Impact of Traffic Signal Timing on Sidewalk-Level Particulate Matter Concentrations

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Improving the efficiency of urban traffic operations along arterials is a priority for many agencies because congestion affects the movement of people and goods in many cities. Advanced traffic management systems are being implemented to optimize traffic signal timing in congested corridors. Pedestrians and transit users are even more exposed to vehicle emissions than are drivers. However, pedestrian exposure to traffic emissions is typically not a consideration when traffic signal timing decisions are made. The relationship between exposure to air pollution and traffic signal timing has not yet been fully explored or modeled. This paper quantifies the factors that contribute to concentrations of sidewalk-level particulate matter (1.0 to 2.5 µm in diameter) at a busy intersection along an urban arterial in Portland, Oregon. The study is the first research effort to combine real-world, detailed traffic signal timing data (at 5-s intervals) and air pollutant concentration data. Several types of variables are included in the statistical analysis: traffic signal timing variables, weather-related variables, traffic volume and composition variables, and variables associated with bus presence and characteristics. Statistical results show the importance of signal timing variables, traffic volumes, and queuing.

Air pollution is a growing concern in cities all over the United States. In urban areas the main contributor to a population's exposure to air pollution is vehicle emissions on or around transportation facilities. The U.S. Environmental Protection Agency (EPA) regulates air pollution by setting standards for various pollutants. There are regulations aimed at in-vehicle testing for tailpipe emissions in addition to regulations concerning ambient levels for criteria pollutants. The regulations are constantly being updated as research sheds new light on the relationship between pollutant levels and health.

Users of the transportation system are exposed to air pollution in urban areas regardless of their mode choice. Many urban arterials are multimodal in nature and facilitate travel by private vehicle, transit bus, bicycle, and walking. The operation of traffic signals can affect emissions in terms of the number of stops and the delay. The efficiency of traffic operations on arterial roadways is influenced by traffic signal timing parameters. The relationship between traffic signal timing and pollutant levels has not yet been fully explored. If the understanding of this relationship can be improved, future traffic signal timing efforts will be able to reduce pollutant levels at sidewalks.

The research reported in this paper measured and modeled particulate matter (PM) pollutant levels on a busy urban arterial, Southeast Powell Boulevard, in Portland, Oregon. Traffic and air quality data from peak travel periods have been used for the statistical analysis.

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LITERATURE REVIEW

Previous researchers have shown the links between changes in traffic signal timing and the number of vehicle stops, vehicle delay, and fuel consumption. However, the relationship between traffic signals and emissions has not been fully explored. That concept is justified in the remainder of this section.

Air Pollutants, Regulations, and Health Effects

EPA, created in 1970, defines air pollution as "the presence of contaminants or pollutant substances in the air that interfere with human health or welfare, or produce other harmful environmental effects." Since the creation of EPA, the number of laws concerning the regulation of air pollution has grown substantially. EPA created the National Ambient Air Quality Standards (NAAQS), which includes regulations for six pollutants: carbon monoxide (CO), PM, nitrogen dioxide, sulfur dioxide, smog, and lead (*1*). This research focuses on PM.

PM is a mixture of solid particles and liquid droplets found in the air and is defined by particle size. It is made up of acids (such as nitrates and sulfates), organic chemicals, metals, and soil or dust particles. $PM_{2.5}$ is between 1.0 and 2.5 µm in diameter and is measured in terms of micrograms per cubic meter. Under the NAAQS, the standards for $PM_{2.5}$ are 15 $\mu g/m^3$ annually and 35 $\mu g/m^3$ for 24 h (*2*). On June 29, 2012, EPA proposed a reduction in the annual $PM_{2.5}$ standard to 12 to 13 $\mu g/m^3$, which would result in a reduction of 13% to 20% (*3*). Ambient $PM_{2.5}$ background concentrations are generally below 16 $\mu g/m^3$ (*4*).

The negative health impacts of PM are widely documented. The anatomy of the human lung enables smaller particles to travel deeper into the lung, and some particles can reach a person's bloodstream. Thus, finer particles pose a greater health risk than do coarse particles (*5*). There are several health effects on the respiratory system from exposure to PM, such as wheezing and exacerbation of asthma, respiratory infections, cardiovascular disease, chronic bronchitis, and chronic obstructive pulmonary disease (*1*).

Traffic Signals and Emissions Models

The most common type of traffic signal timing is time-of-day plans, under which a different signal plan is implemented at predetermined times of the day to meet changes in traffic demands. This is the least expensive type of plan and requires less hardware to operate. As traffic conditions change over time, time-of-day plans must be updated. The process of updating traffic signal plans is called signal retiming. Signal retiming reoptimizes the operation of signalized intersections by adjusting parameters such as cycle length, split times, and offsets. According to FHWA's *Traffic Signal Timing Manual,* signal timing should be reviewed every 3 to 5 years to check for changes in traffic patterns and reoptimize timing plans (*6*). It has also been suggested that retiming should be done at least once a year to keep up with changes in traffic patterns (*7*). Adaptive systems can be used to adjust timing plans automatically to respond to real traffic conditions. Although such systems are more expensive to operate, it is estimated that signal timing can reduce harmful emissions by 5% to 10% (*8*).

The effect of traffic signal timing on air quality can be quantified indirectly through the modeling of emissions and dispersions or through field measurements. In the United States, EPA leads air quality modeling efforts. EPA has developed the Motor Vehicle Emission Simulator (MOVES) and emission dispersion models such as AERMOD.

