

Changes in Ultrafine Particle Concentrations near a Major Airport Following Reduced Transportation Activity during the COVID-19 Pandemic

Sean C. Mueller,* Neelakshi Hudda, Jonathan I. Levy, John L. Durant, Prasad Patil, Nina Franzen Lee, Ida Weiss, Tyler Tatro, Tiffany Duhl, and Kevin Lane



Cite This: *Environ. Sci. Technol. Lett.* 2022, 9, 706–711



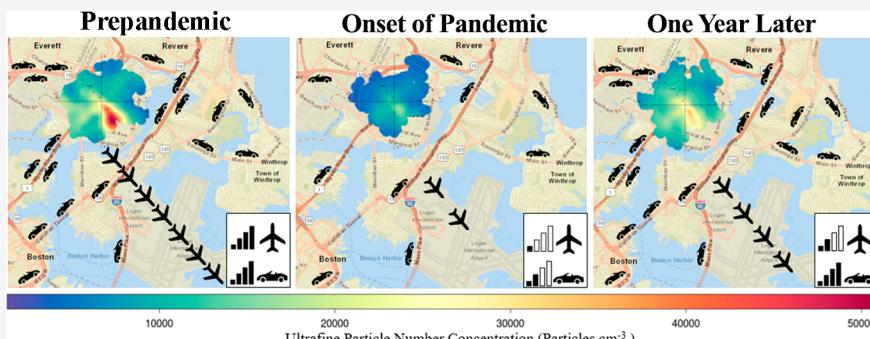
Read Online

ACCESS |

Metrics & More

Article Recommendations

Supporting Information



ABSTRACT: Mobility reductions following the COVID-19 pandemic in the United States were higher, and sustained longer, for aviation than ground transportation activity. We evaluate changes in ultrafine particle (UFP, $D_p < 100$ nm, a marker of fuel-combustion emissions) concentrations at a site near Logan Airport (Boston, Massachusetts) in relation to mobility reductions. Several years of particle number concentration (PNC) data prepandemic [1/2017–9/2018] and during the state-of-emergency (SOE) phase of the pandemic [4/2020–6/2021] were analyzed to assess the emissions reduction impact on PNC, controlling for season and wind direction. Mean PNC was 48% lower during the first three months of the SOE than prepandemic, consistent with 74% lower flight activity and 39% (local)–51% (highway) lower traffic volume. Traffic volume and mean PNC for all wind directions returned to prepandemic levels by 6/2021; however, when the site was downwind from Logan Airport, PNC remained lower than prepandemic levels (by 23%), consistent with lower-than-normal flight activity (44% below prepandemic levels). Our study shows the effect of pandemic-related mobility changes on PNC in a near-airport community, and it distinguishes aviation-related and ground transportation source contributions.

KEYWORDS: COVID-19, air pollution, aviation, ultrafine particles, natural experiment, traffic, emissions reduction impact

INTRODUCTION

Natural experiments have provided insight about air pollution source impacts. For example, policies to reduce vehicular traffic and congestion during the 1996 Olympics (Atlanta, Georgia, USA) reduced peak daily ozone concentrations by 28%.¹ The temporary shutdown of a large steel mill in Utah (USA) in 1986 reduced PM_{10} concentrations by nearly half,² and during the 2008 Olympics (Beijing, China), air pollution emission controls reduced traffic-related emissions between 21% and 61%.³ A recent and significant change to source activities coincided with the onset of the COVID-19 pandemic in 2020. In that year, road transportation and commercial flight activity decreased globally by 50% and 60%, respectively, relative to prepandemic levels.⁴ In comparison to the shutdown of commercial aviation operations in response to the September 11, 2001, attacks, the COVID-19 pandemic disrupted aviation

service more substantially in the short term (96% during COVID-19 vs 33% following 9/11), and travel restrictions continued for a longer period of time.⁵

Changes in air quality associated with the COVID-19 pandemic have been documented in numerous locations, including Asia,^{6,7} Europe,⁸ India,⁹ and the United States.¹⁰ These studies largely focused on short-term (i.e., two to three months) impacts during periods of pandemic-related economic and social disruptions. However, such short-term studies may

Received: May 17, 2022

Revised: August 2, 2022

Accepted: August 3, 2022

Published: August 15, 2022



not adequately capture air pollution changes from differential activities across sectors, especially for pollutants with strong seasonality. This is important for pollutants like ultrafine particles (UFP; <100 nm in aerodynamic diameter) in urban areas with multiple emission sources. Few studies have documented the UFP air quality impacts of the COVID-19 pandemic; a systematic review¹¹ noted only two articles measuring ultrafine particles, with an additional article published more recently. The studies measuring or modeling UFP were short-term in nature, with the longest monitoring campaign being approximately seven weeks, and all were focused on road traffic.^{12–14} Although UFP exposure in near-airport communities has been shown to be elevated¹⁵ in the U.S.^{16–18} as well as other countries^{19–22} during normal airport operations, to date little work has been done to characterize air quality impacts due to sharp decreases in aviation activity during the pandemic.

