Distribution Agreement

Signature:

______________________________ ______________

Justin Han Chen Date

Vehicular Air Pollutants and Noise in Atlanta Commuting

By

Justin Chen
MPH

Environmental Health

Jeremy Sarnat, ScD
Committee Chair

Paige Tolbert
Committee Member

Vehicular Air Pollutants and Noise in Atlanta Commuting

By

Justin Han Chen

B.S.
Georgia Institute of Technology
2010

Thesis Committee Chair: Jeremy Sarnat, Sc.D.

An abstract of
A thesis submitted to the Faculty of the
Rollins School of Public Health of Emory University
in partial fulfillment of the requirements for the degree of
Master of Public Health
in Environmental Health
2012

Abstract

Vehicular Air Pollutants and Noise in Atlanta Commuting
By Justin Han Chen

Drivers in the United States are exposed to high concentrations of air pollutants and noise during commutes. Numerous negative health outcomes, especially in cardiovascular health, have been linked to both forms of exposure. Noise may be acting as a confounder in assessing the relationship between traffic pollution and acute adverse cardiovascular health outcomes. This study was performed in order to quantitatively examine the associations between in-vehicle noise and several traffic pollutants in multiple roadway microenvironments. Sampling was conducted in 3 different sampling scenarios: 1) within a stationary outdoor setting; 2) within an in-vehicle stationary setting; and 3) within a moving in-vehicle setting. This was done in order to differentiate the effect the personally driven vehicle had upon both noise and air pollutant exposure. During the in-vehicle sampling scenarios, ventilation and window status were accounted for. Air pollutants measured were particulate matter 2.5 mass ($PM_{2.5}$), ultrafine particulate matter (UFPM), black carbon (BC), and polycyclic aromatic hydrocarbons (PAH). Noise levels were measured concurrently with air pollutants. Resulting correlation coefficients between measured air pollutants and noise varied upon sampling scenario. The stationary outdoor sampling scenario exhibited the lowest values compared to the two in-vehicle sampling scenarios, with the stationary in-vehicle scenario showing the greatest correlation values for $PM_{2.5}$ and BC, and the moving in-vehicle scenario showing the greatest values for UFPM and PAH. Strengths of association ranged from moderately strong ($R_S > 0.60$) to weak. Vehicle ventilation status had a mixed effect upon pollutant-noise correlations, but the stationary in-vehicle setting generally showed a more pronounced effect compared to the moving in-vehicle sampling scenario. Vehicular speed as a modifier of the linear relationship between measured air pollutants and noise exposure was also examined, and it was found that UFPM and BC may infiltrate the vehicle cabin with greater efficiency at higher speeds. The results of the regression analysis found similar results as the calculated correlation values, and time lagged pollutant exposures generally had a weakening effect upon associations. Noise acting as a confounder or effect modifier of vehicular air pollution is possible depending upon numerous variables, including air pollutant type and the exposure setting.

Vehicular Air Pollutants and Noise in Atlanta Commuting

By

Justin Han Chen

B.S.
Georgia Institute of Technology
2010

Thesis Committee Chair: Jeremy Sarnat, Sc.D.

A thesis submitted to the Faculty of the
Rollins School of Public Health of Emory University
in partial fulfillment of the requirements for the degree of
Master of Public Health
in Environmental Health
2012

Acknowledgements

Special thanks to Dr. Jeremy Sarnat, Dr. Roby Greenwald, and James Gooch for support on this project.

Table of Contents

INTRODUCTION

Many Americans are exposed to high concentrations of air pollutants, both particle-phase and gas-phase chemicals during their commutes[1]. In addition to air pollutants, commuters are frequently exposed to high levels of vehicular noise, especially during periods of heavy traffic volume. It is known that there are a number of negative health outcomes associated with traffic-related air pollutants[1, 2], but it has also been shown that similar outcomes may be associated with high levels of noise exposure[3]. Noise exposure and its relationship with cardiovascular health has been well documented in a built environment setting, but the interaction between noise within transport microenvironments and traffic-related air pollutants has not been particularly well studied.

There is growing evidence that excess noise exposure may pose a risk in the development of hypertension[4, 5], myocardial infarction[6], and ischemic heart disease[7, 8]. Heavy vehicular traffic has been considered one of the most likely sources of excess noise exposure, and investigating an exposure limit has been the focus of several research initiatives. Several epidemiological investigations have observed threshold limits for several noise-related adverse outcomes to be approximately 65 decibels A (dBA)[8]. Babisch et al (2006) reviewed 21 epidemiological studies on traffic and aircraft noise in Europe and Japan, and determined that a threshold of 65 dB(A) was a sensitive indicator of adverse cardiovascular related health outcomes from vehicular traffic noise. Brunekreef et al (2002) also found a similar association of cause-specific mortality with a cohort of 120,000 subjects exposed to traffic related air pollution. In this study, as part of the Netherlands Cohort Study (NLCS), a small association of traffic noise and cardiovascular mortality was detected for 1.6% of the full cohort of subjects at or above 65 dB(A). Also using NLCS data, Beelen et al (2009) reported a significant association between traffic noise exposures above the 65 dB(A) for overall cardiovascular mortality and heart failure mortality [2, 9]. Although there is now a noted threshold amplitude for increased health risk due to noise, these articles fail to account for duration of exposure, which may be as important for estimating health related risks as sheer volume[10].

