Published in final edited form as:
Atmos Environ. 2008 October ; 42(33): 7590–7599. doi:10.1016/j.atmosenv.2008.06.041.

Predicting Airborne Particle Levels Aboard Washington State School Buses

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Abstract

School buses contribute substantially to childhood air pollution exposures yet they are rarely quantified in epidemiology studies. This paper characterizes fine particulate matter ($PM_{2.5}$) aboard school buses as part of a larger study examining the respiratory health impacts of emission-reducing retrofits.

To assess onboard concentrations, continuous $PM_{2.5}$ data were collected during 85 trips aboard 43 school buses during normal driving routines, and aboard hybrid lead vehicles traveling in front of the monitored buses during 46 trips. Ordinary and partial least square regression models for $PM_{2.5}$ onboard buses were created with and without control for roadway concentrations, which were also modeled. Predictors examined included ambient $PM_{2.5}$ levels, ambient weather, and bus and route characteristics.

Concentrations aboard school buses (21 μg/m^3) were four and two-times higher than ambient and roadway levels, respectively. Differences in $PM_{2.5}$ levels between the buses and lead vehicles indicated an average of 7 μg/m^3 originating from the bus's own emission sources. While roadway concentrations were dominated by ambient $PM_{2.5}$, bus concentrations were influenced by bus age,

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diesel oxidative catalysts, and roadway concentrations. Cross validation confirmed the roadway models but the bus models were less robust.

These results confirm that children are exposed to air pollution from the bus and other roadway traffic while riding school buses. In-cabin air pollution is higher than roadway concentrations and is likely influenced by bus characteristics.

Keywords

Air pollution; diesel; school buses; particulate matter; traffic

INTRODUCTION

Diesel vehicles generate a complex mixture of gases and particles formed by incomplete combustion, volatilization of unused fuel, and release of engine lubricating oil. This mixture contains chemical compounds such as particulates, carbon monoxide, sulfur oxides, nitrogen oxides, hydrocarbons, and polycyclic aromatic hydrocarbons. With their small size and high surface area, particles generated by diesel vehicles can penetrate deep into the respiratory tract and deposit adsorbed chemical compounds in the lungs (USEPA 2002). Epidemiologic studies have reported associations between ambient levels of traffic-related pollutants and increased childhood hospitalizations, emergency room visits, and reports of asthma symptoms (Delfino et al. 2002; Gehring et al. 2002; Hirsch et al. 1999; Thompson et al. 2001). Similarly, elevated risks of asthma (Gauderman et al. 2005; Gordian et al. 2006; McConnell et al. 2006; vanVliet et al. 1997) and respiratory symptoms (Bayer-Oglesby et al. 2006; English et al. 1999; Janssen et al. 2003; Morgenstern et al. 2007; Ryan et al. 2005) have been documented among children living on or attending schools closer to busy streets.

Diesel school buses are a significant source of children's daily particulate exposures (Behrentz et al. 2005; Sabin et al. 2005a), yet no published epidemiology studies to date have examined the health effects of in-vehicle exposures to children. Several studies have demonstrated substantial particle levels aboard school buses, with onboard levels as much as two to ten times larger than ambient concentrations (Behrentz et al. 2005; EHHI 2002; Liu et al. 2008; Solomon et al. 2001). Roadway conditions such as traffic congestion appear to contribute to onboard levels, as does the intrusion of self-pollution into the cabin (EHHI 2002; Sabin et al. 2005a). Existing data regarding factors that influence these concentrations remains limited, however, due to the small number of buses studied in any one study.

This paper characterizes concentrations of airborne particles aboard school buses in the Seattle, Washington metropolitan area. We present cabin air monitoring results from a large number of buses with variable bus characteristics, routes, and retrofit technologies. Concurrent samples of on-road pollution levels were also collected. With these data, we constructed the first statistical prediction models for these concentrations using predictors that include ambient conditions, and bus and route characteristics. We present results from the first year of a five year study that compares the respiratory health of approximately 450 elementary school children before and after school bus retrofits with emission control technology (Liu 2004).

METHODS

Monitored School Districts

School buses from the Seattle and Tahoma School Districts in Washington State were monitored between November 2005 and June 2006. As a large urban community, the Seattle School District serves over 46,000 children with nearly 16,500 commuting by school bus. The

Tahoma School District, located approximately 20 miles to the southeast of Seattle (Figure 1), serves a suburban community of 7,000 children with approximately 4,300 school bus riders. In both districts, the median distance traveled by bus riders was 6 miles per day (Washington State 2005–2006).

Study Design

Measurements of particulate matter less than 2.5 microns in aerodynamic diameter ($PM_{2.5}$) were collected from a subset of our participants' school buses during their regular commutes. Monitored buses were selected to provide variations in emission control technology, engine location, and model year that were representative of the range of conditions experienced by our study population. Since differences between $PM_{2.5}$ levels on a bus and lead vehicle (LV) preceding that bus have been shown to be highly correlated with self-pollution estimates derived from dual tracers added to buses' lubricating oil and diesel fuel (Liu et al. 2008), measurements also were collected inside one of several Toyota Prius gasoline hybrid electric cars (model years 2001–2005, median mileage ~50,000) that traveled approximately one block in front of some of the monitored buses with the windows open.

Exposure Measurements

Continuous measurements of $PM_{2.5}$ were collected aboard the school buses and lead vehicles using a Thermo Scientific (Franklin, MA) active personal DataRAM (pDR-1000AN), retrofit with a 2.5 μm sharp-cut cyclone. These pDRs contained 37-mm Teflon filters and were operated at 4 L/min. All pDRs were factory calibrated prior to use and zeroed at the beginning and end of each monitoring session using a HEPA filter.