By using MOVES, Papson et al. analyzed emissions, including oxides of nitrogen (NO_x) and PM, at congested and uncongested signalized intersections. Emission factors from MOVES for each activity mode, including cruising, deceleration, idling, and acceleration (in grams per vehicle second), and time in mode were used to calculate total emissions under various traffic conditions; time in mode was obtained from control delay, queue length, and cycle length outputs from a Synchro model (*9*). Li, Wu, et al. examined the impacts of signal timing on vehicle emissions at an isolated intersection by using three models with pretimed signalization. The three models were optimized by minimizing (*a*) delay, (*b*) stops, and (*c*) delay by limiting stops to a set value or constraint. Some of the inputs are traffic volume, green time, lost time, cycle length, speed, deceleration rate, acceleration rate, and roadway grade. The model results were used to calculate the emissions. The results indicated that reducing the number of stops can reduce CO at the expense of slight increases in carbon dioxide (CO_2), hydrocarbons (HC), and NO_x (*10*). Li, Li, et al. created a model for a signalized intersection that optimizes cycle length and green time by minimizing a weighted sum of delay, fuel consumption, and emissions. The model was applied to an intersection in Nanjing City, China. The results indicated that the optimized signal timing yields reductions in delay and emissions (*11*).

The studies cited in the previous paragraph have examined the impacts of traffic signal timing on emissions by using models; the modeling results have not been verified against field data. Some studies have collected field data related to signalization and emissions, but those studies have focused on in-vehicle pollution, as described below.

Traffic Signals and In-Vehicle Air Pollution

In view of the complexity of air quality modeling, another line of research has focused on linking in-vehicle pollutant levels and traffic signals. Unal et al. examined the effect of signalization on in-vehicle emissions in Cary, North Carolina, by collecting emissions and traffic data before and after signalization of the corridors. The results indicated that in cases where traffic flow significantly improved, emissions followed the same trend. In addition, the highest emission rates were during acceleration and the lowest were during idling. The impact of signalization was measured along the main corridor, and the effect on the side street was not examined (*12*).

Parikh studied the effect of signal coordination on emissions in the Dallas–Fort Worth, Texas, area by collecting real-world emissions data during morning and afternoon peak and off-peak periods every second, including CO_2, NO_x, HC, CO, engine revolutions per minute, vehicle speeds, temperature, and position data with the Global Positioning System. Data were collected before the signal retiming and 1 year later during the same months. The results indicated a reduction in NO_x and an increase in CO_2 after signal coordination (*13*). The impact from atmospheric factors, such as temperature and relative humidity, was not included.

Tao et al. collected real-world emissions data including CO_2, NO_x, HC, and CO during peak and off-peak periods to check for differences in emissions depending on traffic conditions. Coordinated timing was used in the field, while a second car was driven according to a set of rules to emulate noncoordinated conditions. The results indicated that coordinated timing reduced emissions, but the effect was weakened during the peak periods, when the average speed decreased (*14*). That study compared coordinated with noncoordinated timing without actually changing the timing in the field; the results may have been different if data had been collected with a true noncoordinated timing scheme.

The goal of the case studies examined in this literature review was different from that of the research reported in this paper. Those studies focused on pollution for drivers, but they do not help to explain pollution levels for other modes, such as walking or waiting for transit. Drivers have much more control over their environment than do pedestrians and transit users. Empirical research has clearly shown that drivers can reduce their in-vehicle exposure to PM by 83% to 90% by closing the vehicle vents or running the air-conditioning system (*15*).

Pedestrians, outdoor business customers and employees, and transit users do not have the ability to protect themselves from poor air quality. The goal of the research reported here was to examine pollutant levels at the sidewalk level by measuring air quality where transportation users walk or wait. In addition, previous research efforts have not examined the effect of signal timing on emissions by simultaneously incorporating the effect of weather, heavy vehicles, transit vehicles, volume, and signal timing into their data collection and analysis.

STUDY LOCATION

Powell Boulevard is an urban arterial corridor that connects downtown Portland and the city of Gresham, Oregon. Powell Boulevard, also known as US-26, has at least two lanes of traffic in each direction, a center turn lane or median for left turns in some sections, and a variety of land uses. The street route runs east–west and includes the Ross Island Bridge, which crosses over the Willamette River. The arterial is congested during peak traffic hours. The morning peak period is in the westbound direction, toward downtown Portland, and the afternoon peak period occurs in the eastbound direction. Improving the performance of this arterial is difficult because of the competing needs of various types of users, such as pedestrians, transit, and private automobiles, and the need to balance mobility and accessibility for a diverse array of activities and land uses along the corridor.

The study area is located at Powell Boulevard and 26th Avenue, which is ideal for an air quality study for various reasons. The land use surrounding the intersection provides compelling reasons to measure air pollution. Cleveland High School, which serves students from grades 9 through 12, is located at the northeast corner of the intersection. The school has high pedestrian, bicycling, and transit activity during school start and release times. At the southwest corner of the intersection is Powell Park, a publicly owned park that covers 8 acres (*16*). The other two corners of the intersection have businesses. In addition, the intersection is multimodal in nature. Powell is a heavily traveled corridor for private vehicles, especially during peak commuting periods, in addition to being a key transit bus route. Twenty-Sixth Avenue is a two-lane cross street (with auxiliary turn lanes at the intersection) and an important north–south bicycle route with bicycle lanes in both directions.