The goal of this study was to quantify the changes in UFP (measured as particle number concentration, or PNC) at a near-airport site in response to an unprecedented change in flight activity. We analyze PNC measurements collected over multiple years at a rooftop site near a major airport (Logan International Airport, Boston, Massachusetts, USA). Our objectives were to (1) quantify the overall decrease in PNC during the early state-of-emergency (SOE) period that coincided with the maximum decrease in activity for all modes of transportation and (2) examine if changes in PNC in the year following the start of the SOE corresponded to the differential rates of recovery of aviation and road traffic.

MATERIALS AND METHODS

Boston Logan International Airport and Monitoring Site. Logan International Airport is located 1.6 km east of downtown Boston. The airport has six runways, with a preferred operational runway configuration for each wind-direction quadrant. Continuous monitoring of PNC was conducted atop a three-story building located in a mixed-use (including residential) community in Chelsea, 4.0 km NW of the airport. This site and the surrounding area have been described elsewhere;^{23,24} briefly, the site is near several other transportation modalities (major roadway 400 m to the west, a commuter rail line 50 m to the north, and an active shipping channel 1 km to the southeast; see Supporting Information (SI) Figure S1). During SE winds, which occur at 7% frequency and orient the site downwind of the airport, emissions from the airport (i.e., from ground transportation and idling and taxiing aircraft) as well as aircraft landing on runway 15 are advected toward the monitoring site.

Massachusetts State-of-Emergency (SOE). In response to the COVID-19 pandemic, a state-of-emergency (SOE) was declared in Massachusetts on March 10, 2020, which was lifted on June 15, 2021.²⁵ At the beginning of the SOE period, a stay-at-home-advisory was issued, requiring all nonessential businesses, schools, and other organizations to close their physical workplaces, and recommending residents to stay home and avoid travel. The ending of the stay-at-home-advisory on May 18, 2020 initiated the reopening of the Massachusetts economy, with restrictions being relaxed in a gradual process according to four predetermined phases. However, after restrictions were eased from May 2020 through November 2020, they were increased again starting in November 2020 given increasing COVID-19 cases and hospitalizations and gradually rescinded starting in February

2021. Air quality measurements were made from April 2020 through June 2021 and were compared with prepandemic measurements from 2017 and 2018.

Instrument and Data Acquisition. Ambient PNC was monitored using a water-based condensation particle counter (CPC, TSI Inc. Model 3783, D_{50} of 7 nm) from January 2017 through June 2021, with several discrete periods where monitoring did not occur, notably October 2018 through March 2020. Field procedures, the quality assurance (QA) protocol, and the calibration procedures are described in the SI (Table S1). Approximately 5% of data were removed prior to analysis mainly due to automatically flagged CPC parameter exceedances (e.g., nozzle pressure and pulse height). Hourly landing and takeoff (LTO) (hourly totals for landings (arrivals) and takeoffs (departures)) from January 2017–June 2021 were obtained from the Federal Aviation Administration Aviation System Performance Metrics Database.²⁶ Meteorological data collected at Logan Airport (KBOS) were obtained from the National Centers for Environmental Information Automated Surface Observing Systems (ASOS) program and aggregated to hourly resolution via the U.S. Environmental Protection Agency's AERMINUTE and AERMET processors.²⁷ In short, AERMINUTE converts the ASOS 2 min wind direction to x- and y-component wind directions and follows a unit-vector approach to average within a given hour to calculate the hourly wind direction; further details can be found elsewhere.^{28,29} Monthly average daily traffic (MADT) from January 2017–June 2021 was obtained from the Massachusetts Department of Transportation Data Management System.³⁰ Four traffic counters were used, with three counters representing local roads (Rt 1A Revere (Station ID 8087), Rt 1A Boston (Station ID: AET16), and US 1 Boston Tobin (Station ID: AET15)), and a fourth representing an interstate highway at Medford I-93 (Station ID: 82) (Figure S1).

