Impacts of Modifiable Factors on Ambient Air Pollution: A Case Study of COVID-19 Shutdowns

Rebecca Tanzer-Gruener, Jiayu Li, S. Rose Eilenberg, Allen L. Robinson, and Albert A. Presto*

ABSTRACT: COVID-19-related closures offered a novel opportunity to observe and quantify the impact of activity levels of modifiable factors on ambient air pollution in real time. We use data from a network of low-cost Real-time Affordable Multi-Pollutant (RAMP) sensor packages deployed throughout Pittsburgh, Pennsylvania, along with data from Environmental Protection Agency regulatory monitors. The RAMP locations were divided into four site groups based on land use. Concentrations of PM$_{2.5}$, CO, and NO$_x$ following the COVID-related closures at each site group were compared to measurements from “business-as-usual” periods. Overall, PM$_{2.5}$ concentrations decreased across the domain by $\sim 3 \mu g/m^3$. The morning rush-hour-induced CO and NO$_x$ concentrations at the high-traffic sites were both reduced by $\sim 50\%$, which is consistent with observed reductions in commuter traffic ($\sim 50\%$). The morning rush-hour PM$_{2.5}$ enhancement from traffic emissions was reduced nearly 100%, from 1.4 to $\sim 0 \mu g/m^3$ across all site groups. There was no significant change in the industry-related intraday variability of CO and PM$_{2.5}$ at the industrial sites following the COVID-related closures. If PM$_{2.5}$ National Ambient Air Quality Standards (NAAQS) are tightened, this natural experiment sheds light on the extent to which reductions in traffic-related emissions can aid in meeting more stringent regulations.

INTRODUCTION

Sources of urban ambient air pollution are generally associated with human activities such as traffic, cooking, and electricity generation. These sources are modifiable factors; emissions can be modulated by changing either activity levels or the source intensity. Air pollution regulation in the United States has traditionally relied on reducing emission factors rather than curbing activity. Although previous studies have assessed impacts of event-related step changes in emission sources on air quality, social distancing measures implemented in response to COVID-19 offer a natural opportunity to observe and quantify the impacts of modifiable factors, specifically large shocks to activity, on ambient air pollution in real time with unprecedented scope, speed, and duration.

In March 2020, 48 U.S. states implemented precautions to limit the transmission of COVID-19.$^5$ In many cases, these measures represented a step change in activity and accompanying pollutant emissions. This study focuses on data collected in Pittsburgh, Allegheny County, PA, which is representative of the rapid changes in activity associated with social distancing measures. A timeline of the closures affecting Pennsylvania and the upwind state of Ohio can be found in Table S1 and shows that activity was “business as usual” through March 13$^6$$^{10}$ and rapidly transitioned to lower activity, with the majority of schools and non-essential businesses closed or operating in reduced capacity by March 16.

The closing of schools and businesses has a clear impact on activity levels and therefore air pollutant emissions. In this paper, we use data from both a distributed network of low-cost air pollutant sensors and the Environmental Protection Agency (EPA) regulatory network to examine how changes in activity impacted ambient air pollution. We compare concentrations of fine particulate matter (PM$_{2.5}$ for which Allegheny County has been at least partially in non-attainment since 1997$^{11}$), CO, and NO$_x$ from the post-COVID shutdown period (March 14 to April 30, 2020) to business-as-usual periods in 2019 and 2020.

MATERIALS AND METHODS

CO and PM$_{2.5}$ were measured using a distributed network of low-cost sensors. The Real-time Affordable Multi-Pollutant (RAMP) sensor package has been deployed throughout the city of Pittsburgh and surrounding suburbs since 2016.$^{12}$ The RAMPs use electrochemical sensors (AlphaSense LLC) to measure CO. PM$_{2.5}$ is measured via light scattering using either MetOne Neighborhood Monitors or PurpleAir PA-IIs.

Received: May 4, 2020
Revised: June 23, 2020
Accepted: June 23, 2020
Published: June 23, 2020
Previous work details the calibration\textsuperscript{13,14} and deployment\textsuperscript{15–17} of these sensor packages.

In March 2020, there were 27 active RAMP sites in the Pittsburgh region (locations shown in Figure S1). The RAMP sites were grouped into four categories based on land use: High Traffic (n = 3), Urban Residential (n = 11), Suburban Residential (n = 8), and Industrial (n = 4). Site groupings were determined according to the same methodology that was used in previous work\textsuperscript{15} and are described in detail in the Supporting Information.