The pDR was secured inside of a portable foam-lined metal basket (18×14×9 inches). This kit was carried onto the bus and placed on one of the front seats near our study participants. Identical kits were placed in the back seat of the lead vehicle. The kit also contained a TSI (Shoreview, MN) P-Trak 8525 to measure real-time ultra-fine particle counts, a Harvard Personal Environmental Monitor (Thermo Scientific, Franklin, MA) with a 37-mm pre-fired quartz filter at 4 LPM, an Onset HOBO datalogger (Bourne, MA) for temperature and relative humidity (RH), and a global position system (Garmin International Model 60, Olathe, KS). This paper focuses on $PM_{2.5}$ measurements based on our recent findings, which demonstrated a high correlation between self pollution estimates from the pDR measurements and the crankcase emissions, the largest source of bus self-pollution identified in two newer Seattle buses (model years 2000 and 2003) with DOCs (Liu et al. 2008). The pDR has previously been shown to be highly correlated (r~0.9) with $PM_{2.5}$ measurements by the Harvard Impactor and have a good precision (biased-adjusted precision ~ 6%) over a wide range of concentrations (up to 200 $\mu g/m^3$) (Liu et al. 2002) at fixed locations. We observed a precision of 1.9 $\mu g/m^3$ in this study based on laboratory collocation tests (N=827). All data were collected with one-minute resolution and averaged over the duration of the trips. Trips started immediately after the technician boarded the bus with the subject and ended when bus arrived at school or home stop.

During this study, ambient background $PM_{2.5}$ levels were monitored by the Puget Sound Clean Air Agency's (PSCAA's) nephelometers with dryers at the Beacon Hill site in Seattle and at the closest station in Kent for the Tahoma school district. These data were downloaded as hourly averages from http://pscleanair.org/airq/reports.aspx and used as a predictor in our exposure models. Ambient weather data from the University of Washington (UW) and SeaTac airport were obtained from the UW's Department of Atmospheric Sciences (http://www.atmos.washington.edu/data/ and http://www.k12.atmos.washington.edu/k12/grayskies/nw_weather.html).

Bus Information

Bus characteristics, including make, model, engine type, age, mileage, existing emissions control technology, and maintenance schedules were compiled from the PSCAA, school transportation departments, and inspection by our technicians during our annual baseline monitoring in collaboration with the Washington Department of Ecology in the summer preceding our air quality monitoring. The baseline included opacity measurements using a Bosch RTT 100 Smokemeter (San Francisco, CA). Bus route information including stop locations and duration between stops were obtained from the district transportation departments and confirmed by school administrators. These routes were digitized in ArcGIS 9.2 (ESRI Corporation, Redlands, CA) and the fraction of route on a major roadway (i.e, interstate highway, state highway, or major arterial) was calculated in distance using road network data from the King County GIS Center (http://wagda.lib.washington.edu/). Data on each monitored trip were also recorded by our technicians who traveled on the bus with the sampling instrumentation including the location of the monitoring equipment, time-resolved information on the window use (majority open or closed and, if open, the average position (partially, ¼, ½, ¾, fully open), stops, door position (open or closed), and local pollution events such as traffic congestion, other diesel vehicles, or industrial sources.

Data Analysis

To characterize $PM_{2.5}$ during transit, we conceptualized the concentrations on-board the bus (C_{bus}) as being comprised of three primary components: self-pollution from the bus (C_{self}), pollution from surrounding vehicles ($C_{traffic}$), and ambient background pollution (C_{amb}):

$$C_{bus}=C_{self}+(C_{traffic}+C_{amb})$$

Since the levels aboard the lead vehicle (C_{LV}) are equal to the sum of $C_{traffic}$ and C_{amb}, with the LV approach we can also simplify the concentrations on the bus to the following:

$$C_{bus}=C_{self}+C_{LV}$$

Prediction models were created for C_{bus} and C_{LV} using SAS Version 9.1 (SAS Institute, Raleigh NC). Although C_{bus} was our primary variable of interest, C_{LV} also was modeled to explore predictors of background roadway concentrations and provide insight regarding exposures to children who ride in private automobiles to and from school. We employed ordinary least squares (OLS) regression modeling with a backward selection procedure (critical p-value of 0.05) to create a multivariate prediction model. In addition, we fit a multivariate prediction model using partial least squares (PLS) regression. Unlike OLS regression modeling, which minimizes the prediction error only of the response, PLS regression seeks latent factors that explain the variation in both the response and predictors. This technique was selected since it is thought to provide better predictions of the response when there are many correlated predictors and relatively few observations (Geladi and Kowalski 1986). The number of factors extracted in our PLS regression modeling was based on the minimum of the predictive root mean sum square errors.

Tested predictors of C_{LV} included ambient $PM_{2.5}$, meteorological data (temperature, relative humidity, and wind speed), and route characteristics (time of day, total distance traveled, and type of roadway). Variables evaluated as potential predictors of C_{bus} included ambient $PM_{2.5,}$ roadway $PM_{2.5}$, and meteorological data, bus information (age, location of engine, number of seats, mileage, emissions control technology, fuel type, opacity levels, engine type, maintenance frequency, time since last service), and route characteristics (time of day, total distance traveled, type of roadway, window use, number of stops, number of pollution events).

Since not all buses had preceding lead vehicles, models for C_{bus} were constructed with and without C_{LV} as a predictor. Models that control for C_{LV} provided insight of self-pollution levels. All continuous variables were modeled linearly unless diagnostics indicated that another functional form was required. Similarly, we modeled both school districts together when there was no evidence of differences between stratified analyses. Stratification of all models for C_{bus} by window use was also explored based on previous findings of enhanced self pollution with closed windows (Behrentz et al. 2005).

