 transition (Q2-2014 to Q2-2016), the average quarterly ZIP code HyADS reduction was 25,281 (standard deviation (s.d.) = 3,638).

In a difference-in-differences framework, we categorized ZIP codes based on their pre-period HyADS exposure (high versus low). The results indicated that the Q2-2015 energy transition reduced asthma hospitalizations and ERVs by an additional 2.8 visits per ZIP code per quarter in areas with high pre-transition exposure relative to areas with a lower pre-transition exposure (Fig. 4). When we specified pre-transition HyADS as a continuous variable, results were similar when converted into a comparable scale (−0.4 (95% CI: −0.2, −0.7)) asthma hospitalizations and ERVs per ZIP code per 1,000-unit higher pre-period HyADS exposure; Supplementary Fig. 4).

With a first-difference linear regression model, we found that a 1,000-unit ZIP-code-level reduction in HyADS exposure from the

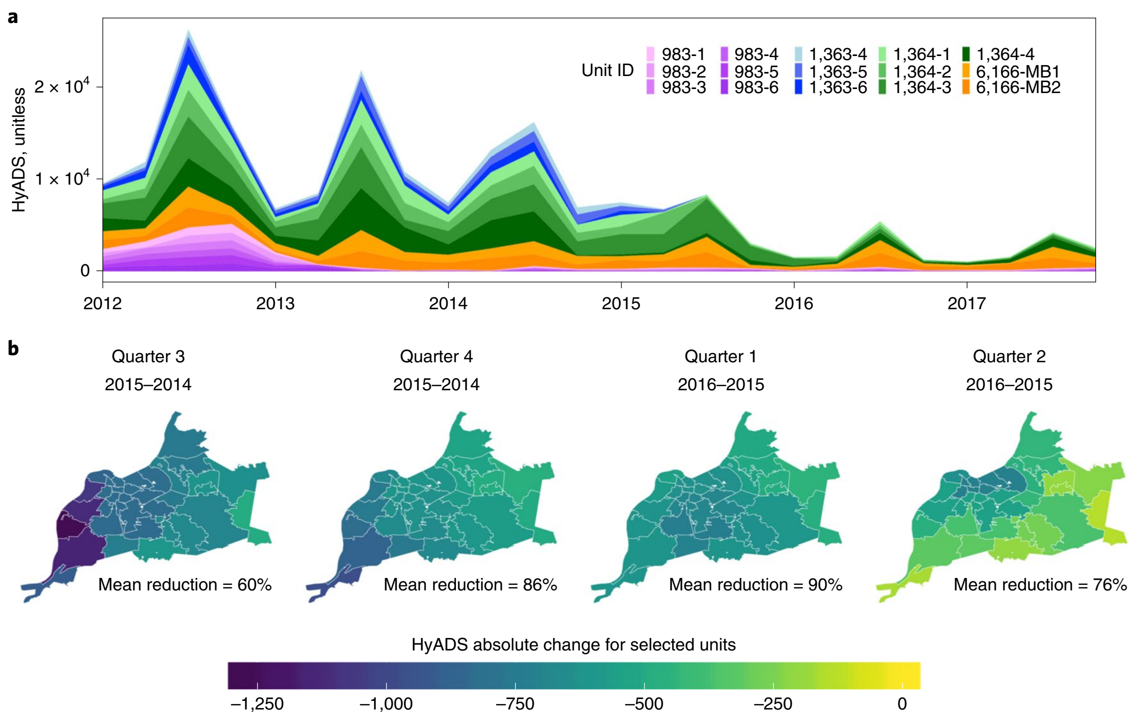

Fig. 2 | Quarterly mean ZIP code-level HyADS exposure in Jefferson County. a, From 2012 to 2017 stratified by coal-fired power plant unit. Clifty Creek, 983; Cane Run, 1,363; Mill Creek, 1,364; Rockport, 6,166. **b**, Absolute change in quarterly ZIP code tabulation area-level HyADS and mean percentage reduction across the two stated years in the stated quarter.

Table 1 | Coal-fired power plant events and HyADS emissions exposures

Coal-fired power plant transition date	%Δ HyADS (95% CI)
Q2-2013	11 (6, 16)
Q4-2014	−27 (−31, −23)
Q2-2015	−55 (−61, −47)
Q2-2016	−29 (−33, −24)

Association between coal-fired power plant events and ZIP-code-level HyADS emissions exposures in the 35 Jefferson County ZIP codes with a population greater than 5. %Δ was calculated relative to countywide average HyADS level in 2012 (11,392 units). Estimates provided from an ordinary least squares linear regression model adjusted for quarterly mean temperature, wind speed, relative humidity and atmospheric pressure, and quarter and ZIP code. Includes Liang and Zeger cluster-robust standard errors. Q1, quarter 1 (Jan–Mar); Q2, quarter 2 (Apr–June); Q3, quarter 3 (July–Sept); and Q4, quarter 4 (Oct–Dec).

year prior to the year after the Q2-2015 energy transitions resulted in, on average, 2.2 fewer asthma hospitalizations and ERVs (95% CI: −4.5, 0.2) per ZIP code per year and a first-difference model that specified categories of ΔHyADS showed the largest effect for the highest ΔHyADS category (Supplementary Fig. 4). Inferences remained stable in sensitivity analyses using baseline population weights instead of adjusting models for baseline population (Supplementary Table 2).

Observed changes in individual-level asthma symptoms

We identified 207 study participants in the AIR Louisville programme who were under observation during the year prior to and the year after the 8 June 2016 Mill Creek power plant scrubber installation. Most participants were female (67%), of white race/ethnicity (63%) and middle-aged (average age of 45 years) (Supplementary Table 3). Participants' median monthly HyADS exposure was 1,915 (IQR: 1,172, 3,050) (Supplementary Fig. 5). Participants had a daily mean of one short-acting beta agonist (SABA) inhaler use (s.d. = 1.5) and a median of no SABA uses (IQR = 0, 1). From visual inspection, daily rescue inhaler use was more prevalent and variable earlier in the study period, probably driven by the smaller number of enrolled participants (Supplementary Fig. 6) and later trended downward (Supplementary Fig. 7).

In a within-person conditional quasi-Poisson model, we observed a reduced monthly average daily SABA use associated with a reduced monthly HyADS exposure (RR = 0.94, 95% CI: 0.89, 0.98, for each 1,000-unit decrease in HyADS).

As the June 2016 Mill Creek scrubber installation resulted in relatively uniform reductions in HyADS exposure across Jefferson county (Fig. 5b), we used an interrupted time-series framework. We identified a level shift in SABA use (at the time of scrubber installation) and a possible slope change (decreasing trend in SABA use) (Fig. 6). The scrubber installation was associated with a 17% reduction in monthly average daily SABA use (RR = 0.83, 95% CI: 0.69, 1.00) and a 2% reduction (95% CI: −5%, 1%) for each month thereafter.