One concern with low-cost pollutant sensors is measurement uncertainty.\textsuperscript{18–22} We have previously shown that the mean absolute error relative to a reference measurement in hourly averaged CO measurements is $\pm 49$ ppb.\textsuperscript{12} Uncertainty in PM$_{2.5}$ is a strong function of averaging time; 1 h data have a relatively large uncertainty ($\sim 4 \mu g/m^3$) that decreases to $<1 \mu g/m^3$ after sufficient averaging time.\textsuperscript{13,20} In this paper, grouping sites increases the effective averaging time, reducing the uncertainty to $0.6 \mu g/m^3$.\textsuperscript{20}

To supplement the RAMP data, EPA Air Quality System (AQS) data collected by the Allegheny County Health Department (ACHD) from two NO$_2$ sites was also analyzed [one high-traffic site and one suburban residential site (shown in Figure S1)].

To quantify traffic reduction, we compared traffic camera data on Interstate 376, a main commuter highway, in March 2020 (postclosures) to historical vehicle counts (preclosures) during the same time of day (8 a.m., morning rush hour). We estimate that rush-hour commuter vehicle traffic decreased by 48%. This estimate is consistent with Google mobility data that estimate that in Allegheny County workplace-related mobility decreased by 45%.\textsuperscript{23}

\textbf{RESULTS AND DISCUSSION}

\textbf{Concentration Reductions Due to Activity Changes.}

Figure 1 and Table S2 compare CO and PM$_{2.5}$ concentrations for pre- and post-COVID periods. Overall, concentrations during the pre-COVID period in 2020 (March 1–13) are similar to the same period in 2019. March 2019 concentrations are shown as box plots and cumulative distribution functions (CDFs) in Figure 1. The data in Figure 1 suggest that the main emission sources and atmospheric conditions were similar between 2019 and 2020 before social distancing.

CO and PM$_{2.5}$ concentrations are lower during the post-COVID period (March 14 to April 30, 2020) compared to those of the “business-as-usual” periods in both 2019 and 2020. For example, across the entire RAMP network, mean PM$_{2.5}$ concentrations were 29% ($\sim 3 \mu g/m^3$) lower following the COVID-related closures (6.7 $\mu g/m^3$) compared to March 2019 (9.5 $\mu g/m^3$).

We treat CO as a marker of fresh combustion emissions from vehicular traffic and industrial activity. At the High Traffic and Urban Residential sites, traffic is the dominant source of CO. The CO time series at these site groups is punctuated by occasional traffic-related spikes; these spikes decreased by 19% (High Traffic) and 23% (Urban Residential) postclosure. The reduced frequency of high CO spikes is also evident in the CDFs. The median CO is identical for High Traffic and Urban Residential for pre- and post-COVID, but the mean and 90th percentile concentrations at High Traffic sites are 19% and
38% lower, respectively, because of a lower frequency of high-concentration events.

The impact of traffic on the High Traffic and Urban Residential sites is also evident in the diurnal patterns in Figure 2. Pre-COVID there is a clear increase in CO concentrations between an overnight stable period (2−3 a.m.) and the morning rush hour (7−8 a.m.). During the post-COVID period, both the absolute peak CO and the intraday difference that can be attributed to traffic are smaller.

NO₂, which is also a marker for traffic emissions, shows a pattern similar to that of CO (Figure S3). Concentrations are lower and less variable, and the morning rush-hour enhancement is smaller in the post-COVID period when compared to March 2019.

The Industrial sites also have frequent spikes in CO (Figure 1), though these are dominated by industrial emissions. These industrially driven CO spikes persist in the post-COVID period. The CDFs in Figure 1 are indistinguishable for pre- and post-COVID, suggesting that the Industrial sites continued emitting post-COVID closures.

Figures 1 and 2 show trends for PM₁.₅ similar to those for CO. Concentrations during the pre-COVID period in 2020 are similar to those of March 2019. Concentrations in the post-COVID period are lower and less variable. For example, Figure 2 shows that for the High Traffic sites the PM₁.₅ increase associated with the morning rush hour fell from 1.4 μg/m³ in 2019 to zero in the post-COVID period.