It is also possible that noise may be serving as a confounder in assessing the relationship between traffic pollution and acute adverse cardiovascular health outcomes [1, 2, 6-8, 11]. Generally, for confounding to exist, the joint distributions of both noise and a traffic pollutant must be correlated with each other as well as with an outcome of interest, which include numerous cardiovascular endpoints in this setting. While it has been shown that there is significant exposure to both noise and air pollutants within the cabin of a vehicle [12-14], the correlation between noise and speciated air pollution in a commuting microenvironment ('in-vehicle') is poorly understood. The few, initial studies that have been conducted examining in-vehicle noise and traffic pollution have shown that several factors may influence the relationship between vehicular air pollutants and noise including the number of lanes on a travelled roadway, number of vehicles, and the number of major intersections along a roadway[11]. Spatial proximity among vehicles is also central for understanding the influence of these factors[15], and although these association were examined primarily within a built environment setting by Allen et al (2009), the conclusions drawn are applicable to an in-vehicle microenvironment as well.

The current study was conducted to quantitatively examine the associations between in-vehicle noise and several predominant traffic pollutants in a range of roadway microenvironments. Broadly, we view these results as an initial means of elucidating the role of noise in traffic pollution epidemiology; as a potential confounder, modifier, or as an additional risk factor contributing to a dynamic pollutant mixture.

MATERIALS AND METHODS

To examine the associations between noise and pollutant levels, we conducted sampling using three different sampling scenarios: 1) within a stationary outdoor setting; 2) within a stationary in-vehicle setting; and 3) within a moving in-vehicle setting.

The purpose of the three sampling scenarios was to differentiate the effect of the personally driven vehicle (PDV) on exposures to both noise and air pollution. The stationary outdoor scenario was designed to assess actual ambient relationships among the noise and pollutant variables without the influence of filtering or emission of both noise and pollution from the PDV. The in-vehicle stationary scenario provided a means of assessing relationships among the measured noise and pollutant parameter that were affected by filtering from the vehicle envelope. Finally, the moving in-vehicle sampling scenario was the most dynamic of the three and included noise generated by the PDV as well as sampling conditions that occur during an actual commute including continually changing traffic volume, as well as variable spatial sampling distances and traffic speeds. Both stationary sampling scenarios were compared to the moving scenario to examine how much of the measured noise and air pollutant emissions were attributable to the PDV itself.

The two stationary sampling scenarios were conducted in a parking lot adjacent to Interstate 75/85 in midtown Atlanta, Georgia. Each sample was collected between approximately 7AM to 9AM to capture concentrations during peak morning rush hour periods. In addition to the data collected by the sampling instrumentation, records were logged on vehicular traffic volume, number of large diesel vehicles that passed, and other notable exposure factors that took place during sampling periods. A total of 6 sampling periods were recorded for the outdoor stationary sampling scenario.

The PDV used throughout this study for the in-vehicle stationary and moving scenarios was a 2008 Honda Civic. The stationary in-vehicle sampling scenario had several controlled variables introduced by the PDV that had to be taken into account during exposure sampling sessions, including window and fan status. During the entire two hour daily sampling period, open window status was alternated from being completely open to completely close every 30 minutes (i.e., each sampling session included 2 open and 2 closed window periods). During the closed window periods, the vehicle cabin fan was turned to the mid-strength setting with fresh air being from the exterior of the vehicle. The fan was shut off during the open window periods. The sampling manifold containing all of the instruments was placed in the passenger seat of the vehicle. A total of 6 sampling periods were recorded for the in-vehicle stationary sampling scenario.

The moving vehicle sampling scenario took place during the same two hour period in the morning between approximately 7AM and 9AM. Driving was mainly restricted to the highways of Atlanta, specifically to Interstate 285, Interstate 75, Interstate 85, and Interstate 20. A similar route was used during each sampling period. The same 30 minute cycling period between windows up and windows down was employed, with the same vehicular fan settings used for the windows up period. Notes on traffic volume and other notable observations were recorded via voice recorder and a digital camera recording every 2 seconds from the dashboard of the PDV. A global positioning device was used to record data on location and speed of the vehicle. A total of 6 sampling periods were recorded for the in-vehicle moving sampling scenario.

Continuous concentrations of particulate matter 2.5 μm volume (expressed in $\mu m^3 \cdot cm^{-3}$) was measured using a TSI™ Aerotrak. These recorded volume measurements were converted to mass ($\mu g \cdot m^{-3}$) data for particulate matter 2.5 μm or less based on a 1 second sampling frequency by multiplying them with a synthetic density value constant measured in grams per cubic centimeter ($g \cdot m^{-3}$). Particle number concentrations (expressed in $\# \cdot cm^{-3}$), indicative of ultrafine particulate matter (< 0.1 μm in aerodynamic diameter), were continuously measured using both a TSI™ CPC and P-Trak. The CPC was used throughout the majority of the study, but the P-Trak was phased in during the latter portion of the study to correlate data and gather redundant data in case the CPC failed due to a mechanical failure. Each device took samples on a 1 second sampling frequency. A Magee Scientific™ microaethlometer was used to continuously measure black carbon concentrations (expressed in $\mu g \cdot m^{-3}$) on a 1 minute sampling frequency. An EcoChem™ photoelectric aerosol sensor (PAS) was used to continuously measure particle bound polycyclic aromatic hydrocarbon (PAH) concentrations (expressed in $ng \cdot m^{-3}$) on a 1 second sampling frequency. Noise levels were continuously measured using an audio dosimeter recording in decibels(A) on a 1 second sampling frequency. Finally, speed during the moving PDV sampling scenario was measured using global positioning system (GPS) device recording trip information on a 1 second sampling frequency. All exposure collection devices were housed in a custom fabricated manifold (figure 1). The sampling frequencies of recording instruments varied from resolutions of 1 second to 1 minute. In order to create comparable data sets, data for instruments with measuring frequencies of less than 1 minute were averaged to 1 minute mean data points. The recorded exposure data was also averaged to 5 minute mean data points in order to decrease the influence of outlying data points on the calculation of correlation and modeling statistics.