In two sensitivity analyses, we evaluated the change in odds of having any daily SABA use (monthly average of ≥1 use day^{-1} versus <1 use day^{-1}) and high daily SABA use (monthly average of ≥4 uses day^{-1} versus <4 uses day^{-1}) at the time of scrubber installation. We found an apparent larger immediate effect on higher monthly average daily SABA use (32% reduction (odds ratio = 0.68, 95% CI: 0.45, 1.02]) and a trend in reduced monthly average daily use of ≥1 uses (17% reduction each month after the scrubber installation (odds ratio = 0.83, 95% CI: 0.71, 0.97]) (Supplementary Table 4).

Discussion

The top four coal-fired power plants in terms of emissions that affect air quality in Louisville in 2012 either retired or installed SO_2 emission controls between 2012 and 2016. The resulting air-quality improvements translated into reductions in both acute asthma outcomes—measured by quarterly ZIP-code-level asthma-related

Fig. 3 | Quarterly ZIP-code-level counts of asthma hospitalizations and ERVs in Jefferson County. a, Countywide from 2012 to 2016. **b**, By ZCTA from 2012 to 2016. Data provided by the Louisville Metro Department of Public Health and Wellness.

Table 2 | Relative risk of ZIP-code-level asthma hospitalization and ERV

Coal-fired power plant transition date	RR (95% CI)
Q2-2013	1.08 (0.96, 1.19)
Q4-2014	0.90 (0.75, 1.06)
Q2-2015	0.81 (0.70, 0.92)
Q2-2016	0.91 (0.80, 1.03)

These estimates of relative risk are related to each coal-fired power plant event in the 35 Jefferson ZIP codes with a population greater than 5. They are provided from a quasi-Poisson regression model with a ZIP-code-level annual population offset and adjusted for annual percentage non-Hispanic black individuals, unemployed individuals, individuals living below the federal poverty threshold, quarterly mean temperature, wind speed, relative humidity and atmospheric pressure, and year, quarter and ZIP code. Includes Liang and Zeger cluster-robust standard errors.

hospitalizations and ERVs—and daily symptoms, as measured by sensor-collected SABA use. In the spring of 2015, coal-fired power plant units retired at Cane Run and SO_2 controls were installed at Mill Creek and Rockport. These energy transitions resulted in approximately three fewer hospitalizations and ERVs per ZIP code per quarter in the following year, which translates into nearly 400 (−2.8 per ZIP quarter × 4 quarters × 35 ZIPs) avoided hospitalizations and ERVs in Jefferson County annually. At the individual level, the Mill Creek SO_2 scrubber installed in June 2016 was associated with immediate reductions in SABA use and a marginally declining trend in use through May 2017.

Uniquely, this study found that exposure reductions to coal-fired power plant emissions were consistently associated with a reduced asthma morbidity at two spatial and temporal resolutions: monthly average daily SABA use within individuals and acute quarterly ERVs and hospitalizations at the ZIP-code level. Acute outcomes, such as hospitalizations, represent an important, yet more infrequent, severe and costly[32] signal of asthma morbidity. SABA use can represent the daily burden of disease and the future risk of adverse outcomes[33]. Our analyses used digital medication sensors to objectively track the time and location of SABA use and avoid the potential recall bias associated with the diaries used in previous studies of short-term air pollution levels and asthma[15,34,35].

In 2014, US power plants accounted for 64% of SO_2, 14% of NO_x and 7% of $PM_{2.5}$ economy-wide emissions, of which coal power comprised 98% of SO_2 and >82% of both NO_x and $PM_{2.5}$ power plant emissions[2]. Exposures to these air pollutants, even at relatively low levels, are associated with asthma morbidity[7,8,10,36]. Four main mechanisms—oxidative stress, airway remodelling, inflammation or immunological response and an enhanced response to inhaled allergens[37]—likely explain how air pollution contributes to asthma onset and exacerbation. Laboratory studies of SO_2 exposure among asthmatics have demonstrated bronchoconstriction in humans[38] and airway inflammatory and immune responses in rats[39].

In a 2017 report for the US Department of Energy, Massetti et al. characterized SO_2 as the main source of air-pollution-related economic damage associated with coal-fired power plants due to its high volume of emissions and because SO_2 is a $PM_{2.5}$ precursor[2]. Among populations that live close to coal-fired power plants, SO_2 is associated with wheeze and asthma prevalence[13,40], asthma attacks and ERVs[12,15,16], although it is likely that other pollutants play a role. Coal electricity generation contributes to anthropogenic $PM_{2.5}$ levels (which account for 1–3% of all asthma-related ERVs in the Americas[41]) and NO_2 exposures (which may cause 19% of asthma incidence in high-income countries[42]). Among children who lived near Israel's 2580 MW Orot Rabin coal-fired plant, a combined NO_x and SO_2 exposure was more strongly associated with a reduced pulmonary function test performance than either pollutant alone[14].

Several studies characterized exposure via residential proximity to coal-fired power plants, a metric that incorporates, albeit crudely,