DATA COLLECTION AND PROCESSING

A team of three to five people at Powell and 26th simultaneously measured air quality, atmospheric factors, and traffic-related data. Data were collected on Wednesday, October 26, 2011, from 7 to 9 a.m. The data collection consisted of a 2-h temporary setup of a variety of equipment owned by Portland State University. The Dusttrak monitor was used to take measurements of the concentration levels of $PM_{2.5}$ every second. This equipment can measure a concentration range of 0.001 to 150 mg/m^3. The Young ultrasonic anemometer was used to take measurements of wind speed and direction every 5 s. The HOBO data logger was used to take measurements of temperature and relative humidity every 5 s. The equipment was set up at the northeast corner of the intersection on a cart located 3 ft from the side of the bus shelter and 12 ft from the curb (measurements were taken from the center of the cart). A tripod was set up behind the cart to attach the tubing at a 5-ft height; 5 ft is typically assumed in the literature as the breathing height for most people.

Bus presence and heavy vehicle presence were recorded by keeping track of the arrival and departure times of these vehicles to an accuracy of 1 s. For bus presence, the following were recorded: two departure times (the time the bus closed its doors and the time the bus actually left the stop), route number, bus number, and the angle of the tailpipe on the back of the bus. Heavy vehicles within the first 50 ft of the queue in relation to the location of the air quality equipment were recorded. If a heavy vehicle was visibly emitting or had an associated smell, it was recorded as well, even if it was not in the queue. Bus presence and heavy vehicle presence were converted into binary variables, with 1 indicating present and 0 indicating not present.

Detailed traffic signal operation data were recorded, including the start and end times for each phase and the detector volumes. There are a total of five phases, as detailed in Table 1. The movements follow the standard numbering system, where Movements 2 and 6 correspond to through or permitted right movements on Powell Boulevard, Phase A for the main street, and Movement 4 to through, right, or permitted left movements on 26th Avenue (Phase D). Figure 1 shows the ring and barrier diagram at the intersection (no pedestrian movement is included); numbers do not correspond to the letters in Table 1 because the Sydney Coordinated Adaptive Traffic System (SCATS) uses letters. There are three left-turning options and associated phases depending on the detected demand; see Phases C, E, and F in Table 1.

STATISTICAL ANALYSIS

A detailed statistical analysis was conducted by first creating a database including the air pollutant concentrations, atmospheric factors, observed traffic, and traffic signal timing variables. Each row in the database represents a 5-s period. The final database has a sample size of 1,591. If the data measurement was taken per second, it was aggregated to 5 s to fit into the structure of the database. All of the air pollutant concentration levels were averaged over the 5 s. PM concentration levels were expressed in terms of micrograms per cubic meter. To include wind direction, eight direction bins were created: N, NE, E, SE, S, SW, W, and NW. The impact of wind direction and wind speed on pollutant levels was incorporated by creating interaction terms. The eight wind direction bins were multiplied by wind speed to create a new set of inputs in meters per second. The data dictionary is shown in Table 1. It includes descriptive statistics for PM; atmospheric factors, such as temperature, relative humidity, and wind speed and direction; observed traffic; and traffic signal timing.

The data show that traffic volumes are prevalent in the westbound direction (morning peak) and that Powell volumes are more than 10 times the volume on the side street. In addition, atmospheric conditions were fairly stable during the data collection period, and winds were mild and variable.

Scatter plots and wind roses were made to examine trends in $PM_{2.5}$ levels, the predominant wind direction, and volume per cycle, as shown in Figure 2. The plots illustrate the importance of accounting for wind direction in PM concentration levels. When the wind switched direction from the south to the north around 7:45 a.m., almost halfway through the data collection period, there was a noticeable increase in $PM_{2.5}$ levels. There was no clear trend and significant variability on Powell volume per cycle (the cycle length itself is a variable that changes as determined by SCATS). An exploratory analysis was conducted, including descriptive statistics, plots, and correlations. The preliminary analysis led to a regression analysis in which the natural logarithms of $PM_{2.5}$ levels were regressed against the independent variables, as is customary in the air quality literature, to reduce skewness.

Autoregressive Log-Linear Model Regression Results

It is common with pollution data that the error terms of a regression model are not independent of one another. One of the assumptions of ordinary least squares linear regression models is that the error terms are independent. If this assumption is violated, there are problems with the estimation of coefficients and their standard errors. The Durbin–Watson test determined that there was significant positive correlation between contiguous error terms. Autocorrelation function plots confirmed that autocorrelation was a problem, which was dealt with by using an autoregressive model of order 1 [AR(1)]. AR(2) was not included because an AR(1) corrected the Durbin–Watson values and autocorrelation. The best model was selected on the basis of Akaike's information criterion (AIC) to balance model fitness and the number of parameters.