Data Processing and Analyses. Data collected prior to August 2017 were recorded at 30-s averaging periods, with subsequent data recorded at 1-s averages. Processed data were aggregated to hourly resolution ($n = 41,904$ h) and merged with flight activity (landings, takeoffs, and sum of landings and takeoffs [LTO]), meteorological data, and MADT. Data were classified into impact sector or nonimpact sector depending on whether the hourly average wind direction positioned the site downwind of the airport. Impact sector was defined as 135° to 175° based on the azimuth angle of the site to the widest span of runways as done previously (Figure S2).²³ Additionally, data were classified as prepandemic (before March 10, 2020), the early SOE period (March 11, 2020–March 2021, when Massachusetts returned to its Phase III Step 2 reopening), and the late SOE period (April–June 2021). Monthly average and 25th, 50th, 75th, 95th, and 99th percentile PNC were calculated for these three periods.

We used an approach analogous to emissions reduction impact methods within air quality modeling to evaluate the changes in PNC and transportation activity throughout the study period. This approach, described elsewhere,³¹ estimates the impact of a source on pollutant concentration when emissions are reduced in a given sector. First, eq 1 was applied to PNC, road traffic, and aviation to scale the data by prepandemic mean to visualize temporal trends:

$$C'_i = \frac{C_i}{\mu} \quad (1)$$

where C is the measurement value at its highest resolution (hourly for PNC and LTO, monthly for road traffic), i the data type (PNC, road traffic, LTO), and μ the mean measurement value for the i th data type for data before March 10, 2020.

We examined aviation and road traffic activity over the entire study period to identify changes in transportation patterns. To control for seasonal variation and the nonlinear nature of the COVID-19 activity restrictions, we stratified the data set and performed targeted analysis comparing the months of April, May, and June (AMJ) across the data set within the three time periods (prepandemic, early SOE, late SOE) because these months correspond with large changes in transportation patterns (Figure 1C).

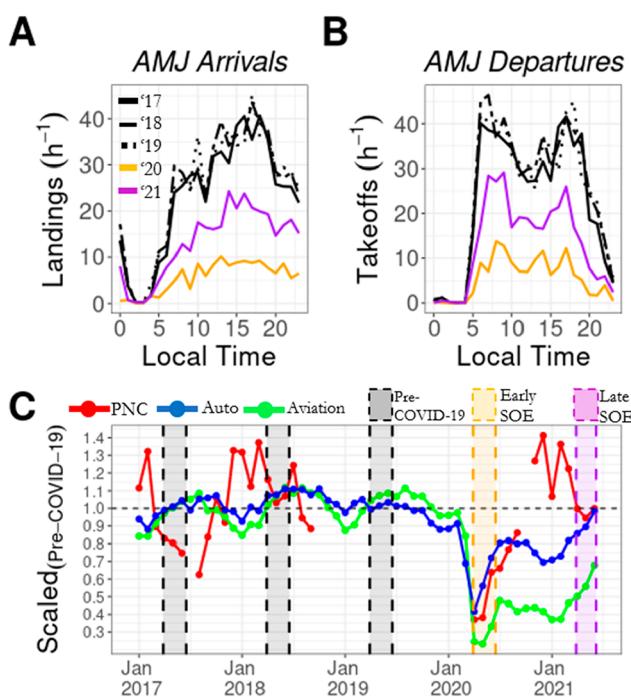


Figure 1. (A, B) Landings and takeoffs per hour for (A) arrivals and (B) departures at Logan Airport from 2017 to 2021 for the months of April, May, and June (AMJ). (C) Time series for PNC (particles/cm³) for all wind directions, automobile traffic at US 1 Boston Tobin (AET15, monthly average daily traffic), and combined landings and takeoffs (operations h⁻¹) scaled by prepandemic mean (before March 10, 2020) following eq 1. Points represent the monthly average of the prepandemic mean scaled value per respective time series. Highlighted boxes within the dotted lines represent the time periods selected for analysis, AMJ 2017–2019 (black), AMJ 2020 (orange), AMJ 2021 (purple).

These changes were analyzed following eq 2:

$$\Delta_m = \frac{\mu_{m,1} - \mu_{m,2}}{\mu_{m,2}} \times 100 \quad (2)$$

where $\mu_{m,1}$ is the 3-month (AMJ) mean in 2020 or 2021, $\mu_{m,2}$ the 3-month (AMJ) mean in 2017–2019, and Δ_m the % change. We did not record PNC data for 2019, but LTO and MADT were available for all three preceding years. Given the influence of meteorological variability on PNC and to control for it, we limited the comparison to the same season (spring/summer months), and further, the mean and standard deviations of key variables (e.g., temperature, precipitation,

relative humidity, etc.) were compared between years. We observed no substantial differences in our time period of interest (Table S2).