Data Analysis

Descriptive statistics were conducted to characterize the central tendencies of the various noise and pollutant distributions. Spearman's correlation coefficients (R_S) assessing the linear relationship between noise levels, the measured pollutant exposures, and speed were calculated based upon the 5 minute average data in order to decrease the influence of extreme observations and noise artifact due to analytical errors. Spearman's correlation coefficients were also warranted due to the non-normality of the observed distributions. Correlation analyses were also conducted on stratified subsets of the data by sampling scenario type and window status (where applicable).

Simple linear regression modeling was also conducted using both 1 minute and 5 minute average data, with noise levels modeled as the independent variable and air pollutant levels modeled the dependent variable. For these models, both the noise and air pollutant data were log transformed (base e) to induce normality, which is assumed within linear regression approaches. Of the data sets, all exposure values were stratified by sampling scenario type, as well as models including interaction product terms between noise and sampling scenarios were used to assess differences in the associations by scenario. Time lag models, where air pollutant levels were either lagged 1 or 5 minute behind noise levels were also modeled using simple linear regression analysis. All correlation analyses and simple linear regression modeling were performed in SAS 9.3 on a Microsoft Windows system. Tableau Desktop software was used to plot noise exposure vs. speed vs. air pollutant exposures.

RESULTS AND DISCUSSION

Summary statistics based upon 5 minute averages for total combined sampling and by scenario type are presented in tables 1, 2, 3, and 4. Each table is subdivided into the specific statistics for each measured variable. There was considerable variation among the measured pollutant by scenario. For particulate matter 2.5 mass ($PM_{2.5}$), the highest mean average was found in the stationary outdoors sampling scenario (29.2 $\mu g \cdot m^{-3}$), with the greatest standard deviation occurring during the stationary in-vehicle sampling scenario, and the greatest max count was found in the moving in-vehicle sampling scenario. For ultrafine particulate matter (UFPM), the highest mean, standard deviation, and max count was measured in the moving in-vehicle sampling scenario (23000 $\# \cdot cm^{-3}$). For black carbon (BC), the highest mean was measured in the moving in-vehicle sampling scenario (6.4 $\mu g \cdot m^{-3}$), but the greatest standard deviation and max count was measured during the stationary outdoors sampling. The highest mean, standard deviation, and max count for polycyclic aromatic hydrocarbons (PAH) was measured in the moving in-vehicle sampling scenario (112.5 $ng \cdot m^{-3}$). For the noise measurements, the highest mean occurred in the stationary outdoors sampling scenario (73dBa), but the greatest standard deviation and max count were found in the moving in-vehicle sampling scenario. Speed was only measured in the moving in-vehicle scenario.

Each sampling scenario was defined by two primary exposure factors; whether or not the sampling took place within or outside of the vehicle, and whether or not the vehicle was moving or stationary. When comparing the two stationary sampling scenarios, the in-vehicle stationary sampling scenario showed lower mean averages for every measured pollutant variable. In contrast, the moving in-vehicle scenario showed the highest means for UFPM, BC, and PAH compared to either of the stationary sampling scenarios.

Correlation between Noise and Pollutant Measurements by Sampling Scenario

Using 5 minute averaged data for all measured distributions, correlation analysis was conducted between each of the four continuous air pollutants ($PM_{2.5}$, UFPM, BC, and PAH) (Figure 2). All pairwise Spearman's correlation coefficients were significant ($p < 0.05$), however, the strength of linear association varied by pollutant and sampling scenario. When aggregated across scenarios, UFPM was found to be the most highly correlated with noise ($R_S = 0.68$). None of the other measured pollutants were shown to have correlation coefficients greater than of 0.49 for the aggregated sampling scenarios.

There were several observable trends in correlation by pollutant by sampling scenario. For $PM_{2.5}$-Noise, correlation coefficients were 50% higher within the stationary in-vehicle scenario than the next highest pairwise correlation ($R_S = 0.69$ for stationary in-vehicle; 0.46 for moving in-vehicle). The correlation coefficients calculated for UFPM show a 31% difference between the highest coefficients values (0.68 for moving in-vehicle scenario) compared to the second highest (0.52 for stationary in-vehicle scenario). The correlation coefficients between PAH and noise showed differences of 67% between the highest value of 0.40 (moving in-vehicle) and the second highest value of 0.24 (stationary in-vehicle), but the highest correlation value doesn't suggest a particularly strong correlation between PAH exposure and noise exposure. Broadly, compared to all other sampling scenarios, the stationary outdoor sampling scenario exhibited the lowest correlation coefficient values for all pollutant types. The stationary in-vehicle sampling scenario had the highest correlation coefficients for $PM_{2.5}$ and BC, and the moving in-vehicle sampling scenario had the highest correlation coefficients for UFPM and PAH. These patterns of correlation coefficients suggest that the differences in each sampling scenario type have an effect on the relationship between noise and air pollutants.

The varied chemical composition and fate and transport properties of traffic-related air pollution provide challenges to understanding the complex relationship they have with traffic-related noise emissions. Despite this, the findings of this study suggest that associations exist between noise and several pollutants. In our quasi-controlled field experiment, we observed strengths of association ranging from moderately strong (i.e., $R_S > 0.60$) to weak depending on a number of factors such as sampling scenario, vehicle speed, and in-vehicle ventilation status. Each measured air pollutant may have numerous emission sources, even if they originated from the same active roadway. On the highways during morning rush hour traffic, vehicle concentration patterns are constantly changing, and the composition of the surrounding vehicles are changing as well. For example, there may be smaller standard petrol burning cars or motorcycles with loud mufflers that may lead to extremely elevated readings, but emit relatively small amounts of air pollutants. On the other hand, there may be large diesel vehicles that emit large quantities of numerous pollutants, but may be driving far enough ahead of a sampling vehicle that any associated excess noise may not be detected.