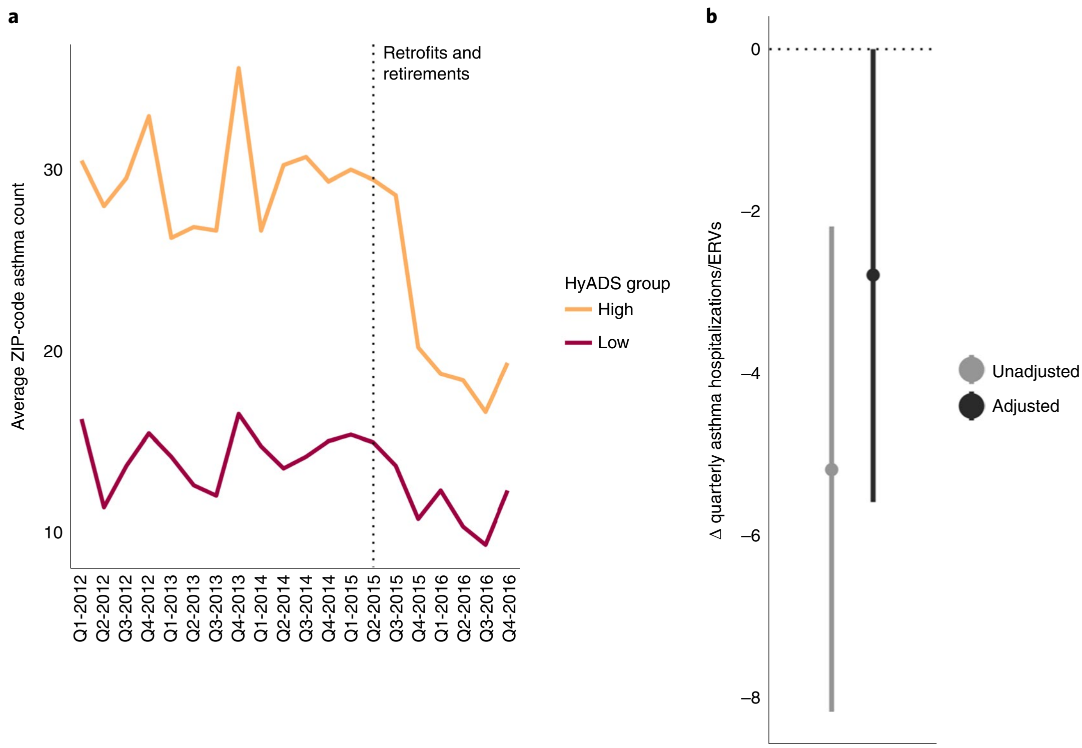

Fig. 4 | Spring 2015 coal-fired power plant events and counts of ZIP-code-level asthma hospitalization and ERVs. a, Trends in count of ZIP-code-level asthma hospitalization and ERVs from Q1-2012 to Q4-2016. The dashed line notes Q2-2015, where the transition took place late in the quarter. Prior to Q2-2015, trends in ZIP-code-level counts of asthma events appear parallel, which provides evidence that we meet the parallel trends assumption of difference-in-differences analysis. **b**, Difference-in-differences results with 95% CI from an ordinary least squares model (equation (3)) with a binary specification of pre-period HyADS (high (≥32,500) versus low (<32,500)). The model was adjusted for annual total population, percentage non-Hispanic black individuals, unemployed individuals, individuals living below the federal poverty threshold, quarterly mean temperature, wind speed, relative humidity and atmospheric pressure, and included fixed effects for year, quarter and ZIP code. Liang and Zeger cluster-robust standard errors were used.

multiple coal-related pollutants[17–19]. The continuous and quantitative HyADS metric improves the exposure characterization around coal-fired power plants and attempts to isolate the effect of collective coal emissions on health. However, the temporal resolution of our data and the HyADS metric make it difficult to compare our findings, in magnitude, to those of prior research that reports the relationships between coal-fired power plant exposure and increased diary-reported respiratory symptoms[12,13,40] and SABA use[15], as well as ERVs and hospitalizations[16,19].

Epidemiologists cannot randomize individuals to differing levels of air pollution, which can make causal inference challenging. Quasi-experimental designs[23] that leverage the circumstances of natural experiments provide one alternative method that, when paired with the appropriate analytical approaches, can mimic pseudo-randomization of individuals and populations to varying levels of environmental exposures[21,22]. Compared to traditional observational studies, quasi-experimental techniques are better equipped to handle unobserved differences in populations that might otherwise confound exposure–outcome associations[43]. A few prior studies of asthma exacerbations used quasi-experimental designs[24,26–28], for example, monitoring changes in asthma-related hospitalizations and acute care visits before, during and after an Olympic Games that reduced local air pollution[26,27]. Environmental exposures tend to follow a social gradient[44] and co-occurring factors, such as high body mass index, smoking, low socio-economic status and area-level racial segregation are risk factors for asthma[45]. Therefore, an abrupt change in an environmental exposure improves our ability to disentangle the social and environmental determinants of health.

To our knowledge, no study has focused on installations for the control of SO_2 emissions or on power plant retirements to assess the potential asthma-related health benefits. We examined multiple interventions across several years and tracked the intervention impacts at several phases (that is, intervention, emissions, exposure and health outcome). An important analytical decision in quasi-experimental studies is the choice of control group. Our difference-in-differences analysis compared changes between ZIP codes that were initially most exposed to the power plants that generated the transition and control ZIP codes that were comparatively less subject to exposure from these plants. In our first-difference analysis, we used ZIP codes that experienced less reduction in HyADS exposure during the study period to control for time trends in hospitalizations and ERVs and other factors over the study period, and thereby minimized the threat of confounding due to such factors. Both designs control for the variation in observed and unobserved fixed characteristics of place[46]. At the individual level, we implemented a within-person analysis, which regards each person as his or her own control, to reduce the threat of bias associated with confounding variables related to differences across people. This case time-series analysis only controlled for the overall linear temporal trends. Individual- and ZIP-code-level analyses consistently supported the notion that the energy transitions improved asthma outcomes.

This study has limitations. The AIR Louisville cohort participants were enrolled through a number of channels and did not have standardized clinical oversight. We lacked access to individual-level data on participants (for example, healthcare utilization, socio-economic status, smoking or tobacco-smoke exposure), although most of these factors are considered time-invariant and controlled for by