To test the robustness of our models, we conducted a 10-fold cross-validation procedure. This involved randomly splitting our data into 10 equal parts and training on each selection of 9-tenths of the data while validating on the final tenth. Backward variable selection was repeated for each cross-validation set in OLS regression, as was factor analysis in PLS regression. Under cross-validation, we calculated R^2 for our prediction models using the formula: 1 – SSE/SST. These cross-validation or "CV" R^2s are reported in addition to naïve R^2s from our OLS and PLS modeling of the entire dataset ("model-based R^2s"). Since the same bus was usually sampled during a morning and afternoon trip, we evaluated the correlation between repeated measures using a mixed model with a random bus effect. Likelihood ratio tests, however, indicated that random effects were not needed so our final models assume independence between all trips.

Results

Seattle and Tahoma Buses

$PM_{2.5}$ was monitored onboard 53 buses between November 2005 and June 2006. These buses serviced 18 schools in the Seattle School District and 4 schools in the Tahoma School District. Descriptive statistics for these monitored buses, all buses used by our study subjects, and the fleet of buses used by each school district are presented in Table 1. The buses ridden by our study subjects had similar characteristics to the overall district bus fleets. Our monitored buses also were comparable to the overall fleet although the monitored Seattle buses had lower opacities and fewer diesel oxidation catalysts (DOCs) than buses ridden by the general study population.

In general, Seattle buses were newer than Tahoma buses (mean body year of 2001 versus 1995), had half of the mileages (mean of 61,000 versus 113,000), and were smaller in seating capacity (70 versus 77). Seattle buses also had a higher prevalence of emission reducing technology and ultra-low sulfur diesel (ULSD) fuel use, as well as lower opacities (7.1 versus 21.8%). In addition, Seattle buses had more frequently scheduled routine maintenance visits (i.e., every 3,000 miles or every 45–60 days) as compared to Tahoma buses, which had maintenance visits required every 5,000 miles traveled.

$PM_{2.5}$ Concentrations

In total, 96% of the raw data ($pDR_{1\ min}$) met our quality control criteria based on the procedures of Wu and colleagues (2005b) and were included for analysis. Raw data were voided due to negative instrument drift (2%) or periods with RH greater than 95% (2%). 73% of our bus and 77% of our lead vehicle trip averages met our trip QC criteria and were included for analysis. Voided trips were the result of a high frequency (>25%) of missing values (8% of bus trips and 7% of lead vehicle trips), high frequency (>25%) of zero values (3% of bus trips and 7% of lead vehicle trips), short durations (14% of bus trips and 9% of lead vehicle trips), and one extreme outlier (mean concentration of 305 μg/m^3).

This resulted in valid $PM_{2.5}$ concentrations for 85 bus trips from 43 buses and 57 lead vehicle trips, with 46 paired trips available to estimate self-pollution levels (Table 2). On average, concentrations aboard buses (21 μg/m^3) were approximately two-times higher than roadway levels measured by the lead vehicle (12 μg/m^3). Levels measured on the buses and roadways were higher than ambient conditions measured at central monitoring stations, which had a mean concentration of 6 μg/m^3 in Seattle and 3 μg/m^3 in Tahoma. Concentrations were also more variable aboard the bus and roadways with standard deviations of 12, 8, and 3 μg/m^3 for the bus, lead vehicle, and ambient monitors, respectively.

Overall, we observed a mean self-pollution concentration of 7 μg/m^3 for the two districts combined, although Seattle buses demonstrated lower self pollution estimates (5.8 μg/m^3) than the older Tahoma buses (8.5 μg/m^3). While the majority of trips demonstrated evidence of self pollution, higher concentrations were observed in the lead vehicle as compared to the bus during a few trips, likely due to slightly different surrounding roadway conditions, resulting in negative estimates for self pollution levels.

Trip Characteristics

Characteristics of the monitored trips aboard these buses are presented in Table 3. The mean duration of all trips was 22 minutes with approximately 4 stops per trip. Seattle bus routes covered more miles and lasted approximately twice as long as Tahoma trips. Similarly, Seattle buses spent a larger fraction of the time on state highways and major arterials than buses in Tahoma. None of the monitored trips used interstate highways during this monitoring period. Window use was relatively common in both districts with approximately 60% of Seattle trips having any open windows as compared to 36% of the routes in Tahoma. Similarly, 35% of Seattle trips had the majority of windows open as compared to 18% in Tahoma. Among buses with available maintenance records, we found a trend of more recent maintenance among Tahoma buses as compared to Seattle buses.

Modeling Results

Roadway concentrations (C_{LV})—As there was no evidence of effect modification by district, all roadway data were pooled for our multivariate prediction models. In OLS modeling, C_{LV} was found to be best predicted by two variables; ambient $PM_{2.5}$ and the total trip distance (Table 4). The majority of the explanatory power was from ambient $PM_{2.5}$ (partial model-based R^2 of 0.56), with a 1.4 (95% CI: 1.0 to 1.7) μg/m^3 increase in C_{LV} predicted per 1 μg/m^3 increase in ambient levels. Total trip distance also was positively associated with C_{LV}, with a 0.4 μg/m^3 (95% CI: 0.04 to 0.7) increase in C_{LV} predicted per kilometer driven. Cross-validation indicated that this multivariate C_{LV} model was generally robust with an R^2 of 0.49. A sensitivity analysis also indicated similar results in a model using all data including trips with durations less than 10 minutes, high frequency of zeros, and high frequency of missing data. In this more inclusive model, ambient concentrations of $PM_{2.5}$ remained a key predictor of C_{LV} (model-based R^2 of 0.52) although total distance traveled was no longer significantly predictive.