Table 2 shows only the results for which independent variables significant at the .05 level remained. To determine whether the autocorrelation was properly addressed, autocorrelation plots and the Durbin–Watson test were performed. The log-linear model and

TABLE 1 Data Dictionary

Name	Description	Data Type	Units	Minimum	Mean	Maximum
Air Pollutant Concentration						
$PM_{2.5}$	Concentration	Numeric	μg/m^3	27.40	38.78	114.80
Atmospheric Factors						
Temp	Temperature	Numeric	°F	39.31	39.94	41.04
RH	Relative humidity	Numeric	%	74.66	78.92	80.97
wsN	Wind speed in the north	Numeric	m/s	0	0.167	1.81
wsNE	Wind speed in the northeast	Numeric	m/s	0	0.052	1.12
wsE	Wind speed in the east	Numeric	m/s	0	0.027	1.42
wsSE	Wind speed in the southeast	Numeric	m/s	0	0.036	0.87
wsS	Wind speed in the south	Numeric	m/s	0	0.067	1.09
wsSW	Wind speed in the southwest	Numeric	m/s	0	0.050	1.13
wsW	Wind speed in the west	Numeric	m/s	0	0.053	1.48
wsNW	Wind speed in the northwest	Numeric	m/s	0	0.073	1.95
Observed Traffic						
Bus	If a bus was present at the westbound direction bus stop	Binary	(0, 1)	0	0.074	1
BusRedLight	Amount of time bus is waiting at a red light at the stop	Numeric	s	0	0.877	45
DPF	If the bus has a diesel particulate filter	Binary	(0, 1)	0	0.049	1
EMP	If the bus has an engine cooling system	Binary	(0, 1)	0	0.020	1
TPAngled	If the bus tailpipe has an angled orientation away from pedestrians	Binary	(0, 1)	0	0.003	1
Heavy vehicle	If a heavy vehicle was within the first 50 ft of the westbound queue	Binary	(0, 1)	0	0.031	1
HV time	Amount of time the heavy vehicle is waiting in the queue	Numeric	s	0	0.896	45
Traffic Volumes						
WBTH	Number of vehicles during the phase per 5 s	Numeric	vehicles	0	1.967	4.25
EBTH		Numeric	vehicles	0	1.250	4.00
Powell volume	Sum of eastbound and westbound through volume	Numeric	vehicles	0	3.212	7.00
SBTH	Number of vehicles during the phase per 5 s	Numeric	vehicles	0	0.229	2.00
NBTH		Numeric	vehicles	0	0.077	1.00
Volume per cycle	Number of vehicles per cycle	Numeric	vehicles	50	95.94	137
Traffic Signal Timing						
Phase A	Green time for EBTH and WBTH	Numeric	s	56	72.05	120
Phase C	Green time for WBTH and WBLT	Numeric	s	0	5.784	22
Phase E	Green time for EBTH and EBLT	Numeric	s	0	1.841	15
Phase F	Green time for EBLT and WBLT	Numeric	s	0	6.631	20
Phase D	Green time for SBTH and NBTH	Numeric	s	12	29.05	33
Cycle length	Cycle length	Numeric	s	80	115.29	168

NOTE: EB = eastbound, NB = northbound, SB = southbound, WB = westbound, LT = left turn, TH = through.

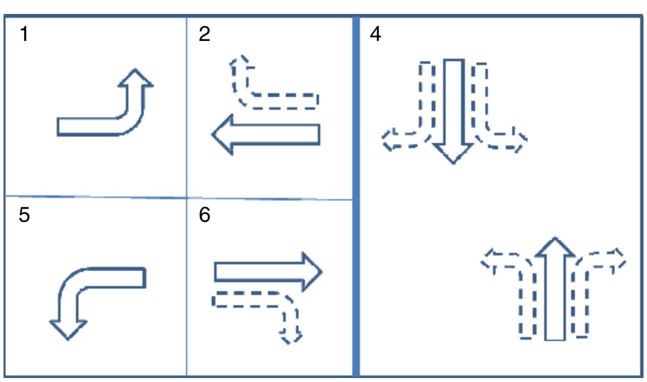

FIGURE 1 Ring and barrier diagram.

the AR(1) model are shown in Table 2, including the regression coefficients, standard error, and significance for each predictor in the model.

As expected, not all terms remained after the addition of the AR(1) term. More important is the fact that the variables that remained as significant in the autoregressive model differed slightly from the log-linear regression model and signs did not change; this highlights the stability of the regression results. Log-linear models not only reduce the skewness of the dependent variable but also facilitate interpretation of the independent variables and their elasticity. Three methods of interpretation are included:

1. Percentage change in the dependent variable per unit change in independent variable X,

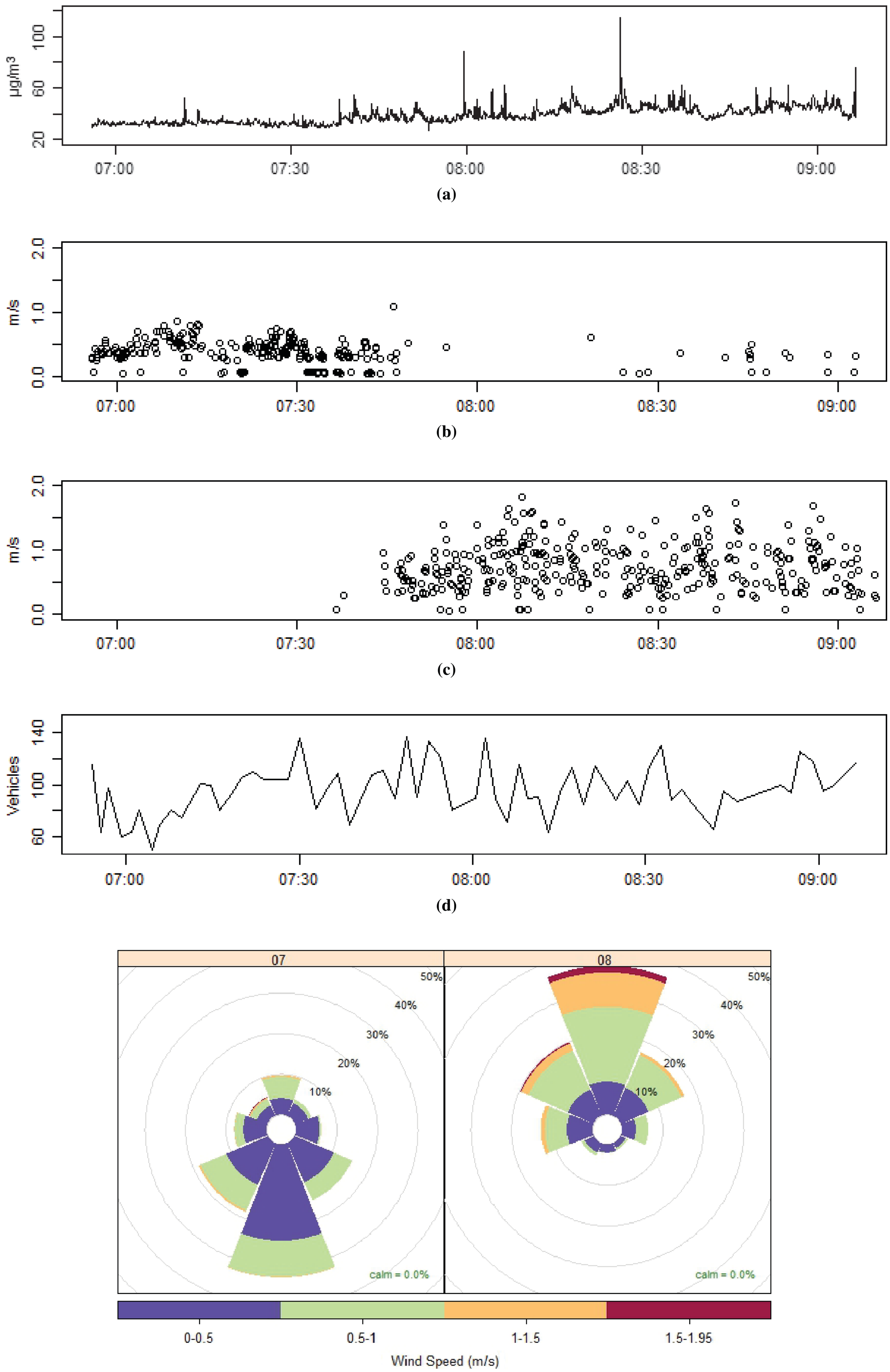

FIGURE 2 Study area trends: (*a*) $PM_{2.5}$ concentration; (*b*) wind speed, south; (*c*) wind speed, north; (*d*) traffic volume per cycle; and (*e*) wind rose plot.

TABLE 2 $PM_{2.5}$ Log-Linear and AR(1) Models

Independent Variable	Linear Model[a]			AR(1)[b]		
	B	SE_B	P-Value	B	SE_B	P-Value
AR(1)	—	—	—	0.8238	0.0163	.0000
Constant	1.6358	0.4768	.0006	6.4178	1.5291	.0000
RH	0.0069	0.0034	.0447	0.0174	0.0092	.0148
Temp	−0.1348	0.0092	.0000	−0.1045	0.0322	.0003
wsSE	−0.1950	0.0268	.0000	−0.0260	0.0197	.0466
wsS	−0.2482	0.0209	.0000	−0.0267	0.0155	.0214
wsSW	−0.1405	0.0198	.0000	−0.0264	0.0135	.0125
BusRedLight	0.0050	0.0005	.0000	0.0013	0.0009	.0343
EMP	—	—	—	−0.0395	0.0280	.0396
Heavy vehicles	0.0780	0.0174	.0000	—	—	—
PowellVol	—	—	—	0.0034	0.0015	.0052
GreenA	−0.0028	0.0003	.0000	−0.0017	0.0007	.0048
GreenE	0.0049	0.0007	.0000	0.0029	0.0015	.0126
GreenF	—	—	—	0.0016	0.0010	.0326
GreenD	0.0025	0.0006	.0000	0.0027	0.0011	.0040
VolCycle	0.0006	0.0002	.0002	0.0005	0.0004	.0359

NOTE: B = regression coefficient, SE_B = standard error of regression coefficient. — = not applicable.
[a]R^2 = 44.63%; Durbin–Watson = 0.6426.
[b]R^2 = 76.38%; sigma^2 = 0.00587; log likelihood = 1,803.32; AIC = −3,576.68; Durbin–Watson = 2.2445.

2. Percentage change in the dependent variable per 1% change in the independent variable X (elasticity for each independent variable evaluated at its mean value), and

3. Percentage contribution of each independent variable evaluated at its mean value (sign and percentage contribution of each independent variable to the mean value of the dependent variable). The mean contribution is relative to a baseline condition, which was established by summing the constant, humidity, and temperature variables evaluated at their mean value. The baseline condition is equivalent to a background value given the average atmospheric conditions at the time of the study.

Table 3 shows results for $PM_{2.5}$ on the basis of all three of the interpretation methods. The unit changes are useful but can be misleading if the reader does not account for the fact that the independent variables have different units and scales. The second and third methods make interpretation more intuitive because the units of the model input do not affect the results. These two methods require the mean values for each model input for the calculations, as previously shown in the data dictionary.