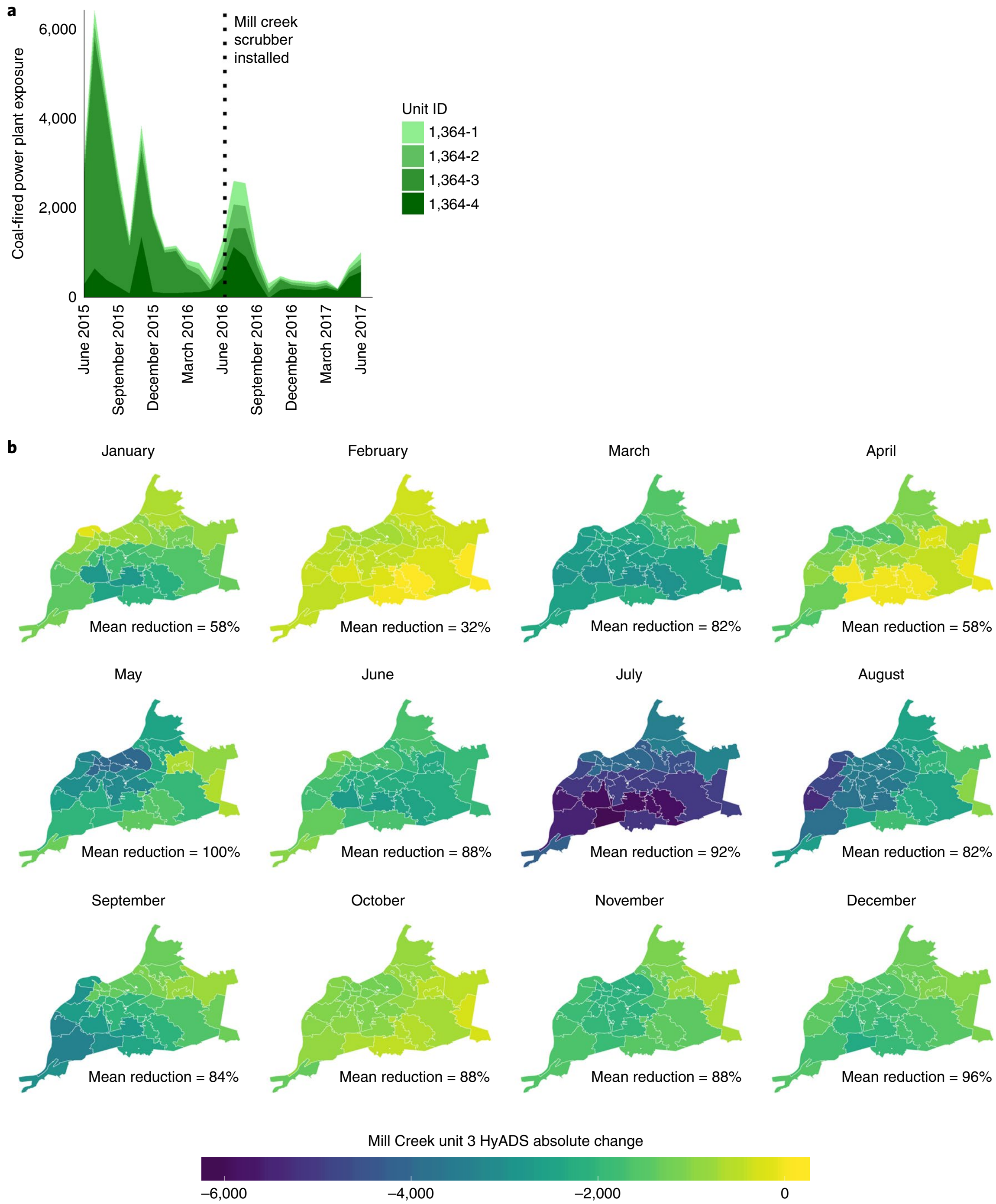

Fig. 5 | Monthly mean ZIP-code-level HyADS exposure from the Mill Creek power plant in Jefferson County, 2015–2017. a, Stratified by Mill Creek power plant unit. **b**, Average change in monthly mean ZIP code tabulation area-level coal-fired power plant air pollution exposure (HyADS) between 2015 and 2016.

the study design. Time-varying factors, however, both at the individual and area level could have confounded our results. A prior study found that the digital health intervention (that is, Propeller inhaler system) may have helped reduce SABA use, with the largest improvements during the first few months[47]. If enrolment in the programme coincided with plant changes, this could have resulted in overestimated effects. However, our within-person interrupted time-series design suggested an abrupt change in SABA use at the time of a SO_2-control installation and a continued decline thereafter. We assumed a linear trend in outcome, although changes may have followed a non-linear pattern. Although the results in Fig. 6 suggest that the largest change in SABA use corresponds to the largest drop in HyADS in Q2-2015, we lacked the individual-level data in the pre-period to assess this statistically. At the ZIP-code level, due to data limitations, we could not consider asthma-related hospitalizations and ERVs separately, nor could we track multiple events within individuals. Finally, we were not able to assess cumulative impacts; for example, the relationship between chronic coal-fired power-plant-related exposures and asthma prevalence or the co-occurrence of asthma and chronic disease. As the evidence is mixed

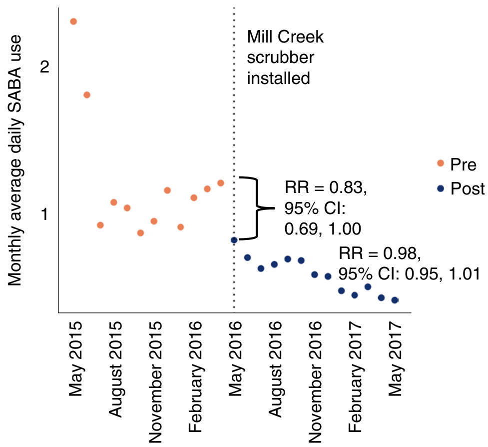

Fig. 6 | Monthly average daily SABA use before and after the June 2016 Mill Creek SO_2 scrubber installation. Orange represents the period prior to the scrubber installation and navy blue that after it. Points are the monthly average daily predicted SABA use from the adjusted model. Relative risks (RR) are from a conditional Poisson case interrupted time-series model, which should be interpreted within individual. The model was adjusted for temperature, humidity, windspeed, ambient pollen (grass, tree and weed), mould counts and long-term and seasonal trends. Lagged residuals were used to account for autocorrelation.

regarding the association between long-term air pollution exposure and asthma[10,48], this presents an area for future research.

Our study focused specifically on the impact of four coal-fired power plants, but took place against the backdrop of changing emissions at other power plants and reductions in vehicle emissions. We did not explicitly include air pollutants that might affect asthmatics, for example, SO_2, $PM_{2.5}$, NO_2 or ozone, but HyADS does represent an index of the mixture of pollutants emitted by power plants. Changes in air quality unrelated to power plants but that trended in time were controlled for in our models. Although the HyADS model provided a summary of coal-fired power-plant-specific exposure, it did so at the monthly level, which limited our ability to assess the relationship between short-term exposure fluctuations and SABA use.

In conclusion, this study showed reductions in coal-fired power plant air pollution exposure after retirements and SO_2 control installations near Louisville. These reductions appear to translate into substantially fewer asthma-related ERVs and hospitalizations, as well as fewer average daily SABA uses. Given that 20.4 million adults, or about 9% of the population, suffered from current asthma in 2016[49], the shift in US energy trends away from coal-fired electricity generation may reduce asthma morbidity below otherwise expected levels. Future research should evaluate this potential impact so that plant controls and retirement sites can be phased to affect neighbourhoods and schools at the highest risk for asthma.

Methods

The natural experiment. The circumstances that support this natural experiment arose in Jefferson County, which fully contains Louisville, a city that covers 842 km^2 and had a population of 600,000 people in 2010. We hypothesized that (1) coal-fired power plant emissions and subsequent population exposures dropped after the coal-fired power plant energy transitions and (2) the lower exposures resulting from energy transitions translated into fewer healthcare utilization events and symptoms. Our analyses used two health outcomes (acute asthma-related healthcare utilization and asthma symptoms) at two spatial scales (ZIP-code and individual level) and employed a measure of coal-fired power plant emission exposure.

Exposure to power plant emissions. From the USEPA Air Markets Program[50], we downloaded data on power plant facilities (which typically comprise multiple generating units) nationwide with at least one unit using coal as its primary fuel between 2008 and 2017. These data included power plant latitude and longitude, number of units and fuel type by unit, monthly SO_2 emissions, SO_2 control type and installation date, and retirement date. We obtained further information on the timing of the Jefferson County coal-fired power plant control installations, retirements and SO_2 emissions from the Louisville Metro Air Pollution Control District.

We estimated the exposure to power plant emissions over time using the recently developed HyADS model[30]. HyADS uses the HYSPLIT air parcel trajectory model[51] to quantify the extent to which any power plant influences air quality across US ZIP code tabulation areas (ZCTAs), which we mapped to ZIP codes using a crosswalk (https://www.udsmapper.org/zcta-crosswalk.cfm) (see Supplementary Note 1 and Henneman et al.[30] for details). This method produces a unitless measure of emissions influence that is highly correlated with related measured and modelled exposure metrics for coal emissions exposure[30,52]. HyADS has previously been applied to estimate US-wide health benefits achieved through reduced coal-fired power plant SO_2 emissions[53].