Vehicle Ventilation Status and Pollutant-Noise Correlations

The influence of window ventilation status for the within vehicle sampling scenarios on the association between the noise and the measured air pollutants was examined by further stratifying the pairwise observation into window status categories. As noted, windows were either fully closed or fully opened for 30 minute intervals during each 2 hour sampling period. Figure 3 shows stratification by window status for the stationary in-vehicle sampling scenario. Figure 4 shows stratification by window status for the moving in-vehicle sampling scenario.

Window status during the stationary in-vehicle sampling scenario was shown to have a pronounced influence on the strength of correlation (Figure 4). When the windows were up, correlation coefficients between $PM_{2.5}$ and noise were 72% higher compared to when windows were down (R_S = 0.64 for when up vs. 0.37 for when down). UFPM-Noise correlations were also substantially higher when windows were up compared to when down (0.49 vs. 0.09, respectively). In contrast, for BC and PAH stronger observed correlations with noise were higher when windows were down compared to the windows up setting. BC had an increase of 39% when windows were down (0.43 for when down vs. 0.31 for when up), and PAH had an increase of 67% (0.30 for when down vs. 0.18 for when up). Similar, but slightly less pronounced differences were seen by window ventilation status in the moving in-vehicle scenario. $PM_{2.5}$, when stratified by window status, was not strongly correlated with noise, however, there was a 30% higher correlation coefficient when windows were up compared to when down (R_S = 0.17 for when up vs. 0.13 for when down). Just as the stationary in-vehicle scenario, there was a higher correlation coefficient value when windows were up then down, but only a 13% increase (0.62 for when up vs. 0.55 for when down). BC-noise pairwise correlations were similar by ventilation status and PAH-noise pairs showed stronger correlations when windows were down compared to when they were up (R_S = 0.51 when down; 0.26 when up).

Generally, differences in correlation values by window status were more pronounced in the stationary in-vehicle scenario compared to the moving in-vehicle scenario, except for PAH. We observed that having the windows down was typically associated with weaker correlation coefficients for both $PM_{2.5}$ and UFPM, regardless of whether the vehicle was stationary or moving, decreasing to levels similar to what was seen in the outdoor sampling scenario. BC and PAH correlation coefficients, on the other, were both stronger when windows were down. The contrasting influence that window status had upon noise-air pollutant correlations deserves further attention. The lesser difference in correlation values dependent upon window status during the moving in-vehicle sampling scenario may suggest that the numerous factors involved with sampling during an actual commute, such as sampling at speed and greater air infiltration, may have an effect upon the robustness of relationship between vehicular noise exposure and air pollutants.

Correlations between the Air Pollutants and Noise by Vehicle Speed

Vehicular speed as a modifier of the linear relationship between the measured air pollutants and noise exposure was also examined. Increased vehicular speed may affect the ventilation of air within the vehicle as there is likely to be an increased rate of particulate deposition [16]. The force of air in contact and infiltrating the vehicle is dependent upon the speed in which the vehicle and the air meet one another. In the moving in-vehicle sampling scenario, differences between window status correlation coefficient values were not as pronounced as in the stationary in-vehicle sampling scenario, except for PAH. The mean average levels of all measured air pollutants except for $PM_{2.5}$ were higher in the moving in-vehicle scenario compared to the stationary in-vehicle scenario, and the same was true for standard deviations (Tables 3 and 4).

A plausible explanation for these observed trends may be increased air infiltration at higher speeds (Figure 5). In-vehicle noise was highly correlated with speed (R_S = 0.80), UFPM and BC were mildly correlated with speed (RS = 0.41 and 0.35 respectively), and $PM_{2.5}$ and PAH were weakly correlated with speed (RS for both ~ 0.20). To further examine the role of speed as a modifier of this relationship, speed and noise measurements for all of the moving in-vehicle scenarios were plotted against each other, with a third variable representing a single measured air pollutant represented as a color gradient (Figure 6). All graphs show a visually noticeable color gradient following the increasing trend line between speed and noise, but the most distinctive increasing color gradient was for UFPM, indicative of an increasing presence of UFPM in the vehicle cabin with both increased speed and noise exposure. This result is consistent with the previously noted findings showing a UFPM-noise correlation 0.68 and a UFPM-speed correlation 0.41. $PM_{2.5}$ exhibited the weakest visual color gradient trend, indicating its weaker correlation with both noise and speed (R_S = 0.46 and 0.19, respectively). These results provide some indication of differential infiltration by particle size at varying speeds, with smaller, ultrafine particles exhibiting higher penetration efficiency into the vehicle's interior environment than larger particles.

Associations between Noise and Air Pollution using Regression Analyses

For further analysis of the relationship between noise and air pollutant exposure in the defined sampling scenarios, simple linear regression was used to create multiple models to simulate sampling conditions. The conditions included exposure average time, the type of sampling scenario (stationary/moving, outdoors/in-vehicle), and time lag periods meant to investigate the temporal cause and effect relationship between noise and air pollutant exposures. The resulting statistics and values are presented in table 5.

As expected, the general R^2 value trends were consistent matched the Spearman's correlation coefficients trends seen in figure 2, using either 1 or 5 minute averaging times. UFPM had the greatest R^2 value for combined sampling scenarios, and $PM_{2.5}$ had the least. For the stationary outdoor sampling scenario, UFPM had the greatest R^2 value, and BC had the least. For the stationary in-vehicle sampling scenario, $PM_{2.5}$ had the greatest R^2 value, and PAH had the least. For the moving in-vehicle sampling scenario, UFPM had the greatest R^2 value, and $PM_{2.5}$ had the least (Figure 7). In all models, UFPM has either the greatest or second greatest R^2 value, suggesting that of all the measured air pollutants, UFPM is most likely to be associated with vehicular noise.