In terms of the percentage change in PM per unit change for each predictor, the variable with the largest impact was temperature; each additional degree Fahrenheit decreases $PM_{2.5}$ by almost 10%. Each increase in relative humidity of 1% increases $PM_{2.5}$ by almost 2%. Temperature and humidity signs are expected and reflect the fact that there is more pollution when the density of the air increases. Wind in the southeast, south, and southwest directions decreases $PM_{2.5}$ by about 2.5% for each meter per second. This is intuitive because $PM_{2.5}$ was measured in the northeast corner. Weather has a large impact on PM levels.

$PM_{2.5}$ is increased by 0.13% for each additional second that the bus waits at a red light. If the bus has an engine cooling system, which increases engine efficiency, pollutant levels are decreased by about 4% compared with buses that are not equipped with this technology. For each additional vehicle per 5 s traveling through on Powell Boulevard, $PM_{2.5}$ increases by 0.3%, whereas for each additional vehicle per cycle (the average cycle length is approximately 2 min, or twenty-four 5-s intervals), $PM_{2.5}$ increases by 0.05%. These two volume variables cannot be directly compared because of differences in the units of the predictors.

In terms of traffic signal timing parameters, each additional second of green time for Phase A decreases $PM_{2.5}$ by 0.17%, whereas

TABLE 3 $PM_{2.5}$ AR(1) Model Interpretation

Independent Variable	Percentage Change per Unit Change in X	Percentage Change per 1% Change in X	Percentage Average Contribution to Baseline[a]
RH	1.75	1.381	—
Temp	−9.93	−4.088	—
wsSE	−2.56	−0.001	−0.09
wsS	−2.63	−0.002	−0.18
wsSW	−2.61	−0.001	−0.13
BusRedLight	0.13	0.001	0.11
EMP	−3.87	−0.001	−0.08
PowellVol	0.34	0.011	1.09
GreenA	−0.17	−0.122	−11.47
GreenE	0.30	0.005	0.54
GreenF	0.16	0.010	1.04
GreenD	0.27	0.079	8.25
VolCycle	0.05	0.051	5.26

NOTE: — = not applicable.
[a]Relative to the baseline condition.

additional green time for other phases increases concentration levels. This can be interpreted as the impact of queuing on the northeast corner: during Phase A vehicles are passing by the northeast corner; during the other phases vehicles are queuing at the northeast corner. These results appear to indicate that queuing increases $PM_{2.5}$ levels.

For the mean contribution of the independent variables, all numbers are in reference to the baseline value provided by the sum of relative humidity, temperature, and the constant (background value given the average atmospheric conditions at the time of the study). The largest contribution is provided by the green time for Phase A with a value of −11%, followed by +8% for green time for Phase D. This result highlights the importance of signal timing and queuing time for $PM_{2.5}$ levels. Volume per cycle is the third variable with a 5% contribution. On the basis of the mean contribution interpretation, it is clear that the impact from volume per cycle is larger than volume on Powell Boulevard, which is different from the unit change interpretation previously discussed.

Lagged Autoregressive Log-Linear Model Regression Results

The autoregressive model previously discussed used cross-sectional data (i.e., did not include the impact of previous periods, lagged variables, on the $PM_{2.5}$ level at the present time). However, emissions are expected to have a delayed response, which is caused by the time taken to travel from the vehicle tailpipe to the measuring station. To determine whether there were lagged effects, cross correlation plots were made for each traffic-related variable and $PM_{2.5}$ levels. The cross correlation plots for vehicle movements, including eastbound, westbound, southbound, and northbound through volumes are shown for up to 2 min or twenty-four 5-s lags before and after time 0 in Figure 3.

The cross correlation plots shown in Figure 3 clearly demonstrate the cyclic impacts of vehicle movements on $PM_{2.5}$ levels. A cycle is about 2 min long (or twenty-four 5-s lags). The peaks and valleys of the graphs are roughly 12 periods, or half a cycle. The plots confirm the cyclic nature of the relationship between vehicle movements, phases, and pollutant levels and the value of including lagged variables in the model.

The R^2 value for the regression has improved, as have the AIC value and the log likelihood. The lagged autoregressive model has an AR(1) term of 0.7873, which is similar to the value from the nonlagged autoregressive model. The columns of Table 4 are similar to the columns in Table 3 and have the same interpretation. For variables that were significant at more than one lag, the weighted average lag time is included to facilitate its interpretation.

After addition of the lagged variables, the nonlagged variable coefficients did not change in sign, and many of their values and contributions are of similar magnitude (see Tables 3 and 4). This shows the robustness of the model and its results.

Eight independent variables show significant lagged effects. It takes on average 42 s for the impact of bus waiting time during a red light to be measured at the northeast corner location where the instrument was located, and a 0.66% increase in PM is provided per each second that the bus is waiting (idling). As seen previously, buses with engine cooling systems reduce $PM_{2.5}$ by levels of 5% compared with buses that do not have this technology (average lag effect is 40 s, close to the bus waiting time variable). Buses that have an angled tailpipe (pointing away from the sidewalk or northeast corner)