Figure 2 shows that the majority of the PM₂.₅ enhancement at the industrially influenced sites occurs at night, consistent with previous studies. This is because of a combination of emissions and boundary layer height. During overnight hours, the boundary layer is low. Many sources, such as traffic, have less activity overnight, whereas the steel mill and coke plant impacting the Industrial sites operate 24 h. Thus, there are local enhancements of PM₂.₅ overnight at the Industrial sites. Although PM₁.₅ concentrations decreased at the Industrial sites in the post-COVID compared to pre-COVID periods (24% reduction), these sites still had higher concentrations than all other site groups, suggesting industrial activity continued during the shutdown.

### Table 1. Intraday Source Specific Concentration Changes Associated with Traffic and Industrial Emissions at Each Site Group

| site group          | pre-COVID traffic-related intraday enhancement | post-COVID traffic-related intraday enhancement | pre-COVID industry-related intraday enhancement | post-COVID industry-related intraday enhancement |
|---------------------|-----------------------------------------------|-----------------------------------------------|-----------------------------------------------|-------------------------------------------------|
|                     | PM₁.₅ (μg/m³)                                 |                                               |                                               |                                                 |
| high traffic        | 1.4                                           | 0.0                                           | n/a                                           | n/a                                             |
| urban residential   | 1.4                                           | 0.2                                           | n/a                                           | n/a                                             |
| suburban            | 1.2                                           | −0.2                                          | n/a                                           | n/a                                             |
| industrial          | 0.4                                           | −0.5                                          | 2.8                                           | 1.7                                             |
| CO (ppb)            |                                               |                                               |                                               |                                                 |
| high traffic        | 180                                           | 89                                            | n/a                                           | n/a                                             |
| urban residential   | 86                                            | 41                                            | n/a                                           | n/a                                             |
| suburban            | 96                                            | 25                                            | n/a                                           | n/a                                             |
| industrial          | 104                                           | −25                                           | 82                                            | 110                                             |
| NO₂ (ppb)           |                                               |                                               |                                               |                                                 |
| high traffic        | 8.2                                           | 4.1                                           | n/a                                           | n/a                                             |
| suburban            | 2.8                                           | 0.4                                           |                                               |                                                 |

The traffic enhancements for PM₁.₅ and NO₂ were calculated for all four site groups. NO₂ data were available for only two ACHD sites. Industrial enhancements were computed for only the Industrial sites. Enhancements larger than the instrumental uncertainties are shown in bold.

Figure 2. Average diurnal patterns for selected site groups for CO (left) and PM₁.₅ (right). Dashed lines show the preclosure diurnal patterns from March 2019, and the solid lines show the 2020 post-COVID period. The shaded areas around the lines for the Suburban postclosure (left) and High-Traffic postclosure (right) diurnal indicate the instrument uncertainty for each instrument (0.6 μg/m³ and 49 ppb for PM₁.₅ and CO, respectively). Intraday variability in CO and PM₁.₅ concentrations decreased drastically following the COVID-related closures.
There are several potential challenges when attributing the observed changes in pollutant concentrations (Figures 1 and 2) to activity changes for specific sources. One challenge is decoupling changes attributable to sources from changes in meteorology. We benchmarked the pre- and post-COVID periods to historical weather data from NOAA and sounding data. A second challenge is how to define the base case (i.e., the period without impacts of COVID). Our analysis presented above compares the post-COVID period in 2020 to both pre-COVID 2020 (March 1–13) and March 2019. Figures S6 and S7 show that annual average PM2.5 concentrations in Pittsburgh have been nearly constant since 2012, and that PM2.5 concentrations measured at 27 of 30 RAMPs operating in 2018 and 2019 did not have statistically significant differences between years. Thus, our overall conclusions should not be strongly impacted by the choice of base case.

One additional challenge with attributing PM2.5 reductions to changes in human activity is that the majority of PM2.5 mass is secondary. In the following section, we compare intraday enhancements that focus on traffic and industry-related emissions (Table 1). We define the traffic-related enhancement as the difference between the morning rush-hour peak (mean of 7–8 a.m.) and the overnight stable period with a minimum in traffic volume (mean of 2–3 a.m.) for PM2.5, CO, and NO2 for pre-COVID (n = 31 days) and post-COVID (n = 48 days). The differences are averaged across all sites in each group. The industrial enhancement is defined as the difference between the overnight mean (2–4 a.m.) for each of the Industrial group sites and the mean of the five Suburban Residential sites with the lowest concentrations. As with the traffic enhancement, the industrial enhancement is calculated daily for each of the Industrial sites and then averaged for the site group.