We ran HyADS for each of the over 1,009 US coal-fired power plant units in operation (located at 478 facilities) nationwide in 2012, 2014 and 2016. In 2012, we ranked each unit's exposure contribution in each Louisville ZIP code and identified the four facilities that had the highest influence on Louisville ZIP codes (Supplementary Fig. 8). These four facilities subsequently underwent retirement or control installations before 2017. We ran HyADS for each facility's units for years 2012–2017 to estimate the ZIP-code-level monthly (used in individual-level analyses) and quarterly (as the average of monthly, used in ZIP-code-level analyses) influence of each unit's emissions on Louisville air quality over time (Supplementary Data).

Emissions exposures for the four plants of interest. The four highest-ranked facilities by HyADS impact in 2012 included Cane Run, a 943 MW plant located 14 km southwest of downtown Louisville; Clifty Creek, a 1,303 MW plant located about 75 km northeast of Louisville that had the greatest impact of any coal-fired power plant in the country on east Jefferson County; Mill Creek, a 1,717 MW plant located 25 km southwest of downtown Louisville that had the greatest impact of any coal-fired power plant in the country on west Jefferson County and Rockport, a 2,600 MW plant located about 100 km west of Louisville.

Clifty Creek installed wet limestone scrubbers for units 1–3 on 20 March 2013 and for units 4–6 on 15 May 2013. The Mill Creek plant installed wet limestone scrubbers for unit 4 on 9 December 2014, for units 1 and 2 on 27 May 2015 and for unit 3 on 8 June 2016[54]. Cane Run retired its three active units in May 2015, after which a 650 MW natural gas combined cycle plant began operating at the site. Rockport installed dry sodium scrubbers on its two coal units in April 2015.

Area-level confounders of asthma symptoms. We assembled several indicators of community socio-economic status and demographic composition at the ZIP-code level from the US American Community Survey (ACS)[55]. These are variables potentially associated with coal-fired power plant exposure that might also predict asthma exacerbations[56] and included total population, number of non-Hispanic black individuals, number of individuals without health insurance coverage, number of individuals 16 years and older that were unemployed, number of individuals 25 years and older without a high school diploma or equivalent and number of individuals with income in the previous 12 months below the federal poverty level. To create a time-varying dataset, we linked multiple 5-yr surveys because annual ZCTA-level estimates were not available. For example, we used the 2008–2012 ACS to estimate ZCTA characteristics in 2012 and the 2009–2013 ACS for 2013, which we then assigned to ZIP codes using a crosswalk. Finally, we downloaded ZIP-code-level meteorological data on ambient temperature, relative humidity, windspeed and atmospheric pressure from the USEPA[57].

Jefferson County quarterly ZIP-code-level asthma data. The Louisville Metro Department of Public Health and Wellness provided quarterly combined counts of asthma-related hospitalizations and ERVs among all ages for the years 2012–2016 for all Louisville ZIP codes, which we restricted to the 35 ZIP codes with population greater than 5 in 2012. Hospitalizations and ERVs were considered asthma related if the following International Classification of Diseases 9 or 10 diagnosis codes were present in the first through to the third diagnosis positions: 493.XX or J45.X. To present health data spatially, we used a crosswalk to map ZIP codes to ZCTAs.

Participant recruitment for individual-level asthma data. Data for the individual-level analyses came from the AIR Louisville pilot (2012–2014) and full programme (2015–2017)[47]. Eligible participants ($n=1,021$ from pilot and full programme) were enrolled from 2012 to 2016 through multiple channels, which included employer partner wellness programmes, clinics, community events and social media campaigns. Inclusion criteria consisted of a self-reported diagnosis of asthma, a current prescription for a compatible inhaled medication for asthma and a home or work address in Jefferson County. Additional details on the study are given elsewhere[47]. Participants all agreed to and signed Propeller Health's Terms of Service, which stated that their data may be used in an aggregated fashion for public-health-oriented analyses. We also received a waiver of consent and exemption (PRH1-17-508) from the Copernicus Group Independent Review Board. The protocol was additionally approved by the University of California Berkeley Committee for Protection of Human Subjects.

We included participants in the analyses if they had inhaler-use data collected in the year before and the year after the coal-fired power plant energy transitions. We focused on the 8 June 2016 SO_2 scrubber installation for Mill Creek Unit 3, because this date supported the largest participation cohort for the individual-level analyses ($N = 207$, 20.3% of the entire AIR Louisville cohort) (Supplementary Fig. 9).

Digital health platform. All participants received digital sensors (Propeller Health, Madison) to attach to their inhaled SABA (that is, 'rescue') medications. The sensor and platform comprised a US Food and Drug Administration-cleared digital health intervention that combined inhaler sensors, mobile apps, web-based dashboards and predictive analytics for patients and clinicians[47,58,59]. The sensor objectively monitored the use of inhalers, capturing the date, time of day and number of actuations, and wirelessly transmitted these data back to secure servers through a smartphone application or hub base station. Actuations that occurred within 2 min were grouped into a single-use event, and therefore each use could represent multiple actuations. The sensors regularly transmitted medication use data back to the server ('sync') through the smartphone or hub, and also transmitted a 'heartbeat' signal, which reported sensor battery life, confirmed no actuations had occurred since the previous sync and recorded the participant's GPS (global positioning system) location from which we assigned HyADS exposure estimates. Heartbeats occurred approximately every 3 h .

The majority (98%) of participants entered the cohort in 2015 or 2016 with a mean (standard deviation) duration of follow-up of 602 (321) days from first to last day under observation. We used the monthly average count of SABA use events per person per day as our outcome of interest.

Individual meteorological data and plant-specific exposures. Over 85% of SABA-use events and heartbeats had a recorded location. For those SABA events without a GPS location (about 6%), we retro-filled the location information with the most recent recorded location within 24 h before or after the index event. If no location was available, we assigned the participant's home address location. At the time and place of inhaler use or sensor heartbeat, we assigned hourly meteorological data, which included temperature, wind speed, atmospheric pressure and relative humidity from the National Oceanic and Atmospheric Administration for the years 2008–2016[60]. These data were averaged first to daily and then to monthly means. A specialty clinic, Family Allergy & Asthma, provided daily counts of grass, weed and tree pollen, as well as of mould spores from their National Allergy Bureau-certified pollen-counting station in Louisville. We assigned each SABA use or heartbeat event daily pollen or mould counts based on the event date, with events that occurred on the same day assigned the same pollen or mould counts. For analyses, we took the monthly mean of the pollen or mould count. We assigned monthly HyADS exposures based on the ZIP code in which the participant spent the most time that month. We linked a measure of community social vulnerability in 2014 from the US Centers for Disease Control and Prevention to each individual's census tract of residence[61].