To visualize and explore PNC trends with respect to wind direction and wind speed, we created bivariate polar plots that group PNC by wind speed and direction using the “openair” R package.³²

RESULTS

Changes in Transportation Activity During the Pandemic. Both flight and ground traffic were reduced following the start of the SOE. While flight activity was reduced by 74%, road traffic was reduced by only 39% based on counts from the three nearest surface road counters and 51% on the nearest interstate highway counter during AMJ 2020 compared to the prepandemic (2017–2019) average for the same months. Upon easing of the travel restrictions, road traffic recovered to prepandemic volume ($\pm 10\%$) by AMJ 2021; however, flight activity remained 44% lower (Table S3 and Figures S7–S8).

The diurnal patterns of flight activity during early and late SOE were similar to prepandemic years, but at lower volumes (Figure 1). Flight activity peaked in the morning (0600–1000 h) and the afternoon (1500–1900 h). The morning had a higher percentage of departures, and the afternoon had a higher percentage of arrivals (Figure 1(A), (B)). Throughout the study period flight activity during 0100–0400 h was minimal, in accordance with noise abatement policy.

Changes in PNC during the Pandemic. Overall, mean PNC was 48% lower during early SOE compared to prepandemic mean for AMJ (Figure 1(C)), but by late SOE, it was comparable to the prepandemic mean ($\pm 5\%$). Reductions during early SOE were greater for impact sector winds (-61.4%) than nonimpact sector winds (-48.0%). During late SOE (AMJ 2021), mean PNC remained lower than prepandemic levels for impact sector (-23.1%) but not nonimpact sector winds ($+5.4\%$).

During the early SOE, both the concentrations and the impact sector vs nonimpact sector difference were reduced (Table S3). Mean impact sector PNC ($14,000 \pm 8600$ particles/cm³) was 2.1 times higher than mean nonimpact sector PNC (6700 ± 4000 particles/cm³) in early SOE compared to mean impact sector PNC ($36,300 \pm 24,900$ particles/cm³) being 2.8 times higher than mean nonimpact sector PNC ($12,900 \pm 9100$ particles/cm³) in the prepandemic period. These patterns (i.e., impact sector PNC greater than nonimpact sector PNC, a reduced relative difference between impact sector and nonimpact sector PNC during early SOE, and a recovery to prepandemic levels for nonimpact sector PNC but not impact sector PNC during late SOE) were consistent across all hourly aggregations of PNC (25th, 50th, 75th, 95th, and 99th percentile PNC; Table S3 and Figure S9).

Furthermore, the greatest decrease in impact sector PNC in the early SOE period occurred during regular LTO activity (0500–0000): a 62% decrease compared to prepandemic levels (Table S4), i.e., $40,900 \pm 24,900$ particles/cm³ vs $15,600 \pm 9100$ particles/cm³. During regular LTO activity, impact sector PNC in the early SOE period ($15,600 \pm 9100$ particles/cm³) was essentially comparable to nonimpact sector PNC prepandemic ($13,700 \pm 9500$ particles/cm³). Prior to the pandemic, during impact sector winds, PNC was 2.7 times higher during regular LTO (60 flights h⁻¹) as compared to periods of limited LTO (2 flights h⁻¹); however, in early SOE,

impact sector wind PNC was only 1.8 times higher during regular LTO (14 flights h^{-1}) than during limited LTO (1 flight h^{-1}). Analyses by wind speed and direction (Figure 2) indicate