Figure 2 presents the overall normalized parameter estimates for the PLS regression modeling of C_{LV}. As in the OLS modeling, ambient $PM_{2.5}$ levels were found to be the most influential predictor of C_{LV}. No other factors had a strong influence on C_{LV}. This model had a model-based R^2 of 0.66 and an R^2 of 0.65 under cross-validation. These results also were robust under sensitivity analysis to inclusion of trips removed from the main analysis due to short durations, high frequency of zeros, and high frequency of missing data.

In-bus concentrations (C_{bus})—All bus data were pooled for multivariate modeling since there was no strong evidence of effect modification by district. Our multivariate OLS modeling results are presented in Table 5. Without controlling for roadway concentrations, C_{bus} was best fit by four predictors: an indicator for newer buses with DOC technology (as new buses and

DOC are perfectly confounded in our study buses), ambient RH, opacity, and an indicator for frequent routine maintenance. This model explained approximately 45% of the total variability in C_{bus} according to the model-based R^2. Most of the explanatory power (21%) was due to decreased concentrations in buses with DOCs, which also had low mileage (<10,000 miles) and were newer than 2005. Under cross-validation, the indicator for new buses with DOCs remained consistent across models but the other variables were less robust, yielding an overall R^2 of 0.17. Sensitivity analysis with our complete dataset selected the same model with slightly less explanatory power.

Additional variability was explained by including roadway concentrations in our model (Table 5). With a partial R^2 of 36%, controlling for C_{LV} increased the total model-based R^2 to 62%. In this model, the indicator for new buses with DOCs remained an important predictor and was associated with a similar decrease in concentrations as our earlier model. Maintenance frequency also remained important although a different indicator was selected. Like our previous indicator (i.e., scheduled maintenance every 60 days or less), the number of days since last servicing indicated higher concentrations among buses with more frequent maintenance. Window use also was included in this model with decreased concentrations predicted for window use. Consistent with the roadway concentrations being an important factor, the inclusion of C_{LV} in the model enhanced the robustness of the findings with a cross-validation R^2 of 0.32. As before, this model was not changed by inclusion of all data including trips with durations less than 10 minutes, high frequency of zeros, high frequency of missing data, and an extreme trip, although the overall explanatory power was slightly less.

Our PLS modeling results are presented in Figure 3. For models of all available bus measurements and those with matched lead vehicles, ambient characteristics (i.e., on-road $PM_{2.5}$, ambient $PM_{2.5}$, temperature, and RH) were consistently important predictors of C_{bus} levels. Ambient $PM_{2.5}$ and RH were positively associated with $C_{bus,}$ while C_{bus} was negatively associated with ambient temperatures. Among trips with concurrent lead vehicle samples, roadway levels were found to be the strongest predictor with positive associations demonstrated with C_{bus}. Most trip and bus characteristics had weaker impacts with the major exception of new buses with DOCs. As in our OLS modeling, this factor was found to be the strongest predictor of C_{bus} levels and was associated with substantially lower levels of onboard $PM_{2.5}$. The number stops, frequent maintenance, and engine type also were found to be moderate predictors of C_{bus}. Time of day also predicted $C_{bus,}$ with higher concentrations demonstrated in the morning, but this was only found in our analysis without C_{LV}. Interestingly, although several bus characteristics were only present in Seattle (e.g., ULSD, new buses (>2005), DOCs, and frequently scheduled maintenance visits <60 days), minimal differences were observed in the overall means of C_{bus} between districts.

Similar to the OLS models, PLS models accounted for 51 and 65% of the total variability in C_{bus} with and without C_{LV}, respectively. These models demonstrated signs of instability under cross-validation, however, with a cross-validation R^2 of 0.2 for models with and without C_{LV}. As with our OLS models, these results were generally unchanged by inclusion of all data but contained more unexplained variability in C_{bus}.

Among buses with the windows closed, the indicator for new buses with a DOC remained a consistent predictor of C_{bus}. This variable had good predictive power for buses with and without a paired lead vehicle (partial model-based R^2s of 0.36 and 0.28, respectively) and was robust throughout cross-validation. As anticipated based on the previous findings of Sabin and colleagues (2005a, 2005b), bus-related factors were generally not predictive in buses with the windows open. On these trips, only C_{LV} was found to be consistently predictive.

Discussion

Our characterization of $PM_{2.5}$ on roadways and aboard 43 school buses in the Seattle area has demonstrated that children are exposed to an elevated level of particulate air pollution during their commutes to and from school. Concentrations during routine school bus rides were four-times higher than ambient levels at central monitoring stations and nearly two-times higher than levels on surrounding roadways. While changes in ambient $PM_{2.5}$ levels explained most of the variability in roadway concentrations, ambient conditions were less predictive of bus concentrations. In fact, the strongest predictors of bus levels were roadway concentrations and an indicator for new buses with DOCs. New buses with DOCs were associated with substantially lower in-cabin concentrations, especially when the bus windows were closed. As such, this dataset confirms that bus characteristics including emission reducing technologies may be quite important to childhood exposures to traffic-pollution.