Statistical analysis. We conducted ZIP-code and individual-level analyses to test the hypothesis that coal-fired power plant energy transitions altered air quality and thereby asthma morbidity among populations living nearby. In Supplementary Table 5, we provide a roadmap for all the analyses, which includes questions, datasets, analyses and locations of results. We performed analyses using R Statistical Software version 3.5.1 (R Core Team (2018) https://www.R-project.org/). Individual-level analyses were conducted using the gnm package (https://cran.rproject.org/package=gnm). All the tests were two-sided.

ZIP-code level HyADS analysis. We first tested whether the energy transitions were associated with reduced HyADS exposures throughout Louisville. To do so, we used linear regression to fit the equation:

$$\begin{aligned}\text{HyADS}_{pqr} = \beta_0 + \beta_1\text{Transition1}_{pqr} + \beta_2\text{Transition2}_{pqr} + \beta_3\text{Transition3}_{pqr} \\ + \beta_4\text{Transition4}_{pqr} + \boldsymbol{\lambda}_{pqr} + P_p + Q_q + \varepsilon_{pqr}\end{aligned} \quad (1)$$

HyADS_{pqr} is the level of HyADS in ZIP code p, quarter q, and year r. Transition1_{pqr}–Transition4_{pqr} are indicator variables equal to 1 if the energy transition has occurred and 0 otherwise. For example, Transition1_{pqr} equals 1 after Q2-2013 and 0 beforehand, Transition2_{pqr} equals 1 after Q4-2014 and 0 beforehand. P_p and Q_q are indicator variables for the ZIP code and quarter of year, respectively. $\boldsymbol{\lambda}_{pqr}$ is a set of quarterly meteorological variables that include temperature, wind speed, relative humidity and atmospheric pressure. Coefficients β_1–β_4 can be interpreted as the change in HyADS associated with their respective energy transition; negative values indicate decreased HyADS post-transition.

ZIP-code-level quasi-Poisson asthma analysis. We then used three approaches to estimate the relationship between energy transitions and ZIP-code-level asthma hospitalizations and ERV counts. The first was a generalized linear model with a quasi-Poisson distribution, which accommodates overdispersion, and a log link:

$$\begin{aligned}\log\left[E\left(\text{Asthma}_{pqr}\right)\right] = \log\left(\text{totpop}_{pr}\right) + \beta_0 + \beta_1\text{Transition1}_{pqr} + \beta_2\text{Transition2}_{pqr} \\ + \beta_3\text{Transition3}_{pqr} + \beta_4\text{Transition4}_{pqr} + \boldsymbol{\lambda}_{pqr} + \boldsymbol{\theta}_{pr} + P_p + Q_q + R_r\end{aligned} \quad (2)$$

where $E(\text{Asthma}_{pqr})$ represents the expected quarterly asthma hospitalization and ERV counts, totpop_{pr} is the estimated ZIP-code-level population. $\boldsymbol{\theta}_{pr}$ is a set of demographic variables from the ACS that includes percentage non-Hispanic black individuals, percentage individuals living in poverty and percentage unemployed individuals. R_r is the year indicator variable. We included population as an offset.

ZIP-code-level difference-in-differences asthma analysis. A second analysis of the natural experiment posed by the Q2-2015 transitions used a quasi-experimental difference-in-differences design to evaluate how asthma outcomes differentially changed in ZIP codes defined as either 'low' or 'high' HyADS exposure based on the average pre-period (Q2-2014 to Q2-2015) HyADS exposure. The post-period spanned the year after Q2-2015, so the analysis covered the time period that surrounded the installation of the scrubbers on units 1 and 2 of the Mill Creek plant and both units of the Rockport plant, and the retirement of Cane Run's three units. Difference-in-differences analysis is commonly used in studies of natural experiments and can effectively eliminate both observed and unobserved confounding variables that do not vary in time[46,62]. We categorized ZIP codes as 'low' when their pre-period average HyADS was <32,500 (near the median) and 'high' when their pre-period HyADS was ≥32,500, selecting the cutoff based on the change's distribution (Supplementary Fig. 10). By estimating the change in asthma hospitalization and ERVs from the pre- to the post-period (difference 1) and subtracting off the difference between the exposed and control exposure ZIP codes (difference 2), we estimated the effect of the Q2-2015 energy transitions in Jefferson County. We used the parametric equation:

$$\begin{aligned}\text{Asthma}_{pqr} = \; & \beta_0 + \beta_1 H_{pqr} + \beta_2 C_{pqr} + \beta_3 H_{pqr} \times C_{pqr} + \boldsymbol{\lambda}_{pqr} + \boldsymbol{\theta}_{pr} \\ & + P_p + Q_q + R_r + \varepsilon_{pqr}\end{aligned} \quad (3)$$

where H_{pqr} is an indicator variable equal to one for ZIP codes with pre-period HyADS ≥ 32,500 (that is, exposed). The group of ZIP codes with pre-period HyADS <32,500 served as the control group because these ZIP codes were less exposed in the pre-period and therefore benefitted less from the Q2-2015 energy transitions, but experienced similar secular trends as the high pre-period HyADS group. C_{pqr} is an indicator variable equal to one when the quarter is after Q2-2015. β_3 represents the difference-in-differences estimate of interest. We also specified a continuous model by comparing ZIP codes with differing levels of pre-period HyADS rather than creating a cut point. To do so, we replaced the H_{pqr} indicator variable with the pre-period continuous HyADS level. We opted to include the described set of potential confounding variables in equation (3) based on a priori hypotheses, causal diagrams[63] and the correlation structure of potential covariates (Supplementary Fig. 11). For example, annual unemployment and uninsured status had a Spearman correlation of 0.84, so we included only unemployment in our models to avoid instability in the parameter estimation due to multicollinearity. Difference-in-difference analysis relies on the parallel trends assumption, that is, in the absence of intervention, trends in the outcome in the pre-period continue[62]. We visually inspected trends over time by low and high pre-Q2-2015 HyADS and found no evidence of a violation (Fig. 4a).

ZIP-code-level first-difference analysis. In a secondary analysis, we used a first-difference design[64] to evaluate the relationship between the pre-post change in HyADS and pre-post change in ZIP-code-level hospitalization and ERVs (Supplementary Note 2). This model took the form:

$$\Delta\text{Asthma}_{pr} = \beta_0 + \beta_1\Delta\text{HyADS}_{pr} + \Delta\boldsymbol{\lambda}_{pr} + \Delta\boldsymbol{\theta}_{pr} + \Delta\varepsilon_{pr} \quad (4)$$

where ΔAsthma_{pr} represents the differences between counts of ZIP-code-level asthma hospitalization and ERVs in the year prior to Q2-2015 and the year after Q2-2015 and ΔHyADS_{pr} represents the ZIP-code-level difference in HyADS exposure to the three facilities with energy transitions from the year prior to Q2-2015 to the year after Q2-2015. We took differences in the meteorological and demographic variables ($\Delta\boldsymbol{\lambda}_{pr}$ and $\Delta\boldsymbol{\theta}_{pr}$) by subtracting the average value between Q2-2014 and Q1-2015 from the average value between Q3-2015 and Q2-2016. This estimator is unbiased when ε_{pr} is independent of ΔHyADS_{pr}, $\Delta\boldsymbol{\lambda}_{pr}$ and $\Delta\boldsymbol{\theta}_{pr}$. In a separate model, we allowed for non-linearity in the association between $\Delta HyADS_{pr}$ and ΔAsthma_{pr} by specifying quintiles of ΔHyADS_{pr}. In both the difference-in-differences and first-difference models, we accounted for correlation within the ZIP codes using Liang and Zeger cluster-robust standard errors[65]. We also completed a sensitivity analysis using baseline population weights rather than adjusting equations (3) or (4) for estimated total population.