For all site groups, the pre-COVID traffic enhancements of NO2 and CO scale with traffic intensity. CO enhancements are largest at the High Traffic sites (180 ppb), approximately double the enhancement at the other site groups (86–104 ± 49 ppb). The correlation between land-use (i.e., traffic volume) and traffic-related CO enhancements, along with the fact that CO is nonreactive, supports the use of CO as a tracer for traffic emissions in these locations. NO2 traffic enhancement at the High Traffic ACHD site was 8.2 ppb (±0.05 ppb) compared to 2.8 ppb (±0.2 ppb) at the suburban site. The traffic enhancements fell after COVID closures. Enhancements of CO and NO2 fell at High Traffic sites by 50%; this is consistent with the observed 48% reduction in commuter traffic. Morning CO enhancements fell to nearly zero in suburban areas [96 to 25 ppb (±49 ppb)], suggesting a larger fractional reduction in traffic volumes in those areas, consistent with people working and schooling from home. The traffic CO enhancement became negative in industrial areas, meaning that concentrations at 7–8 a.m. were lower than at 2–3 a.m., possibly from dilution as the boundary layer grows coupled with reduced emissions.

PM2.5 enhancements during the morning rush hour in the pre-COVID period were more uniform across site groups. For High Traffic, Urban Residential, and Suburban Residential groups, the morning rush-hour PM2.5 enhancement was 1.2–1.4 μg/m³, suggesting that impacts of traffic on PM2.5 are broadly distributed. There is a regional increase in morning PM2.5, consistent with the more regional nature of PM2.5. In the post-COVID period, the PM2.5 morning traffic enhancements for all site groups are within instrument uncertainty of zero. Enhancements decreased by 0.4–1.4 μg/m³, demonstrating the regional impact of traffic on PM2.5.

The overnight industrial PM2.5 enhancement at Industrial sites was 2.8 μg/m³ in the pre-COVID period and 1.7 μg/m³ post-COVID. Thus, during both pre- and post-COVID, there is a PM2.5 enhancement at Industrial sites that is larger than the measurement uncertainty (0.6 μg/m³). The corresponding CO industrial enhancement (82 ppb pre-COVID, 110 ppb post-COVID) was also larger than instrument uncertainty in both periods. Thus, while operations at the industrial sources may have changed between pre- and post-COVID, our measurements indicate that these sources remained in operation in the post-COVID period.

One additional challenge with attributing PM2.5 reductions to changes in human activity is that the majority of PM2.5 mass is secondary. One additional challenge with attributing PM2.5 reductions to changes in human activity is that the majority of PM2.5 mass is secondary. One additional challenge with attributing PM2.5 reductions to changes in human activity is that the majority of PM2.5 mass is secondary. One additional challenge with attributing PM2.5 reductions to changes in human activity is that the majority of PM2.5 mass is secondary. One additional challenge with attributing PM2.5 reductions to changes in human activity is that the majority of PM2.5 mass is secondary.
mended a revision to the annual PM$_{2.5}$ NAAQS to as low as 9 μg/m$^3$. Such a reduction is estimated to reduce the PM$_{2.5}$-related mortality rate by 21–27%. The Pittsburgh domain considered here has an annual average PM$_{2.5}$ concentration of 9.5 μg/m$^3$. While evaluating the full impact of vehicle traffic on PM$_{2.5}$ requires a more thorough assessment of impacts on primary and secondary PM$_{2.5}$, we can use the observed changes in the morning rush-hour peak to make a first-order estimate for the impacts of major changes to vehicle emissions on the annual average PM$_{2.5}$. Table 1 shows that the morning rush-hour peak enhancement decreased from 1.4 to ∼0 μg/m$^3$. This translates to a reduction of 0.12 μg/m$^3$ in the daily average PM$_{2.5}$ concentration, which would account for a third of the necessary reduction to reach a hypothetical 9 μg/m$^3$ standard. Thus, reductions beyond morning rush-hour traffic emissions may be needed to reach 9 μg/m$^3$ in urban areas.

ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acsestlett.0c00365.

Additional details, figures, and tables outlining the timeline for COVID-19-related closures, a description of site grouping criteria, a map of measurement sites, CO and PM$_{2.5}$ measurements for suburban residential sites, a table of CO and PM$_{2.5}$ metrics over the measurement domain, significance testing, NO$_x$ measurements from the Allegheny County Health Department (ACHD), boundary layer height measurements, weather data, sensitivity analysis for traffic enhancements, determination of restaurant activity and electricity consumption reduction, year-to-year differences in PM$_{2.5}$ and impacts on reference year selection, annual average PM$_{2.5}$ measured across Allegheny County, empirical CDFs (ECDF) of hourly PM$_{2.5}$ measured at two RAMP locations, and PM$_{2.5}$ and CO measurements from regulatory monitors (PDF).

AUTHOR INFORMATION

Corresponding Author

Albert A. Presto — Department of Mechanical Engineering, Carnegie Mellon University, Pittsburgh, Pennsylvania 15213, United States; orcid.org/0000-0002-9156-1094; Email: apresto@andrew.cmu.edu

Authors

Rebecca Tanzer-Gruener — Department of Mechanical Engineering, Carnegie Mellon University, Pittsburgh, Pennsylvania 15213, United States; orcid.org/0000-0001-8994-4814

Jiayu Li — Department of Mechanical Engineering, Carnegie Mellon University, Pittsburgh, Pennsylvania 15213, United States

S. Rose Eilenberg — Department of Mechanical Engineering, Carnegie Mellon University, Pittsburgh, Pennsylvania 15213, United States

Allen L. Robinson — Department of Mechanical Engineering, Carnegie Mellon University, Pittsburgh, Pennsylvania 15213, United States; orcid.org/0000-0002-1819-083X

Complete contact information is available at: https://pubs.acs.org/10.1021/acs.estlett.0c00365

REFERENCES

(1) Rich, D. Q.; Liu, K.; Zhang, J.; et al. Differences in birth weight associated with the 2008 Beijing olympics air pollution reduction: Results from a natural experiment. Environ. Health Perspect. 2015, 123 (9), 880–887.

(2) Ransom, M. R.; Pope, C. A., III External Health Costs of a Steel Mill. Contemporary Economic Policy 1995, 13 (2), 86–97.

(3) Friedman, M. S.; Powell, K. E.; Hutwagner, L.; Graham, L. R. 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. J. Am. Med. Assoc. 2001, 285 (7), 897–905.

(4) Heinrich, J. J.; Hoelscher, B. J.; Frye, C. J.; Meyer, I.; Pitz, M.; Cyrys, J.; Wjst, M.; Neas, L.; Wichmann, H.-E. Improved Air Quality in Reunified Germany and Decreases in Respiratory Symptoms. Epidemiology 2002, 13 (4), 394–401.

(5) Sergent, J.; Petras, G.; Bravo, V. 5 maps show how states differ on protecting Americans against coronavirus. https://www.usatoday.com/in-depth/news/2020/03/24/coronavirus-state-measures-contain-disease-vary-widely/289795001/; 2020 (accessed 2020-04-22).

(6) Williams, A. Pennsylvania, Delaware Close All Schools Due to Outbreak. 2020. https://www.nbcphiladelphia.com/news/peninsula-schools-closed-coronavirus/2325564/ (accessed 2020-04-22).

(7) Parsons, J. Gov. Wolf orders restaurants, bars to close dine-in service in several counties, including Allegheny. 2020. https://www.wtae.com/article/gov-wolf-orders-restaurant-bars-to-close-dine-in-several-counties-including-allegheny/31649498 (accessed 2020-04-22).

(8) Wolf, T. All non-life-sustaining businesses in Pennsylvania to close physical locations as of 8 PM today to slow spread of COVID-19. March 19, 2020. https://www.governor.pa.gov/newsroom/all-non-life-sustaining-businesses-in-pennsylvania-to-close-physical-locations-as-of-8-pm-today-to-slow-spread-of-covid-19/ (accessed 2020-04-22).