Interaction models were also created as a supplemental analysis to stratification, with the interaction term expressed as follows:

$$Interaction\,Term = Noise\ Exposure\ Level\ (dBa)x\ Sampling\ Scenario\ Type$$

The sampling scenario types were categorized as 1 being stationary outdoors, 2 being stationary in-vehicle, and 3 being moving in-vehicle. The resulting model showed UFPM with the greatest R^2 value and $PM_{2.5}$ with the least. The coefficient of determination for each model varied widely by pollutant and sampling scenario, where $PM_{2.5}$ showed a max R^2 value of 0.53 for 1 minute average stationary in-vehicle sampling scenario models, and a minimum R^2 value of 0.04 in the 1 minute average stationary outdoor sampling scenario. UFPM had a max R^2 value of 0.51 in the 5 minute average moving in-vehicle sampling scenario, and a minimum value of 0.11 in the 1 minute average stationary outdoor scenario. BC had a max R^2 value of 0.30 in the 5 minute average moving in-vehicle sampling scenario, and a minimum value of 0.00 in the 5 minute stationary outdoor sampling scenario. These results suggest that the physical characteristics of each measured pollutant type play a role in how associated they are with corresponding noise. More specifically, it is possible that noise is more strongly associated with larger particulate matter in more stable sampling environments, like the interior of a stationary vehicle, but not in a less stable environment like a moving vehicle or outdoors.

The 5 minute average models typically had higher R^2 values compared to models using 1 minute averages. The percentage differences in R^2 values of the same sampling scenario and pollutant type range from 0% to 50% increases. These results indicate that by reducing the influence of extreme observation through longer averaging times, noise becomes a more accurate predictor of corresponding air pollutant concentrations. Despite this, the highest R^2 value were only 0.51 for UFPM in the moving in-vehicle sampling scenario for 5 minute averages, suggesting that measured audio exposure only explain slightly more than half of the variability in UFPM concentrations for this specific sampling scenario.

An apparent trend from the current analyses is that the sampling environment is a key determinant in predicting exposures to both in-vehicle noise and air pollution. In this study, the vehicle itself acted as a buffer to all forms of externally-emitted pollutant exposures, as shown when comparing statistics between the stationary outdoor and stationary in-vehicle scenario. This buffering effect may have served as a stabilizing factor for sampling, where there are generally consistently higher correlation coefficients and R^2 values for the relationship between noise and air pollutants. It is possible that the vehicle shell is functioning as a filter to noise and air pollutant exposures, allowing only greater levels to infiltrate and, thus, possibly creating the greater statistics of association. The outdoor sampling environment, in contrast, is completely defined by external factors, including weather patterns, wind speed, and air pressure. The in-vehicle sampling scenarios have both passive and active filters, where passive filters include the exterior frame and noise dampening technology, and active filters include controllable fan ventilation settings and whether or not windows are open or closed. Although the environment outside of the PDV is not controlled by the driver, air ventilation rates can be modified by speed of driving and in-vehicle fan and air conditioning settings. Noise dampening caused by the PDV may also filter out quieter sounds with no direct association with air pollutant emissions, but the louder noise of an adjacent revving engine, marking increased air pollutant emission, may infiltrate and be registered by the audio dosimeter.

We also observed more varied strengths of association while conducting the moving vehicle sampling scenario. When the vehicle was moving, concentrations of all the measured air pollutants were higher compared to the other sampling scenarios, as were the measured noise levels when compared to the stationary in-vehicle sampling scenario. These results indicate a greater infiltration efficiency occurring at higher speeds for all of the measured pollutant parameters. This is consistent with particle infiltration theory which states that air change rates are dependent on numerous factors including leakage characteristics, wind conditions, and the speed with which a vehicle is moving[17]. Moreover, it is plausible that the finding of higher noise levels at higher speeds is due to the fact that overall traffic noise due to engine revolutions, exhaust system performance and tire-road noise is also greater when vehicles are travelling faster[18, 19]. All weights being equal, vehicle traffic traveling at a consistently higher speed with no acceleration will create more noise than those traveling at lower speed due mostly to increased tire noise with mechanical noise from the drivetrain playing a factor as well. The strengths of association between noise and both UFPM and PAH concentrations were also stronger at higher speeds, but weaker for both $PM_{2.5}$ and BC. It is plausible that differential infiltration rates into a vehicle cabin exist between smaller UFPM and $PM_{2.5}$, which is an explanation supported by particle infiltration theory.

For UFPM and PAHs, the current findings suggest that infiltrations rates may be more similar to the rate of sound wave infiltration into a vehicle cabin. Ultrafine particles are defined as having a diameter of 100 nanometers (nm) or less, thus their smaller physical profile may have been a factor for vehicle infiltration. At higher speeds, there is an increased air flow rate towards the PDV, and by impaction theory, smaller particles are unable to bypass obstructions due to fluid resistance and insufficient momentum, possibly resulting in UFPM and other small particles being caught by the PDV at greater rates than larger ones[20]. In a temporal perspective, smaller particles (UFPM) tend to also have much shorter half-lives than larger particles[21]. Thus, when there is an increased noise level, there is likely to be an increased level of UFPM, and when there is a decreased noise level, there is likely to be decreased UFPM levels.

The time between a noise emission occurring immediately outside of the vehicle and a measured noise reading for any single event is nearly instantaneous. However, an air pollutant emission associated with that same event may only be measured at a later time due to physical properties related to pollutant-specific fate and transport principles. We used simple linear regression models for both non-lagged and lagged data sets to investigate whether lagged association between noise and the pollutants existed at a 1 or 5 minute time scale (Table 5).