Individual-level case time-series analysis. We used a case time-series analysis that included 207 participants under observation in the year prior and year after the

June 2016 Mill Creek scrubber installation. The case time-series design is a within-person analysis that allows for the control of individual-level confounders similar to other case-only methods such as case-crossover and self-controlled case-series designs[66,67]. Unlike the case-crossover design, the case time-series design does not rely on the assumptions of risk-set sampling[68]. It maintains the temporal structure of the time-series format, which allows for modelling of trends over time. It can also accommodate count data and account for overdispersion and autocorrelation in counts within stratum (that is, the individual). The conditional Poisson model assumes no unmeasured confounding that is not homogeneous within the strata. We adjusted for measured time-varying meteorological variables and seasonal trends. The model also assumes no residual autocorrelation of counts (to this end we adjust for the lagged residuals). We also relaxed the assumption of the Poisson distribution to allow for overdispersion of counts and assessed the relationship between exposure to coal-fired power plant emissions and monthly average daily SABA use with the conditional quasi-Poisson model:

$$\log[E(\mathrm{Inhaler\_use}_{im})] = \alpha_i + \beta_0 + \beta_1 T + \beta_2 \mathrm{HyADS}_{im} + \boldsymbol{\lambda}_{im} + s_m + r_{im-1} \quad (5)$$

assuming a quasi-Poisson distribution to account for overdispersion. $\mathrm{Inhaler\_use}_{im}$ is the average daily count of SABA uses for individual i in month m (conditional on the total number of SABA uses for individual i), α_i is a parameter for individual level effects (see equation (6) for more detail), T is the number of days elapsed since May 2015, HyADS_{im} is the total HyADS exposure in participant i's ZIP code in month m, $\boldsymbol{\lambda}_{im}$ is a vector of meteorological variables including natural cubic splines for temperature, relative humidity, wind speed, atmospheric pressure and mould counts, and linear terms for ambient pollen concentrations (that is, weed, tree and grass) and s_m is a harmonic term with 2 sine–cosine pairs and a period of 12 months to account for seasonal trends. The model adjusts for autocorrelation by adding the residuals r_{im-1} for individual i in month $m-1$, which were estimated as the residuals of a model fitted as in equation (5) without the residual term and lagged by one month[66,69]. The parameters α_i are not estimated by the model, but are rather conditioned out, by conditioning on the sum of the total number of inhaler uses for each individual i, $\sum_i \mathrm{Inhaler\_use}_{im}$, which results in a multinomial model with the likelihood:

$$\mathrm{Inhaler\_use}_{im} \Big| \sum_m \mathrm{Inhaler\_use}_{im} \approx \mathrm{Multinomial}(\pi_m)$$
$$\pi_m = \frac{\exp(\beta_0 + \beta_1 T + \beta_2 \mathrm{HyADS}_{im} + \boldsymbol{\lambda}_{im} + s_m)}{\sum_j \exp(\beta_0 + \beta_1 T + \beta_2 \mathrm{HyADS}_{ij} + \boldsymbol{\lambda}_{ij} + s_j)} \quad (6)$$

where $j \in$ the subset of m with observations for each participant i. Next, we sought to directly test the relationship between the June 2016 Mill Creek energy transition and SABA use. Unlike the Q2-2015 energy transitions, the June 2016 Mill Creek unit 3 scrubber installation resulted in fairly uniform reductions in exposure to plant emissions across Jefferson County (Fig. 4b). This precluded the assembly of a control group based on exposure change analogous to that in the ZIP-code-level difference-in-differences analysis. Instead, we implemented an interrupted time-series design, which construes each person's study time during the pre-installation period as a control for his or her time during the post-installation period. To do so, we modified equation (5) by replacing HyADS_{im} with a single indicator variable, cntrl_{im}, of exposure to the SO_2 control installation at Mill Creek in June 2016, which took the value of 1 beginning in May 2016 (Mill Creek unit 3 was turned off in May for the June control installation) and 0 otherwise. We also added an interaction between cntrl_{im} and T to estimate trends in changing SABA use over time. A negative coefficient for the cntrl_{im} variable indicates that the average number of rescue inhaler uses decreased after the scrubber installation. Likewise, a negative β on $\mathrm{cntrl}_{im}T$ indicates a downward linear trend in rescue inhaler use over time after the installation.

To assess the sensitivity of the individual-level analysis, we evaluated the association between the June 2016 Mill Creek event and two different binary specifications of SABA use: any use and high use. We followed a similar model specification to that in equation (5), but used a logistic regression model and substituted for the $\mathrm{Inhaler\ use}_{im}$ variable an any-SABA-use variable (monthly average of ≥ 1 use day^{-1} versus <1 use day^{-1}) and a high-SABA-use variable (monthly average of ≥ 4 uses day^{-1} versus <4 uses day^{-1}).

Reporting summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

The ZIP-code-level asthma hospitalization and ERV data are available from the authors following the submission of an analysis proposal and written approval granted by the Louisville Metro Public Health and Wellness. The AIR Louisville monthly medication use data are considered Protected Health Information under the Health Insurance Portability and Accountability Act of 1996 (HIPAA) in the United States, and as such may be accessible from the authors for analysis only after specific written authorization of access following HIPAA guidelines and Institutional Review Board approval. We provide Jefferson County ZIP-code-level monthly HyADS estimates on GitHub at https://github.com/joanacasey/ky_asthma_coal.

Code availability

An R package is available on GitHub for running the HyADS model (https://github.com/lhenneman/disperseR). We also provide analysis code on GitHub at https://github.com/joanacasey/ky_asthma_coal.

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Author contributions

J.A.C., T.S. and M.A.B. secured funding for the study. J.A.C., J.G.S., L.R.F.H., C.Z., A.M.N., R.C., S.S.M., Y.-T.C., J.S. and M.A.B. designed the study and provided exposure and outcome data. J.A.C. and A.M.N. carried out the statistical analyses. J.A.C., J.G.S., L.R.F.H., C.Z., A.M.N., R.C., R.G., Y.-T.C., L.K., S.S.M., V.C., G.S., T.S., J.S. and M.A.B. reviewed and critically revised the manuscript.