(9) Bosco, T. 3 COVID-19 cases confirmed in Ohio, DeWine declaring state of emergency. March 9, 2020. https://abc6onyourside.com/news/local/gov-dewine-ohio-has-3-confirmed-covid-19-cases (accessed 2020-04-22).

(10) Kiser, J. Coronavirus in Ohio: Governor orders schools to take extended spring breaks starting Monday. 2020. https://www.nbc4i.com/news/local-news/coronavirus-in-ohio-governor-orders-schools-to-take-extended-spring-breaks-starting-monday/ (accessed 2020-04-22).

ACKNOWLEDGMENTS

This work is part of the Center for Air, Climate and Energy Solution (CASES, www.cases.us). This publication was developed under Assistance Agreement RD83587301 awarded by the U.S. Environmental Protection Agency (EPA). This publication has not been reviewed by the EPA. The views expressed in this manuscript do not necessarily represent those of the funding agency. The authors thank Aliaksei Hauryliuk for maintaining the RAMP sensor network.

The authors declare no competing financial interest.

Content in this paper was previously submitted to a preprint server: Tanzer-Gruener, R.; Li, J.; Eilenberg, S. R.; Robinson, A. L.; Presto, A. A. Impacts of Modifiable Factors on Ambient Air Pollution: A Case Study of COVID-19 Shutdowns. ChemRxiv 2020, 10.26434/chemrxiv.12237182. https://chemrxiv.org/articles/Impacts_of_Modifiable_Factors_on_Ambient_Air_Pollution_A_Case_Study_of_COVID-19_Shutdowns/12237182 (accessed May 25, 2020).
(11) Pennsylvania Department of Environmental Protection. Attainment Status by Principal Pollutants. https://www.dep.pa.gov/Business/Air/BAQ/Regulations/Pages/Attainment-Status.aspx (accessed 2020-05-26).

(12) Zimmerman, N.; Presto, A. A.; Kumar, S. P. N.; et al. A machine learning calibration model using random forests to improve sensor performance for lower-cost air quality monitoring. Atmos. Meas. Tech. 2018, 11, 291–313.

(13) Malings, C.; Tanzer, R.; Hauryliuk, A.; et al. Fine particle mass monitoring with low-cost sensors: Corrections and long-term performance evaluation term performance evaluation. Aerosol Sci. Technol. 2020, 54 (2), 160–174.

(14) Malings, C.; Tanzer, R.; Hauryliuk, A.; et al. Development of a general calibration model and long-term performance evaluation of low-cost sensors for air pollutant gas monitoring. Atmos. Meas. Tech. 2019, 12, 903–920.

(15) Tanzer, R.; Malings, C.; Hauryliuk, A.; Subramanian, R.; Presto, A. A. Demonstration of a Low-Cost Multi-Pollutant Network to Quantify Intra-Urban Spatial Variations in Air Pollutant Source Impacts and to Evaluate Environmental Justice. Int. J. Environ. Res. Public Health 2019, 16 (14), 2523.

(16) Zimmerman, N.; Li, H. Z.; Ellis, A.; et al. Improving correlations between land use and air pollutant concentrations using wavelet analysis: Insights from a low-cost sensor network. Aerosol Air Qual. Res. 2020, 20 (2), 314–328.

(17) Subramanian, R.; Ellis, A.; Torres-Delgado, E.; et al. Air Quality in Puerto Rico in the Aftermath of Hurricane Maria: A Case Study on the Use of Lower Cost Air Quality Monitors. ACS Earth Sp Chem. 2018, 2 (11), 1179–1186.

(18) Castell, N.; Dauge, F. R.; Schneider, P.; et al. Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates? Environ. Int. 2017, 99, 293–302.

(19) Cross, E. S.; Williams, L. R.; Lewis, D. K.; et al. Use of electrochemical sensors for measurement of air pollution: Correcting interference response and validating measurements. Atmos. Meas. Tech. 2017, 10 (9), 3575–3588.

(20) Eilenberg, R.; Subramanian, R.; Malings, C.; Hauryliuk, A.; Presto, A. A.; Robinson, A. L. Using a Network of Lower-Cost Monitors to Identify the Influence of Modifiable Factors Driving Spatial Patterns in Fine Particulate Matter Concentrations in an Urban Environment. Submitted for publication, 2020.