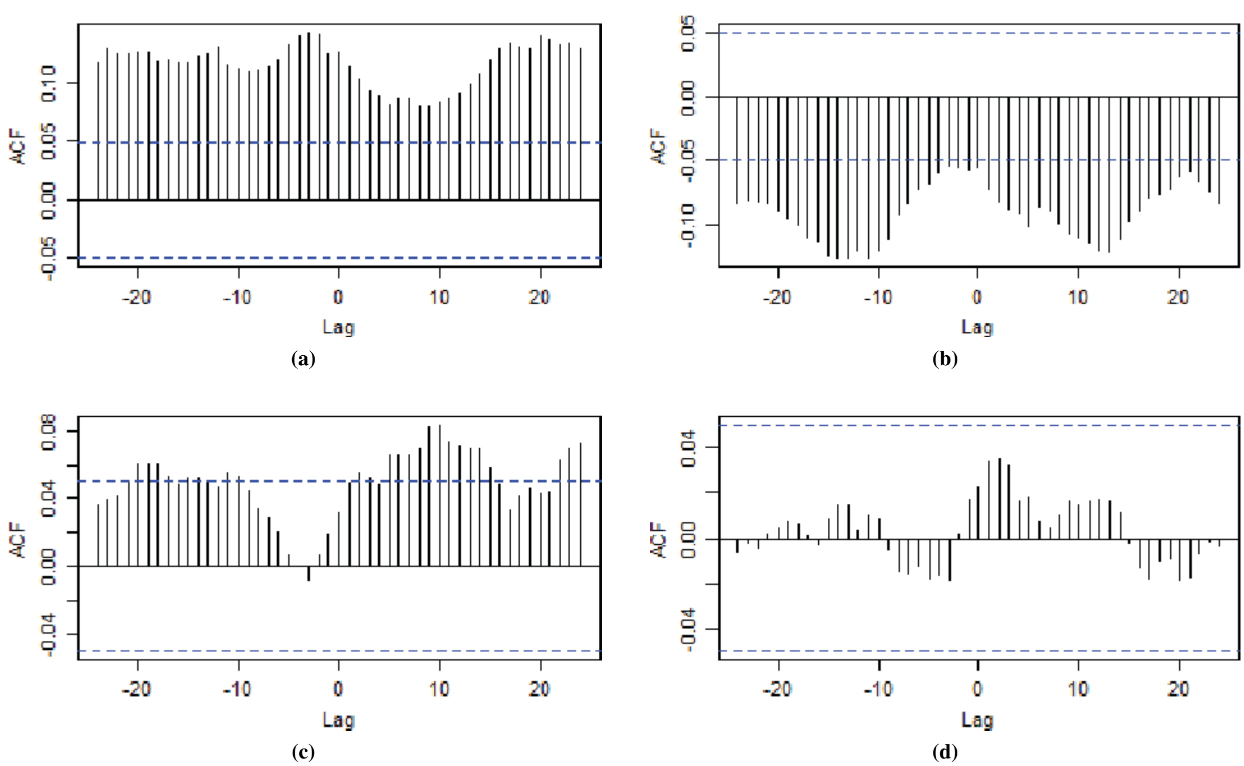

FIGURE 3 Cross correlation plots: (*a*) eastbound through, (*b*) westbound through, (*c*) southbound through, and (*d*) northbound through.

TABLE 4 $PM_{2.5}$ Lagged AR(1) Model Interpretation

Independent Variable	Average Lag	Seconds	Minutes	Percentage Change per Unit Change in *X*	Percentage Change per 1% Change in *X*	Percentage Average Contribution to Baseline[a]
RH	—	—	—	1.65	1.299	—
Temp	—	—	—	−13.28	−5.530	—
wsSE	—	—	—	−3.08	−0.001	−0.11
wsS	—	—	—	−2.74	−0.002	−0.18
wsSW	—	—	—	−2.96	−0.002	−0.15
EMP	—	—	—	−4.00	−0.001	−0.08
PowellVol	—	—	—	0.44	0.014	1.41
GreenA	—	—	—	−0.20	−0.143	−13.31
GreenE	—	—	—	0.20	0.004	0.37
GreenD	—	—	—	0.33	0.097	10.20
BusRedLight	8.4	42	0.70	0.66	0.006	0.58
EMP	8	40	0.67	−4.88	−0.001	−0.10
TPAngled	14.9	75	1.24	−81.50	−0.002	−0.23
HV time	18	90	1.50	0.13	0.001	0.11
EBTH	13	65	1.09	7.13	0.089	8.92
WBTH	15.4	77	1.28	−6.58	−0.130	−12.95
SBTH	3	15	0.25	−1.71	−0.004	−0.39
VolCycle	54.1	280	4.67	0.14	0.130	13.44

NOTE: R^2 = 78.45%, sigma^2 = 0.00555; log likelihood = 1,780.55; AIC = −3.471.10; Durbin–Watson = 2.1838. — = not applicable.
[a]Relative to the baseline condition.

reduced $PM_{2.5}$ levels by 82% compared with a backward-oriented (parallel to the sidewalk) tailpipe. Heavy vehicles queuing on average 1.5 min earlier contribute 0.13% to PM per additional second.

Each additional vehicle per 5 s in the eastbound direction from 1 min before (half a cycle in duration) increases pollutant levels by 7%, while each additional vehicle westbound decreases pollutant levels by 6.5%. Southbound vehicles reduce $PM_{2.5}$ by 2% per vehicle during a 5-s period 15 s earlier. Each vehicle per cycle adds 0.14% to $PM_{2.5}$ levels, and the average lag is almost two traffic signal timing cycles (4.5 min). The remaining lagged variables have elasticity values under 0.2%, which indicates a relatively small sensitivity. Only three of the lagged variables have an average contribution relative to the baseline over 5: eastbound traffic, westbound traffic, and volume per cycle.