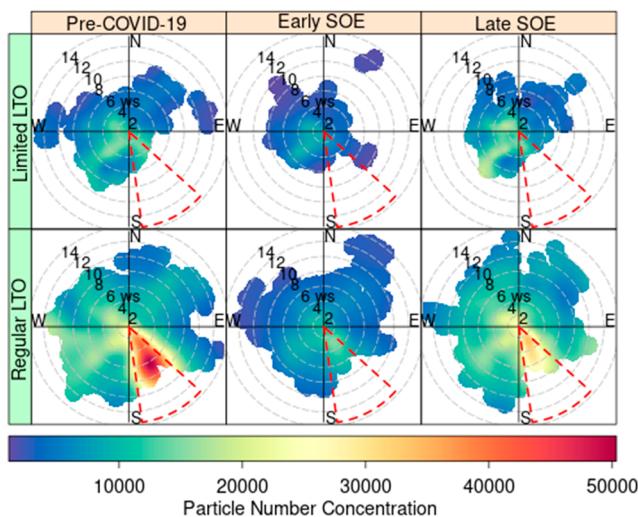


Figure 2. Polar plots showing the interactions between the hourly mean PNC (particles/ cm^3) during April, May, and June (AMJ), wind speed (ms^{-1}), and wind direction. Columns subset data by prepandemic levels (mean AMJ of 2017 and 2018), in the early months of the Massachusetts state-of-emergency (SOE) (AMJ 2020), and a year later (AMJ 2021), while rows subset by periods of limited LTO (0100–0400) and regular LTO (0500–0000). Dotted red lines represent winds from the aviation impact sector. Variations in plot shape are a function of wind speed and wind direction, while variations in color are a function of PNC (particles/ cm^3).

a pronounced signal under impact sector winds at relatively high wind speeds during regular LTO activity pre-pandemic, which is muted in the SOE periods during regular LTO activity.

DISCUSSION

Air quality management involves identifying and quantifying the emissions sources that contribute most to air pollution levels in a given area or region. The dramatic decrease in transportation sector activity in response to the COVID-19 pandemic provided a natural experiment with which we could better understand the emissions reduction impact of transportation sources on ambient PNC in a near-airport setting. During the early months of the COVID-19 pandemic, we observed that PNC was dramatically reduced (48% on average, for all wind directions) near an international airport and that daytime PNC was similar to prepandemic PNC during nighttime hours with no flight activity. In addition, we observed that mean PNC mirrored automobile ground traffic volume patterns throughout the pandemic, but under wind conditions that placed the monitor downwind from the airport, mean PNC more closely followed flight activity volume patterns. The fact that the two predominant source types in a near-airport setting had different activity profiles and different associations with wind speed and direction allowed us to better differentiate their relative impacts on ambient PNC. While the highest PNC was observed when the site was downwind from the airport throughout the study period, the difference between downwind and nondownwind PNC was negligible during the early SOE, providing a sharp contrast to

clearly indicate airport contributions under aviation impact sector winds.

Our findings can be compared with previous studies of PNC during the pandemic, although most previous studies were conducted over a shorter duration and with a primary focus on road traffic-related emissions. For example, Hudda et al.¹² quantified changes in air quality in Somerville, MA, due to traffic reductions using a seven-week-long mobile monitoring campaign at the onset of the pandemic. They found daily traffic on a major highway in the community (I-93) decreased approximately 50% and that median PNC was 44%–57% lower in March–May 2020 as compared to prepandemic concentrations. We found a similar magnitude reduction though with the ability to better distinguish between specific source contributions over time. Xiang et al.¹³ found a more modest 7% reduction in PNC near a major interstate in Seattle, WA, USA, where median traffic volume decreased by 37% at the onset of pandemic-related activity restrictions. They identified larger relative decreases in smaller diameter ultrafine particles (<20.5 nm) but were only able to compare with approximately two weeks of UFP measurements prior to the onset of the pandemic. Dai et al.¹⁴ used dispersion-normalized positive matrix factorization analysis to investigate source contributions to PNC before and during the COVID-19 outbreak in a suburban site in Tianjin, China. They found that traffic-related PNC decreased 44% after the outbreak and that residential heating was the largest source of PNC before and during the outbreak. The magnitude of PNC decrease we observed during the pandemic is comparable to the road-based study in Boston, MA, USA,¹² and the suburban site study in Tianjin, China¹⁴ but were substantially larger than the road-based study in Seattle, Washington, USA.¹³ However, our study is the only one performed to date in a near-airport community with a long-term monitoring campaign specifically sited to distinguish the separate contributions from roadway and airport emissions.

A limitation of natural experiments is that they are observational in nature, and potential confounders cannot be manipulated. Therefore, it is necessary to try to control for them in analysis.³⁴ For a pollutant like PNC that exhibits substantial seasonality, it is essential to have the appropriate comparison period, which we addressed by matching the month-to-month percent change in PNC across three distinct time periods within a given season. While we had approximately 20 months of PNC data to establish baseline conditions, we had a data gap in 2019. However, our findings regarding impact sector PNC in our baseline period agree with a prior study assessing aviation impacts on UFP in Boston.²³ This reinforces the value of long-term monitoring for UFP and other pollutants to capture both acute and gradual shifts in source contributions, ideally with monitoring locations that capture emissions sources beyond road traffic to allow for analyses of source impacts in complex urban environments which contain multiple emission sources. Such data can provide the foundation for more accurate source attribution analyses.

ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at <https://pubs.acs.org/doi/10.1021/acs.estlett.2c00322>.

Study area map (Figure S1), impact sector calculation (Figure S2), description of data quality assurance procedures (Table S1), and seven figures and three tables showing data distributions throughout the study period ([PDF](#))

■ AUTHOR INFORMATION

Corresponding Author

Sean C. Mueller — *Department of Environmental Health, Boston University School of Public Health, Boston, Massachusetts 02118, United States; [ORCID](#) 0000-0001-9471-3930; Email: muellers@bu.edu*

Authors

Neelakshi Hudda — *Department of Civil and Environmental Engineering, Tufts University, Medford, Massachusetts 02155, United States; [ORCID](#) 0000-0002-2886-5458*

Jonathan I. Levy — *Department of Environmental Health, Boston University School of Public Health, Boston, Massachusetts 02118, United States*

John L. Durant — *Department of Civil and Environmental Engineering, Tufts University, Medford, Massachusetts 02155, United States*

Prasad Patil — *Department of Biostatistics, Boston University School of Public Health, Boston, Massachusetts 02118, United States*

Nina Franzen Lee — *Department of Environmental Health, Boston University School of Public Health, Boston, Massachusetts 02118, United States*

Ida Weiss — *Department of Civil and Environmental Engineering, Tufts University, Medford, Massachusetts 02155, United States*

Tyler Tatro — *Department of Civil and Environmental Engineering, Tufts University, Medford, Massachusetts 02155, United States*

Tiffany Duhl — *Department of Civil and Environmental Engineering, Tufts University, Medford, Massachusetts 02155, United States*

Kevin Lane — *Department of Environmental Health, Boston University School of Public Health, Boston, Massachusetts 02118, United States*

Complete contact information is available at:

<https://pubs.acs.org/10.1021/acs.estlett.2c00322>

Notes

The authors declare no competing financial interest.

■ ACKNOWLEDGMENTS

We are grateful to The Neighborhood Developers in Chelsea for housing our stationary site. This research was funded by the U.S. Federal Aviation Administration Office of Environment and Energy through ASCENT, the FAA Center of Excellence for Alternative Jet Fuels and the Environment, and Project 18 through FAA Award Number 13-C-AJFE-BU under the supervision of Jeetendra Upadhyay. Any opinions, findings, conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the FAA. S.C.M. was supported by a National Science Foundation Research Traineeship (NRT) grant to Boston University (NSF NRT DGE 1735087).