This investigation validates past findings, which have indicated that children are routinely exposed to a large fraction of their daily exposure to PM while in transit (Allen et al. 2003; Behrentz et al. 2005; Wu et al. 2005a). Although the absolute concentrations onboard school buses in the Seattle metropolitan area (21 $\mu g/m^3$) were generally lower than other investigations (45 $\mu g/m^3$ in Los Angeles school buses (Behrentz et al. 2005) and 35–40 $\mu g/m^3$ in London transit buses (Adams et al. 2001; Kaur et al. 2005)), the observed increases above ambient levels were similar and remained sizeable. In fact, the average self-pollution levels observed in our buses (7 $\mu g/^3$) were similar to those previously reported for two Seattle buses (8 $\mu g/m^3$) monitored as part of a dual-tracer self pollution study (Liu et al. 2008). The overall concentrations in this investigation might over- or under-estimate the levels experienced by some children since there are mixed results regarding the influence of position within a bus on concentrations. Behrentz and colleagues (2004) demonstrate higher levels of a tracer of bus exhaust in the rear of the bus, however, Hill and colleagues (2005) reported higher concentrations of $PM_{2.5}$ in the front of a bus due to penetration of pollutants through the cabin door. These differences in distribution might be due to the major source of pollution (i.e., the exhaust or crankcase), which can vary by bus fleet.

Previous investigations have indicated that concentrations onboard school buses are influenced by bus and route features (Behrentz et al. 2005; EHHI 2002; Hammond et al. 2007a; Hill et al. 2005; Liu et al. 2008; Sabin et al. 2005a; Sabin et al. 2005b; Solomon et al. 2001). Such investigations were limited by the small number of buses monitored. With 43 buses sampled during 85 trips, this paper presents the first published attempt to produce a statistical prediction model for pollution levels onboard diesel school buses. One major finding of these models was the importance of local roadway concentrations in the prediction of in-cabin concentrations. This was evident by the fact that C_{LV} was substantially more predictive of bus concentrations than ambient data from a remote central monitor. Although we hypothesized that emissions from other vehicles might account for some of this added explanatory power (Adams et al. 2001; Behrentz et al. 2005; Ott et al. 1994), our crude indicators of traffic volumes (i.e., roadway type) were not found to be strong predictors of in-cabin or on-road concentrations. Neither were acute pollution events predictive of bus concentrations averaged over an entire trip.

Our second major finding was that the presence of a DOC on new school buses (2005 or later) resulted in substantially lower levels of $PM_{2.5}$. This bus feature was consistently the most important predictor in both our OLS and PLS results, explaining as much as 20% of the variability in bus concentrations. These findings are supported by two other investigations, which reported lower levels of ultrafine particles onboard Alabama school and transit buses retrofitted with DOCs (Hammond et al. 2007a; Hammond et al. 2007b) . Although those investigations did not present results for $PM_{2.5}$, their findings indicate that some components of $PM_{2.5}$ are reduced by DOCs. Also similar to the results of Hammond and colleagues (Hammond et al. 2007b), our analysis suggested that these reductions were predominantly for buses with their windows closed. This confirms past findings, which have indicated that self pollution is highest when the bus windows are closed (Liu et al. 2008; Sabin et al. 2005b).

Although it would be compelling to conclude that the DOC was responsible for the dramatic reductions observed in $PM_{2.5}$, uncertainty exists since all of our sampled buses with DOCs were also new buses (>2005). This makes it difficult to conclusively determine that the reduced concentrations were due to DOCs and not another characteristic of the new bus. One study of two Michigan school buses casts some doubt as to the causality of the DOC. In that investigation, no reductions in tailpipe or in-cabin levels of $PM_{2.5}$ were observed following retrofit with a DOC (Hill et al. 2005). Another finding that suggests that DOCs might not be responsible is that $PM_{2.5}$ from self-pollution was shown to be dominated by crankcase emissions while ultrafine particle counts are more typical of the tailpipe (Hill et al. 2005; Liu et al. 2008). Since DOCs are designed to reduce tailpipe but not crankcase emissions, this suggests that our findings may be reflective of another, currently unidentified, feature of buses newer than 2005. Interestingly, a continuous factor for age of the bus was not found to be important in our analysis. On the other hand, engine type, which was related to age of the bus (all buses with Caterpillar engines were older), was found to be modestly associated with $PM_{2.5}$ concentrations.

Number of stops and time of day also were found to be modestly predictive of concentrations on the bus. Other studies have demonstrated that the number of stops is predictive of in-transit concentrations (Alm et al. 1999, Hill et al. 2005, Behrentz et al. 2005, Hammond et al 2007b,). For example, Hill and colleagues demonstrated that the majority of $PM_{2.5}$ originating from school buses enters the cabin during stops. The authors attributed this finding to more door openings and thus more entrainment of $PM_{2.5}$ from crankcase emissions. Exposure to tailpipe emissions also likely occurs during stops as Beherntz and colleagues have demonstrated that the bus exhaust can reach the front door under the proper wind conditions (Behrentz et al 2004). One unexpected finding of this investigation was the result that higher concentrations were predicted on buses with more frequent and recent maintenance. Since maintenance scheduling was directly related to the bus base, these results may also be confounded by another factor such as type of oil used or maintenance procedures performed.

In spite of general consistency with past investigations, our prediction models explained a modest fraction of the variability in the bus concentrations. One possible explanation for the residual unexplained variation is the imprecision in predictors related to bus characteristics since many of the bus characterization data (e.g., body year, mileage, maintenance frequency) were not originally collected for scientific research. Another likely contributor to our modest explanatory power is the use of $PM_{2.5}$ as the outcome variable. $PM_{2.5}$ is not specific to traffic-related pollution, and it has been shown to have less predictive power for in-vehicle levels than other more-specific indicators such as black carbon and polycyclic aromatic hydrocarbons (Sabin et al. 2005b). $PM_{2.5}$ was selected for this analysis, however, based on our past research which demonstrated that differences between bus and roadway $PM_{2.5}$ as measured by the light scattering pDR (which is most efficiently responsive to $PM_{0.1}$) is highly related to crankcase emissions. Crankcase emissions were of interest as they were found to accounts for 80% of the bus's self pollution in two previously monitored Seattle buses (years 2000 and 2003) with DOCs (Liu et al. 2008). Although these two buses might not be representative of older buses, there is supporting evidence from Hill and colleagues (2005) that crankcase emissions also were substantial contributors to onboard $PM_{2.5}$ levels in newer buses (year 2000) without control technologies. Nevertheless, future work should include an evaluation of more specific traffic-related markers as well as increased numbers of buses and retrofit technologies to be measured.