CONCLUSIONS

The research presented here concerns pollutant levels along an urban arterial and traffic variables. The results of this research are novel; to the best of the authors' knowledge, this is the first research work that has quantified the impacts of traffic signal timing on PM pollution levels. The level of granularity (5 s) and the large number of traffic, signal, bus, and atmospheric variables included in the analysis are also unique. Model results with and without lagged variables or autocorrelation terms have shown statistically significant results and a high degree of robustness and consistency. Although more research is needed in this area, some of the results are likely transferable to other congested corridors and urban areas. More research is needed to quantify the links among traffic emissions and pedestrian exposure and health outcomes, but the research presented here is a novel step in this direction.

To a high degree, this research has shown that pollutant levels can be considered an outcome of traffic signal timing decisions made by cities and counties. The statistical results have shown the impact that signal timing and queuing have on pollutant concentrations at the sidewalk level. Longer green times along the main corridor can significantly reduce PM for transit users and pedestrians waiting at the sidewalk of the intersection, whereas time allocated to crossing streets increases queuing and pollution along the main corridor. Future research can compare whether and quantify the extent to which delays and emissions predicted by traffic simulation packages and emission models accurately predict sidewalk-level measurements of PM. The use of more detailed PM measurements, by number and size distributions, would be an interesting addition to the study design.

The impact of heavy-duty diesel engines is also clear. Heavy-vehicle volume was a significant variable, as was the presence of buses. The reduction of bus idling time through more efficient operations and transit signal priority is likely to reduce pollution levels. Transit agencies can also reduce pollution significantly by improving the efficiency and cleanliness of their engines. TriMet (the local transit agency) initiatives to improve fuel efficiency by installing engine-cooling devices improve not only fuel efficiency but also air quality. Additional research is needed to quantify the impact of traffic variables on PM concentrations at three or more corners and at midblock locations simultaneously.

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REFERENCES

1. Vallero, D. *Fundamentals of Air Pollution.* Academic Press, 2008.
2. National Ambient Air Quality Standards. Environmental Protection Agency, Nov. 8, 2011. http://www.epa.gov/air/criteria.html. Accessed Dec. 29, 2011.
3. *Federal Register* Proposed Rules. Environmental Protection Agency, June 29, 2012. http://www.gpo.gov/fdsys/pkg/FR-2012-06-29/pdf/2012-15017.pdf.
4. Bedada, G., J. Heinrich, T. Gotschi, S. Downs, B. Forsberg, D. Jarvis, C. Luczynska, A. Soon, K. Torenh, and N. Künzli. Urban Background Particulate Matter and Allergic Sensitization in Adults of ECRHS II. *International Journal of Hygiene and Environmental Health,* Vol. 210, No. 6, 2007, pp. 691–700.
5. Particulate Matter: Air and Radiation. Environmental Protection Agency. http://www.epa.gov/oar/particlepollution/. Accessed July 2, 2011.
6. Kittelson and Associates, Inc. *Traffic Signal Timing Manual.* FHWA, U.S. Department of Transportation, 2008.
7. Sunkari, S. The Benefits of Retiming Traffic Signals. *ITE Journal,* Vol. 74, No. 4, 2004, pp. 26–29.
8. Peters, J., R. McCourt, and R. Hurtado. Reducing Carbon Emissions and Congestion by Coordinating Traffic Signals. *ITE Journal,* Vol. 79, No. 4, 2009, pp. 25–29.
9. Papson, A., S. Hartley, and K.-L. Kuo. Analysis of Emissions at Congested and Uncongested Intersections with Motor Vehicle Emission Simulation 2010. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2270,* Transportation Research Board of the National Academies, Washington, D.C., 2012, pp. 124–131.
10. Li, J.-Q., G. Wu, and N. Zou. Investigation of the Impacts of Signal Timing on Vehicle Emissions at an Isolated Intersection. *Transportation Research Part D,* Vol. 16, 2011, pp. 409–414.
11. Li, X., G. Li, S.-S. Pang, X. Yang, and J. Tian. Signal Timing of Intersections Using Integrated Optimization of Traffic Quality, Emissions and Fuel Consumption: A Note. *Transportation Research Part D,* Vol. 9, No. 5, 2004, pp. 401–407.
12. Unal, A., N. M. Rouphail, and H. C. Frey. Effect of Arterial Signalization and Level of Service on Measured Vehicle Emissions. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1842,* Transportation Research Board of the National Academies, Washington, D.C., 2003, pp. 47–56.
13. Parikh, R. I. *Effectiveness of Signal Coordination as an Emission Reduction Measure for Vehicles.* Master's thesis. University of Texas at Arlington, 2006.
14. Tao, F., Q. Shi, and L. Yu. Evaluation of Effectiveness of Coordinated Signal Control in Reducing Vehicle Emissions During Peak Hours Versus Nonpeak Hours. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2233,* Transportation Research Board of the National Academies, Washington, D.C., 2011, pp. 45–52.
15. Bigazzi, A., and M. Figliozzi. The Impact of Freeway Traffic Conditions on In-Vehicle Exposure to Ultrafine Particulate Matter. *Atmospheric Environment,* Vol. 60, 2012, pp. 495–503.
16. *Oregon Department of Transportation: Transportation Operations Innovation and Demonstration Program.* City of Portland, Ore., 2008.

Any errors or omissions are the responsibility of the authors.

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