■ REFERENCES

- (1) Friedman, M. S.; Powell, K. E.; Hutwagner, L.; Graham, L. M.; Teague, W. G. Impact of Changes in Transportation and Commuting Behaviors During the 1996 Summer Olympic Games in Atlanta on Air Quality and Childhood Asthma. *JAMA* **2001**, *285* (7), 897–905.
- (2) Pope, C. A.; Schwartz, J.; Ransom, M. R. Daily Mortality and PM10 Pollution in Utah Valley. *Arch. Environ. Health* **1992**, *47* (3), 211–217.
- (3) Wang, Y.; Hao, J.; McElroy, M. B.; Munger, J. W.; Ma, H.; Chen, D.; Nielsen, C. P. Ozone Air Quality during the 2008 Beijing Olympics: Effectiveness of Emission Restrictions. *Atmospheric Chem. Phys.* **2009**, *9* (14), 5237–5251.
- (4) Global Energy Review 2020 — Analysis. IEA. <https://www.iea.org/reports/global-energy-review-2020> (accessed 2022-04-21).
- (5) Twenty Years Later, How Does Post-9/11 Air Travel Compare to the Disruptions of COVID-19? Bureau of Transportation Statistics. <https://www.bts.gov/data-spotlight/twenty-years-later-how-does-post-911-air-travel-compare-disruptions-covid-19> (accessed 2022-04-21).
- (6) He, G.; Pan, Y.; Tanaka, T. The Short-Term Impacts of COVID-19 Lockdown on Urban Air Pollution in China. *Nat. Sustain.* **2020**, *3* (12), 1005–1011.
- (7) Lu, D.; Zhang, J.; Xue, C.; Zuo, P.; Chen, Z.; Zhang, L.; Ling, W.; Liu, Q.; Jiang, G. COVID-19-Induced Lockdowns Indicate the Short-Term Control Effect of Air Pollutant Emission in 174 Cities in China. *Environ. Sci. Technol.* **2021**, *55* (7), 4094–4102.
- (8) Eleftheriadis, K.; Gini, M. I.; Diapouli, E.; Vratolis, S.; Vasilatou, V.; Fefatzi, P.; Manousakas, M. I. Aerosol Microphysics and Chemistry Reveal the COVID19 Lockdown Impact on Urban Air Quality. *Sci. Rep.* **2021**, *11* (1), 14477.
- (9) Yadav, S. K.; Kompalli, S. K.; Gurjar, B. R.; Mishra, R. K. Aerosol Number Concentrations and New Particle Formation Events over a Polluted Megacity during the COVID-19 Lockdown. *Atmos. Environ.* **2021**, *259*, 118526.
- (10) Bekbulat, B.; Apte, J. S.; Millet, D. B.; Robinson, A. L.; Wells, K. C.; Presto, A. A.; Marshall, J. D. Changes in Criteria Air Pollution Levels in the US before, during, and after Covid-19 Stay-at-Home Orders: Evidence from Regulatory Monitors. *Sci. Total Environ.* **2021**, *769*, 144693.
- (11) Silva, A. C. T.; Branco, P. T. B. S.; Sousa, S. I. V. Impact of COVID-19 Pandemic on Air Quality: A Systematic Review. *Int. J. Environ. Res. Public Health* **2022**, *19* (4), 1950.
- (12) Hudda, N.; Simon, M. C.; Patton, A. P.; Durant, J. L. Reductions in Traffic-Related Black Carbon and Ultrafine Particle Number Concentrations in an Urban Neighborhood during the COVID-19 Pandemic. *Sci. Total Environ.* **2020**, *742*, 140931.
- (13) Xiang, J.; Austin, E.; Gould, T.; Larson, T.; Shirai, J.; Liu, Y.; Marshall, J.; Seto, E. Impacts of the COVID-19 Responses on Traffic-Related Air Pollution in a Northwestern US City. *Sci. Total Environ.* **2020**, *747*, 141325.
- (14) Dai, Q.; Ding, J.; Song, C.; Liu, B.; Bi, X.; Wu, J.; Zhang, Y.; Feng, Y.; Hopke, P. K. Changes in Source Contributions to Particle Number Concentrations after the COVID-19 Outbreak: Insights from a Dispersion Normalized PMF. *Sci. Total Environ.* **2021**, *759*, 143548.
- (15) Stacey, B. Measurement of Ultrafine Particles at Airports: A Review. *Atmos. Environ.* **2019**, *198*, 463–477.
- (16) Hudda, N.; Simon, M. C.; Zamore, W.; Durant, J. L. Aviation-Related Impacts on Ultrafine Particle Number Concentrations Outside and Inside Residences near an Airport. *Environ. Sci. Technol.* **2018**, *52* (4), 1765–1772.
- (17) Hudda, N.; Gould, T.; Hartin, K.; Larson, T. V.; Fruin, S. A. Emissions from an International Airport Increase Particle Number Concentrations 4-Fold at 10 Km Downwind. *Environ. Sci. Technol.* **2014**, *48* (12), 6628–6635.
- (18) Austin, E.; Xiang, J.; Gould, T. R.; Shirai, J. H.; Yun, S.; Yost, M. G.; Larson, T. V.; Seto, E. Distinct Ultrafine Particle Profiles Associated with Aircraft and Roadway Traffic. *Environ. Sci. Technol.* **2021**, *55* (5), 2847–2858.

(19) Stacey, B.; Harrison, R. M.; Pope, F. Evaluation of Ultrafine Particle Concentrations and Size Distributions at London Heathrow Airport. *Atmos. Environ.* **2020**, *222*, 117148.

(20) Janssen, N. a. H.; Hoekstra, J.; Houthuijs, D.; Jacobs, J.; Nicolai, A.; Strak, M. *Effects of Long-Term Exposure to Ultrafine Particles from Aviation around Schiphol Airport*; Rijksinstituut voor Volksgezondheid en Milieu RIVM, 2022.

(21) Keuken, M. P.; Moerman, M.; Zandveld, P.; Henzing, J. S.; Hoek, G. Total and Size-Resolved Particle Number and Black Carbon Concentrations in Urban Areas near Schiphol Airport (the Netherlands). *Atmos. Environ.* **2015**, *104*, 132–142.