Competing interests

M.A.B., R.G. and L.K. are salaried employees of Propeller Health and J.G.S. receives limited funding from Propeller Health to conduct analyses.

Additional information

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Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	Asthma data were provided by the Louisville Metro Public Health and Wellness and Propeller Health. Inputs for the HyADS model were downloaded from US Environmental Protection Agency's Air Markets Program Database. An R package is available on Github for running the HyADS model (https://github.com/lhenneman/hyspdisp).
Data analysis	We used R statistical software and provide code for the main analyses on GitHub at https://github.com/joanacasey/ky_asthma_coal.

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The ZIP code-level asthma hospitalization/ED visit data are available following approval by the Louisville Metro Public Health and Wellness from the authors.
The AIR Louisville monthly medication use data are considered Protected Health Information (PHI) under the Health Insurance Portability and Accountability Act of 1996 (HIPAA) in the U.S., and as such may be accessible from the authors for analysis only after specific written authorization of access following HIPAA guidelines and IRB approval.
We provide Jefferson County ZIP code-level monthly HyADS estimates on GitHub at https://github.com/joanacasey/ky_asthma_coal.
Other environmental data are publicly-available for download or available from the authors upon request.

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Study description

This study uses two types of data: ZIP code level asthma hospitalization/emergency department quarterly counts from 2012-2016 and individual-level daily rescue inhaler use (aggregated to monthly averages) data from the AIR Louisville Cohort.
Data are longitudinal and quantitative.

Research sample

ZIP code-level data: The Louisville Metro Department of Public Health and Wellness provided quarterly ZIP code-level combined counts of asthma-related hospitalizations and ED visits for the years 2012–2016. Hospitalizations and ED visits were considered asthma-related if the following International Classification of Diseases 9 (ICD-9) or ICD-10 diagnosis codes were present in diagnosis positions 1–3: 493.XX or J45.X. The ZIP code-level data includes all asthma-related hospitalizations and ED visits in Jefferson county over the study period. The median (IQR) ZIP population in 2012 was 21,500 people (13727, 30352).

Individual-level data: Our analysis included 207 participants. The average age was 44.7 years (SD = 17.6) and 67% of participants were women. We used this study sample because these individuals were under observation during the year before and after the June 2016 Mill Creek sulfur dioxide scrubber installation. Participants were enrolled from 2012 to 2016 through a number of channels, including employer partner wellness programs, clinics, community events, and social media campaigns. Inclusion criteria consisted of a self-reported diagnosis of asthma, a current prescription for a compatible inhaled medication for asthma, and living or working in Jefferson County, Kentucky. No incentives were provided for participation, but participants could benefit from no-cost use of the digital health intervention and contribute to a community program. The full AIR Louisville cohort contained 1039 individuals, mean age 34.9 years (SD = 17.6) and also primarily female (n = 659 [63%]). Therefore, our subsample was slightly older but with a similar sex-distribution compared to the full cohort.

Sampling strategy

ZIP code-level: we obtained all hospitalization/ED visits during the study period.

Individual-level: we used the portion of the existing AIR Louisville cohort that had data overlapping the relevant time period (n = 207). The original cohort (n = 1039 participants) made efforts to achieve geographic, socioeconomic and demographic representation similar to that of Jefferson County.

Data collection

ZIP code-level: The Louisville Metro Department of Public Health and Wellness provided the asthma data collected from local hospitals based on diagnostic codes.

Individual-level: Eligible participants were enrolled in the AIR Louisville pilot program from June 2012–December 2016. Basic demographic information (e.g., age, sex) was collected. All participants received digital sensors (Propeller Health, Madison, WI) to attach to their inhaled medications for asthma, including short-acting beta agonist (SABA, i.e., “rescue”) medications. The sensor and platform comprised a U.S. Food and Drug Administration-cleared digital health intervention that combined inhaler sensors, mobile apps, web-based dashboards and predictive analytics for patients and clinicians. The sensor monitored the use of inhalers, capturing the date, time of day, and number of actuations, and wirelessly transmitted these data back to secure servers through a smartphone application or hub base station. Actuations occurring within 2 minutes were grouped into a single use event, therefore each use could represent multiple actuations. The sensors regularly transmitted medication use data back to the server (“sync”) through the smartphone or hub, and also transmitted a “heartbeat” signal, which reported sensor battery life and confirmed no actuations had occurred since the last sync. Heartbeats occurred approximately every 3 hours. Over 85% of SABA use events and heartbeats had a recorded location. For those SABA events missing a GPS location (about 6%), we retro-filled location information with the most recent recorded location within 24 hours before or after the index event. If no location was available, we assigned the participant’s home address location. Researchers involved in this data collection were not aware of the current study question/hypotheses.

Timing

ZIP code-level: collection of hospitalization/ED visit data spanned January 1, 2012 to December 31, 2016.

Individual-level: Eligible participants were enrolled in the AIR Louisville pilot program from June 2012–December 2016. For the present analysis, we only included individuals (n = 207 [20% of the original cohort]) that had observations in the year prior (June 2015-June 2015) and year following (June 2016-June 2017) the June 2016 Mill Creek scrubber installation.

Data exclusions

ZIP code-level: no data were excluded.

Individual-level: we excluded participants from the AIR Louisville cohort who did not have observations in the year before and after the June 2016 Mill Creek scrubber installation. This was determined a priori.

Non-participation

The AIR Louisville cohort used open enrollment between June 2012-December 2016. For the overall cohort, the median follow-up was 436 days (IQR: 188-628). In our subset (n = 207), median follow-up was 549 days (409-740). 81% of our subset had follow-up through the last quarter of 2016. Our within-person analysis should help prevent extrapolation beyond the data (since some individuals were lost to follow-up prior to Q4-2016).

Randomization	Participants were not randomized.

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☒	☐ Clinical data

Methods

n/a	Involved in the study
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☒	☐ MRI-based neuroimaging

Human research participants

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Population characteristics	See above.
Recruitment	ZIP code-level: no recruitment Individual-level: Eligible participants were enrolled in the AIR Louisville pilot program from 2012–2016 through multiple channels, including employer partner wellness programs, clinics, community events, and social media campaigns. Inclusion criteria consisted of a self-reported diagnosis of asthma, a current prescription for a compatible inhaled medication for asthma, and a home or work address in Jefferson County, Kentucky. No incentives were provided for participation, but participants could benefit from no-cost use of the digital health intervention and contribute to a community program. All participants agreed to and signed Propeller Health's Terms of Service, which clearly states that their data may be used in an aggregated fashion for public health-oriented analyses. We also received a waiver of consent from the Copernicus Review Board. An attempt was made via recruitment to achieve geographic, socioeconomic and demographic representation similar to that of Jefferson County. Participants who enrolled via social media campaigns may have been self-selecting as more interested in technology than other enrollees.
Ethics oversight	The protocol was approved by the Copernicus Independent Review Board and the UC Berkeley Committee for Protection of Human Subjects.

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