Models using a 1 minute noise lag (i.e., assessing whether noise from the previous minute predicted current measured pollutant concentrations) exhibited weakly attenuated effects on R^2 values for all models except for in the moving in-vehicle scenario, where slight increases between noise and both $PM_{2.5}$ and BC (of 17% and 6% respectively). For the 5 minute lagged models, greater attenuations in R^2 values were seen in all cases, except for $PM_{2.5}$ in the stationary outdoor and moving outdoor scenario (16% and 61% increase respectively). $PM_{2.5}$ was the only measured air pollutant that had some positive increases in R^2 values using a lagged model structure. These results suggest that either the larger particulate matter fractions travel slower than other measured pollutants, or that there is perhaps an overlap of $PM_{2.5}$ source and noise where consistent levels of larger particulate matter are concurrent with vehicular noise due to its shared and constant source emissions.

Nearly all lagged models showed decreased R^2 values when using a time lagged data set (either 1 minute or 5 minutes lagged), suggesting that at these time resolutions, a time lagged effect was not occurring. This does not necessarily mean that time lag do not exist between noise and air pollutant exposure, but that a more time sensitive recording or complex modeling may be required in order to elucidate their true nature.

CONCLUSION AND RECOMMENDATIONS

The relationship between vehicular noise and air pollutants is highly complex, and likely varies by pollutant, as well as numerous exposure and emission factors that requires more in depth study in order to better understand their relationship with one another. Traffic pollution and noise may lead to similar health endpoints, which make this topic an increasingly important issue for both air pollutant and noise researchers to understand. Neglecting either type exposure may not comprise a complete picture for comprehensive commuters' exposures on a daily basis.

The results of this study suggest that there is a possibility of noise acting as a confounder or effect modifier of vehicular air pollution. The calculated values of correlation and regression models suggest that certain air pollutants are more likely to be associated with noise than others, but all do show that some amount of their variability can be linked with noise exposure levels. Many variables, such as sampling environment, have an effect upon the strength of these associations, suggesting that numerous factors must be controlled to the best of abilities in order to clarify true associations of noise exposure, air pollutant exposure, and the responding health effects. More sensitive data recording, controlled environment study, and more complex modeling techniques may provide a more thorough and intricate understanding of these relationships, making concerns of unknown confounding and effect modifying a non-issue for those studying the effect vehicular traffic and commuting have on human health.

REFERENCES

1. Brunekreef, B., et al., *Effects of long-term exposure to traffic-related air pollution on respiratory and cardiovascular mortality in the Netherlands: the NLCS-AIR study*. Health Effects Institute Research Reports, 2009(139): p. 1-94.
2. Brunekreef, B. and S.T. Holgate, *Air pollution and health*. The Lancet, 2002. **360**(9341): p. 1233-1242.
3. Stansfeld, S.A. and M.P. Matheson, *Noise pollution: non-auditory effects on health*. British Medical Bulletin, 2003. **68**(1): p. 243-257.
4. Chang, T.-Y., et al., *Effects of environmental noise exposure on ambulatory blood pressure in young adults*. Environmental Research, 2009. **109**(7): p. 900-905.
5. Sun, Q., et al., *Air Pollution Exposure Potentiates Hypertension Through Reactive Oxygen Species-Mediated Activation of Rho/ROCK*. Arteriosclerosis, Thrombosis, and Vascular Biology, 2008. **28**(10): p. 1760-1766.
6. Babisch, W., et al., *Traffic Noise and Risk of Myocardial Infarction*. Epidemiology, 2005. **16**(1): p. 33-40 10.1097/01.ede.0000147104.84424.24.
7. Babisch, W., H. Ising, and J.E.J. Gallacher, *Health status as a potential effect modifier of the relation between noise annoyance and incidence of ischaemic heart disease*. Occupational and Environmental Medicine, 2003. **60**(10): p. 739-745.
8. Babisch, W., *Transportation noise and cardiovascular risk: Updated Review and synthesis of epidemiological studies indicate that the evidence has increased*. Vol. 8. 2006. 1-29.
9. Beelen, R., et al., *The joint association of air pollution and noise from road traffic with cardiovascular mortality in a cohort study*. Occupational and Environmental Medicine, 2009. **66**(4): p. 243.
10. Passchier-Vermeer, W. and W.F. Passchier, *Noise exposure and public health*. Environmental Health Perspectives, 2000. **108**(Suppl 1): p. 123.
11. Davies, H.W., et al., *Correlation between co-exposures to noise and air pollution from traffic sources*. Occupational and Environmental Medicine, 2009. **66**(5): p. 347.
12. Riediker, M., et al., *Exposure to particulate matter, volatile organic compounds, and other air pollutants inside patrol cars*. Environmental science & technology, 2003. **37**(10): p. 2084-2093.
13. Adams, H., et al., *Fine particle (PM2. 5) personal exposure levels in transport microenvironments, London, UK*. The Science of the Total Environment, 2001. **279**(1-3): p. 29-44.
14. Watts, G. and P. Nelson, *The relationship between vehicle noise measures and perceived noisiness*. Journal of sound and vibration, 1993. **164**(3): p. 425-444.
15. Allen, R.W., et al., *The spatial relationship between traffic-generated air pollution and noise in 2 US cities*. Environmental Research, 2009. **109**(3): p. 334-342.
16. Thatcher, T.L., et al., *Effects of room furnishings and air speed on particle deposition rates indoors*. Atmospheric Environment, 2002. **36**(11): p. 1811-1819.
17. Fletcher, B. and C. Saunders, *Air change rates in stationary and moving motor vehicles*. Journal of Hazardous Materials, 1994. **38**(2): p. 243-256.
18. Olson, N., *Survey of motor vehicle noise*. The Journal of the Acoustical Society of America, 1972. **52**: p. 1291.
19. Lelong, J. *Vehicle noise emission: evaluation of tyre/road and motor-noise contributions*. 1999: New Zealand Acoustical Society; 1998.

20. Noll, K.E. and M.J. Pilat, *Inertial impaction of particles upon rectangular bodies*. Journal of Colloid and Interface Science, 1970. **33**(2): p. 197-207.
21. Kuhn, T., et al., *Volatility of indoor and outdoor ultrafine particulate matter near a freeway*. Journal of Aerosol Science, 2005. **36**(3): p. 291-302.