In summary, we found that school buses contribute substantially to children's daily exposures to air pollution. Although much of the variability in bus concentrations remained unexplained, we found consistent and significant evidence that some bus features such as new buses with DOCs were associated with reduced concentrations. These data and ongoing sampling of these bus fleets, which are undergoing various retrofit procedures, will provide a rich dataset for cost-benefit analyses. Since exposures during school bus commutes may have important health ramifications, these results can ultimately be combined with epidemiology data to inform decisions regarding the use of clean diesel technologies.

Acknowledgements

This study was sponsored by the NIEHS (#1R01ES12657-01A1), with pilot work by the Washington Department of Ecology. This work would not have been possible without the efforts of René Irish, Erin Corwine, Tim Gould, Alex Ineichen, and the Diesel Bus Monitoring Team. We are thankful for the advice and support of Dr. Jim Krieger (Seattle-King County Department of Public Health), Bridget Anderson, Michelle Zaleski, Doug Sander and Bruce Zahradnik (Tahoma Schools), Jill Lewis (Seattle Schools), Michael Boyer and David Adler (Department of Ecology), Stacy Roberts, Robert Cook, and David Oylear (First Student), and Michael Montgomery (Curtis Transportation). We are also extremely grateful for our collaborations with David Anderson (Seattle Schools Transportation Department) and Paul Carr and John Anderson (PSCAA Diesel Solution Program). We also thank the Seattle and Tahoma principals, teachers, and students whose daily support made this study possible.

Abbreviations

C_{LV}, Lead vehicle or roadway concentrations
C_{bus}, Bus concentrations
C_{self}, Self pollution concentrations
DOC, Diesel oxidative catalyst
OLS, Ordinary least square
pDR, Personal DataRAM
PLS, Partial least squares
PSCAA, Puget Sound Clean Air Agency
$PM_{2.5}$, Particulate matter with aerodynamic diameter ≤2.5 micrometers
RH, Relative humidity
SSE, Sum square error
SST, Total sum square error
TWAC, Time weighted average concentration
ULSD, Ultra-low sulfur diesel
UW, University of Washington

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Figure 1.
Seattle and Tahoma Study Areas