(22) Ungeheuer, F.; van Pinxteren, D.; Vogel, A. L. Identification and Source Attribution of Organic Compounds in Ultrafine Particles near Frankfurt International Airport. *Atmospheric Chem. Phys.* **2021**, *21* (5), 3763–3775.

(23) Hudda, N.; Simon, M. C.; Zamore, W.; Brugge, D.; Durant, J. L. Aviation Emissions Impact Ambient Ultrafine Particle Concentrations in the Greater Boston Area. *Environ. Sci. Technol.* **2016**, *50* (16), 8514–8521.

(24) Simon, M. C.; Hudda, N.; Naumova, E. N.; Levy, J. I.; Brugge, D.; Durant, J. L. Comparisons of Traffic-Related Ultrafine Particle Number Concentrations Measured in Two Urban Areas by Central, Residential, and Mobile Monitoring. *Atmos. Environ.* **2017**, *169*, 113–127.

(25) COVID-19 State of Emergency. *Mass.gov*. <https://www.mass.gov/info-details/covid-19-state-of-emergency> (accessed 2022-04-21).

(26) FAA Operations & Performance Data. *Federal Aviation Administration*. <https://aspm.faa.gov/> (accessed 2022-04-21).

(27) Automated Surface/Weather Observing Systems (ASOS/AWOS). *National Centers for Environmental Information (NCEI)*. <http://www.ncei.noaa.gov/products/land-based-station/automated-surface-weather-observing-systems> (accessed 2022-04-21).

(28) Meteorological Processors and Accessory Programs. *U.S. EPA*. <https://www.epa.gov/scram/meteorological-processors-and-accessory-programs> (accessed 2022-05-16).

(29) Meteorological Monitoring Guidance for Regulatory Modeling Applications. *U.S. EPA*. <https://dokumen.tips/documents/epa-meteorological-monitoring-guidance-for-regulatory-modeling-applications.html> (accessed 2022-07-11).

(30) Transportation Data Management System. *Mass DOT*. <https://mhd.public.ms2soft.com/tcds/tsearch.asp?loc=Mhd&mod=> (accessed 2022-04-21).

(31) Thunis, P.; Clappier, A.; Tarrason, L.; Cuvelier, C.; Monteiro, A.; Pisoni, E.; Wesseling, J.; Belis, C. A.; Pirovano, G.; Janssen, S.; Guerreiro, C.; Peduzzi, E. Source Apportionment to Support Air Quality Planning: Strengths and Weaknesses of Existing Approaches. *Environ. Int.* **2019**, *130*, 104825.

(32) Carslaw, D. C.; Ropkins, K. Openair — An R Package for Air Quality Data Analysis. *Environ. Model. Softw.* **2012**, *27*–*28*, 52–61.

(33) Xiang, J.; Austin, E.; Gould, T.; Larson, T.; Shirai, J.; Liu, Y.; Marshall, J.; Seto, E. Impacts of the COVID-19 Responses on Traffic-Related Air Pollution in a Northwestern US City. *Sci. Total Environ.* **2020**, *747*, 141325.

(34) Rich, D. Q. Accountability Studies of Air Pollution and Health Effects: Lessons Learned and Recommendations for Future Natural Experiment Opportunities. *Environ. Int.* **2017**, *100*, 62–78.

□ Recommended by ACS

High Particle Number Emissions Determined with Robust Regression Plume Analysis (RRPA) from Hundreds of Vehicle Chases

Miska Olin, Panu Karjalainen, *et al.*

JUNE 06, 2023

ENVIRONMENTAL SCIENCE & TECHNOLOGY

READ □

Hourly Ultrafine Particle Exposure and Acute Myocardial Infarction Onset: An Individual-Level Case-Crossover Study in Shanghai, China, 2015–2020

Yixuan Jiang, Haidong Kan, *et al.*

JANUARY 20, 2023

ENVIRONMENTAL SCIENCE & TECHNOLOGY

READ □

Quantification of the Emission of Atmospheric Microplastics and Nanoplastics via Sea Spray

Charbel Harb, Hosein Foroutan, *et al.*

MAY 15, 2023

ENVIRONMENTAL SCIENCE & TECHNOLOGY LETTERS

READ □

A Network of Field-Calibrated Low-Cost Sensor Measurements of PM_{2.5} in Lomé, Togo, Over One to Two Years

Garima Raheja, Daniel M. Westervelt, *et al.*

MARCH 10, 2022

ACS EARTH AND SPACE CHEMISTRY

READ □

Get More Suggestions >