TABLES AND FIGURES

Figure 1. A photo of the sampling device manifold containing the exposure sampling devices.

Variable	Units	N	Mean	Std Dev	Median	Minimum	Maximum
PM2.5 Mass	$\mu g \cdot m^{-3}$	437	22.1	10.6	21.9	2.9	68.9
Ultrafine PM	$\# \cdot cm^{-3}$	414	15596	10643	12078	2810	87125
Black Carbon	$\mu g \cdot m^{-3}$	440	5.3	12	3.7	0.2	243.4
PAH	$ng \cdot m^{-3}$	412	67.4	46.4	54.6	5.7	372.5
Noise	dBa	442	67.1	8.3	68.3	50	80.7
Speed	km/h	132	63.5	34.4	65.1	0	111.5

Table 1. Descriptive statistics for 5 minute averages on all measured variables in combined sampling scenarios.

Variable	Units	N	Mean	Std Dev	Median	Minimum	Maximum
PM2.5 Mass	$\mu g \cdot m^{-3}$	139	29.2	6.5	27.8	19.5	41.5
Ultrafine PM	$\# \cdot cm^{-3}$	139	15515	7048	13210	6723	41648
Black Carbon	$\mu g \cdot m^{-3}$	139	5.9	20.4	3.9	0.3	243.4
PAH	$ng \cdot m^{-3}$	139	53.9	30.1	46.2	14.3	193.9
Noise	dBa	139	73.8	3.2	74.6	64.9	78.7

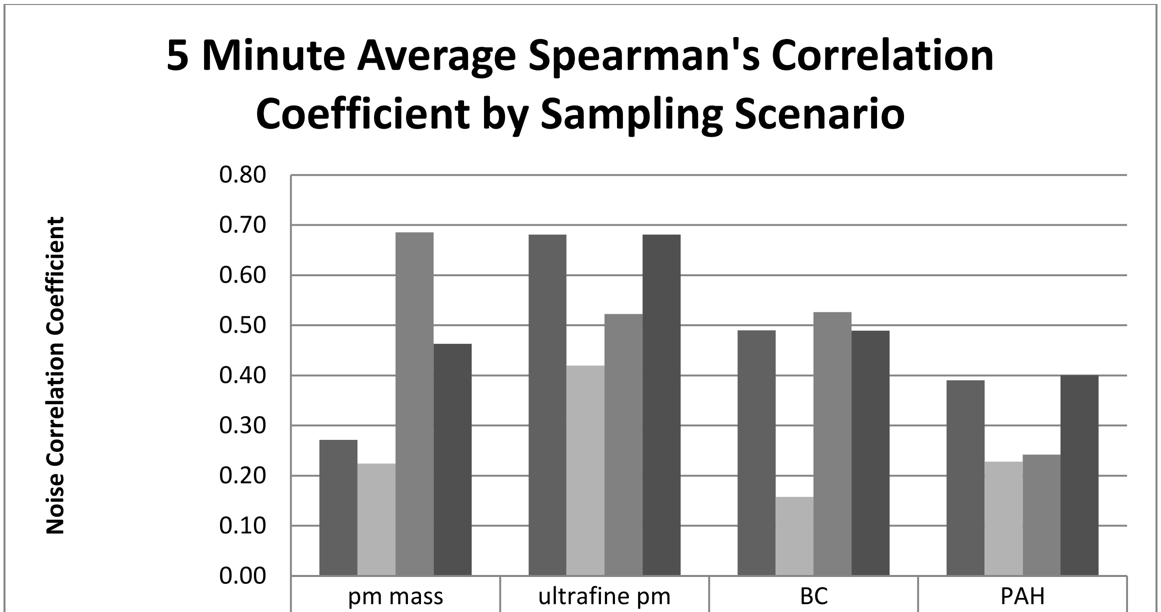
Table 2. Descriptive statistics for 5 minute averages on all measured variables in the outdoor stationary sampling scenario.

Variable	Units	N	Mean	Std Dev	Median	Minimum	Maximum
PM2.5 Mass	$\mu g \cdot m^{-3}$	144	23.6	10.2	23.3	6.3	48.9
Ultrafine PM	$\# \cdot cm^{-3}$	144	8939	4138	7977	2810	22138
Black Carbon	$\mu g \cdot m^{-3}$	143	3.4	2.7	2.8	0.2	21
PAH	$ng \cdot m^{-3}$	143	39.6	19.5	38.8	8.6	101
Noise	dBa	144	58.1	4.9	57.7	50	66.2

Table 3. Descriptive statistics for 5 minute averages on all measured variables in the in-vehicle stationary sampling scenario.

Variable	Units	N	Mean	Std Dev	Median	Minimum	Maximum
PM2.5 Mass	$\mu g \cdot m^{-3}$	154	14.3	8.7	13.3	2.9	68.9
Ultrafine PM	$\# \cdot cm^{-3}$	131	23000	13564	22469	3560	87125
Black Carbon	$\mu g \cdot m^{-3}$	158	6.4	5.1	5.1	0.6	37.7
PAH	$ng \cdot m^{-3}$	130	112.5	48.7	105.4	5.7	372.5
Noise	dBa	159	69.4	6.6	70.6	54.4	80.7
Speed	km/h	132	63.5	34.4	65.1	0	111.5

Table 4. Descriptive statistics for 5 minute averages on all measured variables in the in-vehicle moving sampling scenario.



	pm mass	ultrafine pm	BC	PAH
total	0.27	0.68	0.49	0.39
stationary outdoor	0.22	0.42	0.16	0.23
stationary indoor	0.69	0.52	0.53	0.24
moving indoor	0.46	0.68	0.49	0.40

Figure 2. Spearman's correlation coefficients calculated between noise and various air pollutants that are stratified by sampling scenario. All values significant at $p < 0.05$.