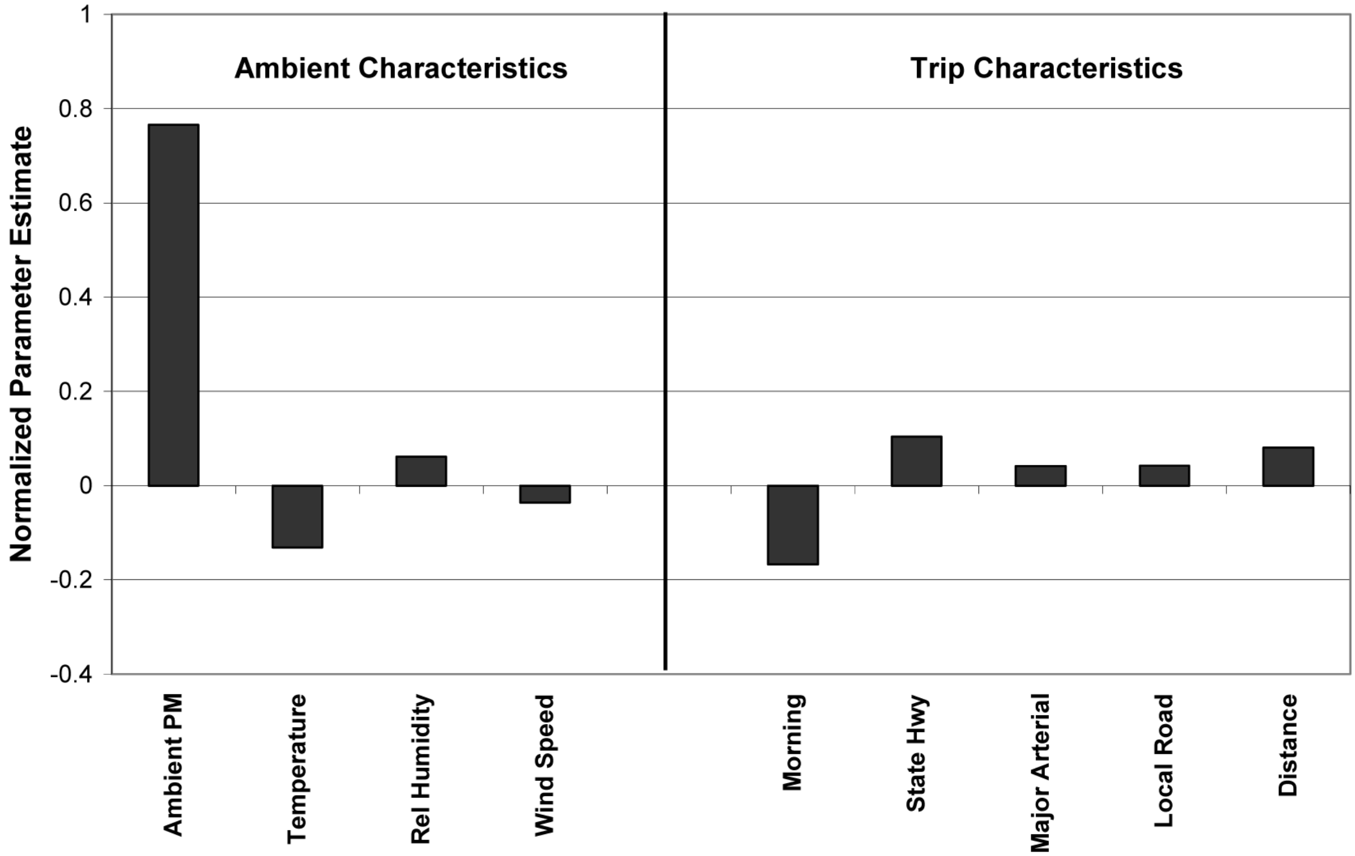

Figure 2.
Normalized Parameter Estimates for Predictors of Roadway Concentrations Using PLS Modeling

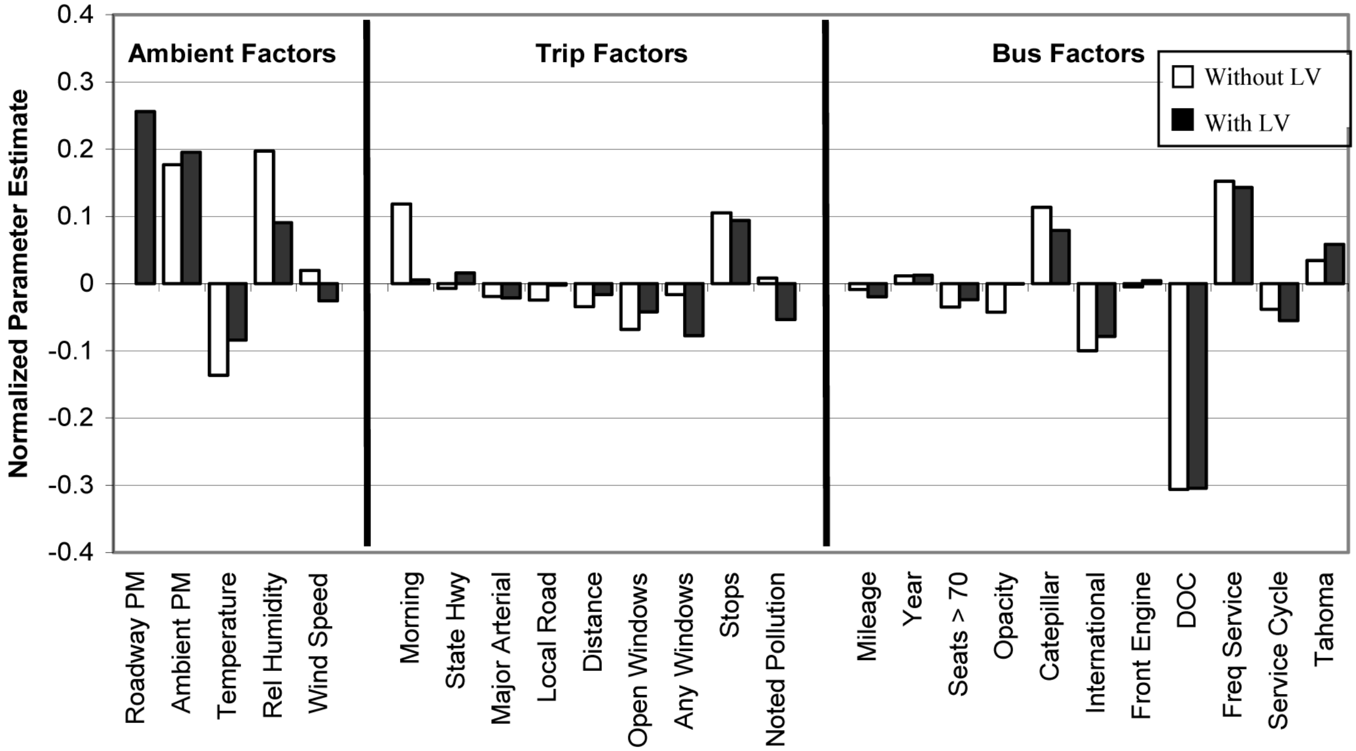

Figure 3.
Normalized Parameter Estimates for Predictors of Bus Cabin Concentrations Using PLS Modeling With and Without Roadway Concentrations

TABLE 1

Descriptive Statistics for Seattle and Tahoma High Capacity School Buses in the 2005−2006 School Year (>50 Seats)

	Seattle			Tahoma		
	All Buses	Subject Buses[a]	Monitored Buses[b]	All Buses	Subject Buses[a]	Monitored Buses[b]
Number of Buses	331	68	24	62	23	19
DOC Usage[c]	40.8%	42.6%	25.0%	3.2%	0%	0%
OEM DOC	24.8%	26.5%	25.0%	3.2%	0%	0%
DPF Usage	4.5%	5.9%	4.2%	0%	0%	0%
ULSD Usage	100%	100%	100%	0%	0%	0%
Bus Mileage (in thousands)	61 (57)	60 (57)	48 (43)	110 (88)	113 (87)	117 (89)
Body Year	2001 (5)	2001 (4)	2003 (4)	1995 (7)	1996 (6)	1996 (6)
Seating Capacity	70 (4)	69 (3)	70 (3)	76 (5)	77 (5)	76 (5)
Engine Manufacturer[d]						
International Truck	54%	53%	46%	48%	52%	53%
Cummins Inc.	1%	0%	0%	13%	4%	5%
Caterpillar	34%	34%	50%	39%	43%	42%
Front Engine	98%	100%	100%	42%	30%	37%
Opacity (%)	7.1 (8.9)	8.4 (10.8)	4.6 (4.8)	21.8 (19.1)	17.5 (16.6)	16.9 (16.5)
Frequent Service (<60 days)	91%	85%	84%	0%	0%	0%
Scheduled Maintenance Frequency (days)	46 (4)	47 (5)	47 (5)	132 (101)	101 (32)	101 (34)

Continuous data are presented as the overall mean (SD).