(21) Hagan, D. H.; Isaacman-Vanwertz, G.; Franklin, J. P.; et al. Calibration and assessment of electrochemical air quality sensors by co-location with regulatory-grade instruments. Atmos. Meas. Tech. 2018, 11, 315–328.

(22) Snyder, E. G.; Watkins, T. H.; Solomon, P. A.; et al. The changing paradigm of air pollution monitoring. Environ. Sci. Technol. 2013, 47 (20), 11369–11377.

(23) Google LLC. Pennsylvania April 11, 2020 Mobility Changes. Mountain View, CA, 2020. https://www.google.com/covid19/mobility/ (accessed 2020-04-24).

(24) Weitkamp, E. A.; Lipsky, E. M.; Pancras, P. J.; et al. Fine particle emission profile for a large coke production facility based on highly time-resolved fence line measurements. Atmos. Environ. 2005, 39 (36), 6719–6733.

(25) Presto, A. A.; Dallmann, T. R.; Gu, P.; Rao, U. BTEX exposures in an area impacted by industrial and mobile sources: Source attribution and impact of averaging time. J. Air Waste Manage. Assoc. 2016, 66 (4), 387–401.

(26) Boogaard, H.; van Erp, A. M.; Walker, K. D.; Shaikh, R. Accountability Studies on Air Pollution and Health: the HEI Experience. Curr. Environ. Heal reports. 2017, 4 (4), 514–522.

(27) Oolman, L. Atmospheric Sounding Data. http://weather.uwyo.edu/upperair/sounding.html. 2020 (accessed 2020-05-28).

(28) National Centers for Environmental Information. NOAA: Local Climatological Data. NOAA. 2020. https://www.ncdc.noaa.gov/data-access/quick-links (accessed 2020-05-26).

(29) Current Results. Average Temperatures for Large US Cities. 2020. https://www.currentresults.com/Weather/US/average-city-temperatures-in-february.php (accessed 2020-05-26).

(30) Robinson, A. L.; Donahue, N. M.; Shrivastava, M. K.; et al. Rethinking Organic Aerosols: Semivolatile Emissions and Photochemical Aging. Science 2007, 315, 1259–1262.

(31) Jimenez, J. L.; Canagaratna, M. R.; Donahue, N. M.; et al. Evolution of Organic Aerosols in the Atmosphere. Science 2009, 326 (5959), 1525–1530.

(32) Möllmann-Coers, M.; Klemp, D.; Mannschreck, K.; Slemr, F. Determination of anthropogenic emissions in the Augsburg area by the source-tracer-ratio method. Atmos. Environ. 2002, 36 (1), 95–107.

(33) Li, H. Z.; Dallmann, T. R.; Gu, P.; Presto, A. A. Application of mobile sampling to investigate spatial variation in fine particle composition. Atmos. Environ. 2016, 142, 71–82.

(34) Tang, W.; Raymond, T.; Wittig, B.; et al. Spatial variations of PM2.5 during the Pittsburgh air quality study. Aerosol Sci. Technol. 2004, 38 (2), 80–90.

(35) Wolf, T. Industry Operation Guidance. 2020. https://www.scribd.com/document/452553026/UPDATED-8-45pm-May-11-2020-Industry-Operation-Guidance#download (accessed 2020-05-28).

(36) Gu, P.; Li, H. Z.; Ye, Q.; et al. Intracity Variability of Particulate Matter Exposure Is Driven by Carbonaceous Sources and Correlated with Land-Use Variables. Environ. Sci. Technol. 2018, 52 (20), 11545–11554.

(37) Morris, R. E.; Jung, J.; Koo, B.; Maranche, J. Application of an integrated plume to regional photochemical model for the allegheny county liberty-clairton PM2.5 attainment demonstration modeling. Air Waste Management Association 2013, 2, 874–901.

(38) U.S. Environmental Protection Agency. Policy Assessment for the Review of the Particulate Matter National Ambient Air Quality Standards. Vol. EPA 452/R-. Research Triangle Park, NC, 2019. https://www.epa.gov/sites/production/files/2019-09/documents/draft_policy_assessment_for_pm_naqs_09-05-2019.pdf (accessed 2020-04-22).

NOTE ADDED AFTER ASAP PUBLICATION

This article published June 25, 2020 with an error in the right panel of Figure 2. The corrected figure published June 26, 2020.