[a]Summarized values for subject buses represent the students' typical buses although substitute buses are occasionally used during periods of servicing or vehicle inspection.

[b]Descriptive statistics presented for buses with valid data only.

[c]25% and 27% of all Seattle buses and Seattle subject buses, respectively, were retrofit with aftermarket DOCs. All other DOCs were original equipment installed by the manufacturer.

[d]Remaining buses have unknown engine types.

TABLE 2

$PM_{2.5}$ Concentrations (μg/m^3) Measured Aboard the Bus, Lead Vehicle, and Estimates of Self Pollution

	Overall		Seattle		Tahoma	
	N	**Mean (SD)**	**N**	**Mean (SD)**	**N**	**Mean (SD)**
All Trips						
Bus	85	20.9 (11.9)	46	20.6 (14.1)	39	21.4 (9.0)
Lead Vehicle	57	12.4 (8.0)	35	12.9 (8.4)	22	11.6 (7.5)
Ambient	117	4.8 (3.4)	63	6.0 (3.6)	54	3.4 (2.7)
Paired Trips[a]						
Bus	46	19.7 (10.8)	25	19.1 (11.5)	21	20.5 (10.1)
Lead Vehicle	46	12.7 (8.4)	25	13.3 (9.2)	21	12.0 (7.5)
Bus Self-Pollution	46	7.0 (9.0)	25	5.8 (9.1)	21	8.5 (8.9)
Ambient	44	5.5 (4.2)	25	6.9 (4.5)	19	3.7 (2.8)

[a]Paired trips imply that a bus and lead vehicle drove the same route simultaneously.

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TABLE 3

Mean (SD) Characteristics of Ambient and Trip Conditions During Monitored Bus Trips

	All Trips			Trips with Paired Lead Vehicle		
	Overall	**Seattle**	**Tahoma**	**Overall**	**Seattle**	**Tahoma**
Ambient Temperature (°F)	53 (11)	53 (10)	52 (11)	51 (11)	51 (11)	52 (12)
Ambient Relative Humidity (%)	65 (18)	66 (16)	64 (20)	63 (19)	63 (18)	62 (21)
Ambient Wind Speed (mph)	6.6 (3.4)	5.3 (2.8)	8.1 (3.4)	6.6 (3.5)	5.1 (3.2)	8.4 (3.0)
Trip Duration (minutes)	22 (12)	28 (12)	16 (7)	24 (12)	30 (13)	18 (8)
Heating Season (Oct - Feb)	33%	35%	31%	39%	40%	38%
Bus Stops	4 (3)	5 (3)	4 (4)	5 (4)	5 (3)	4 (4)
Window Usage						
Any Windows Open	48%	60%	36%	45%	59%	32%
Most Windows Open	27%	35%	18%	31%	41%	21%
Total Distance (miles)	4.8 (3.0)	6.2 (2.7)	3.5 (2.7)	5.0 (2.7)	5.7 (2.5)	4.3 (2.9)
Length of Route by Type (%)						
Interstate	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
State Highway	1 (6)	3 (8)	0 (0)	1 (6)	2 (8)	0 (0)
Major Arterial	48 (26)	63 (16)	30 (24)	49 (28)	67 (13)	31 (28)
Local Roads	51 (27)	34 (15)	70 (24)	50 (28)	31 (11)	69 (28)
Last maintenance (days)	49(60)	90 (70)	17 (15)	54 (65)	97 (71)	14 (152)

TABLE 4

Ordinary Least Squares Multivariate Regression Results for Roadway Concentrations (C_{LV}, μg/m^3)

	Effect Estimate	**Standard Error**	**t-value**	**p-value**	**Model-Based R^2**	**CV R^2**
Intercept	9.53	3.73	6.54	0.01		
Ambient $PM_{2.5}$ (μg/m^3)	1.36	0.18	57.39	<0.001	0.56	
Total Trip Distance (km)	0.41	0.18	5.04	0.03	0.04	
Overall Model Fit					**0.60**	**0.49**

Table 5

Ordinary Least Squares Multivariate Regression Results For In-Cabin Concentrations (C_{bus}, μg/m^3

	Effect Estimate	Standard Error	t-value	p-value	Model-Based R^2	CV R^2
Models Without Roadway Concentrations (N=85)						
Intercept	6.45	4.34	2.21	0.14		
New Buses with DOCs	−15.15	2.89	27.48	<0.001	0.21	
Ambient Relative Humidity (%)	0.26	0.06	18.06	<0.001	0.13	
Frequent Maintenance (<60 days)	5.42	2.33	5.43	0.02	0.07	
Opacity (%)	−0.26	0.12	4.29	0.04	0.04	
Overall Model Fit					**0.45**	**0.17**
Models With Roadway Concentrations (N=46)						
Intercept	30.33	5.15	34.69	<0.001		
Roadway Concentrations (μg/m^3)	0.46	0.14	11.38	0.0017	0.36	
New Buses with DOCs	−13.331	2.77	23.18	<0.001	0.13	
Maintenance Cycle (days)	−0.17	0.05	11.07	0.002	0.08	
Windows Mostly Open	−5.19	2.38	4.74	0.04	0.05	
Overall Model Fit					**0.62**	**0.32**