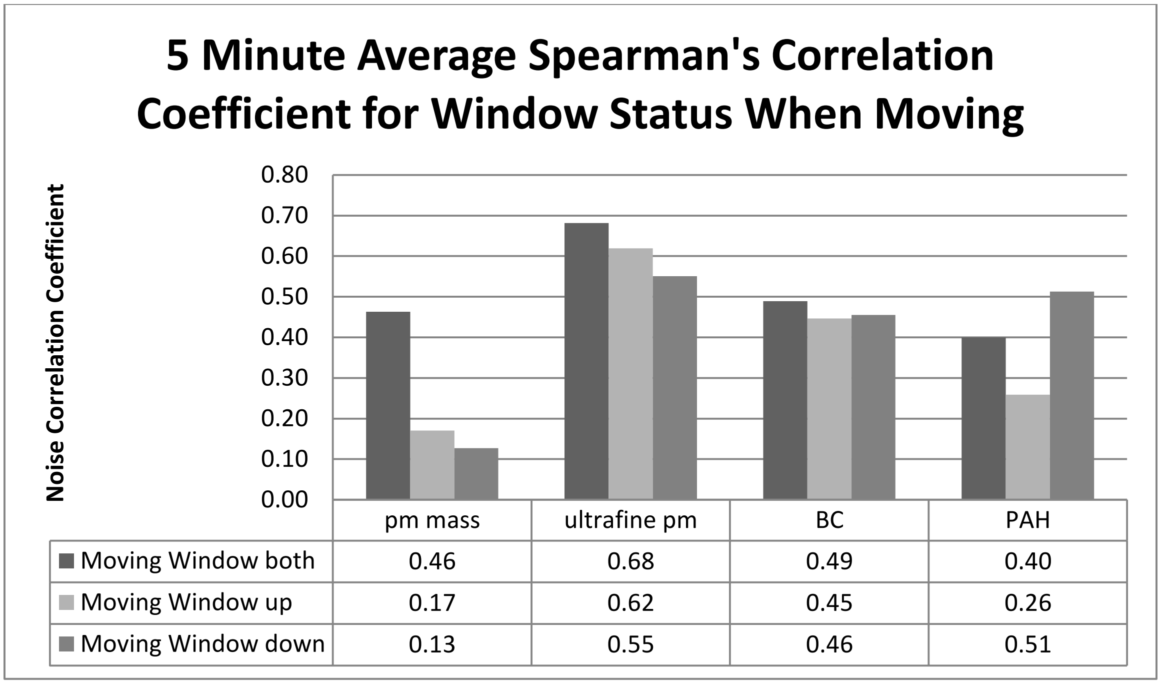


Figure 3. Spearman's correlation coefficients between noise and various air pollutants stratified upon window status for stationary in-vehicle sampling scenario. All values significant at $p < 0.05$ except for PAH windows up (0.11) and UFPM windows down (0.47).

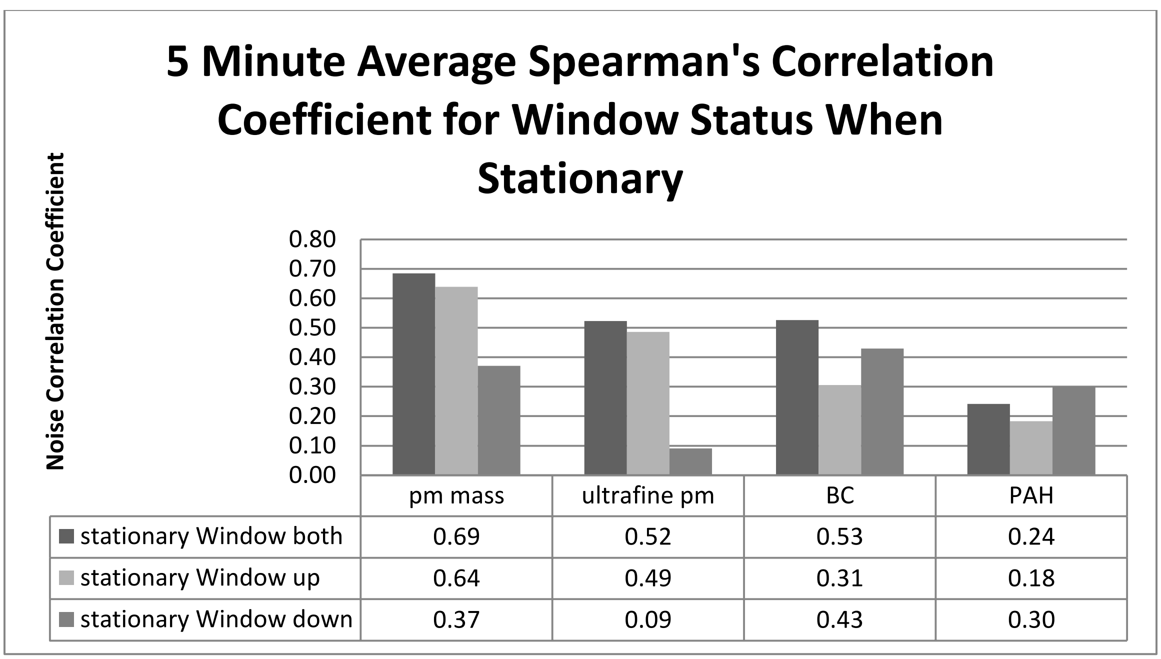


Figure 4. Spearman's correlation coefficients between noise and various air pollutants stratified upon window status for moving in-vehicle sampling scenario. All values significant at $p < 0.05$ except for PM2.5 windows up (0.14) and PM2.5 windows down (0.27).

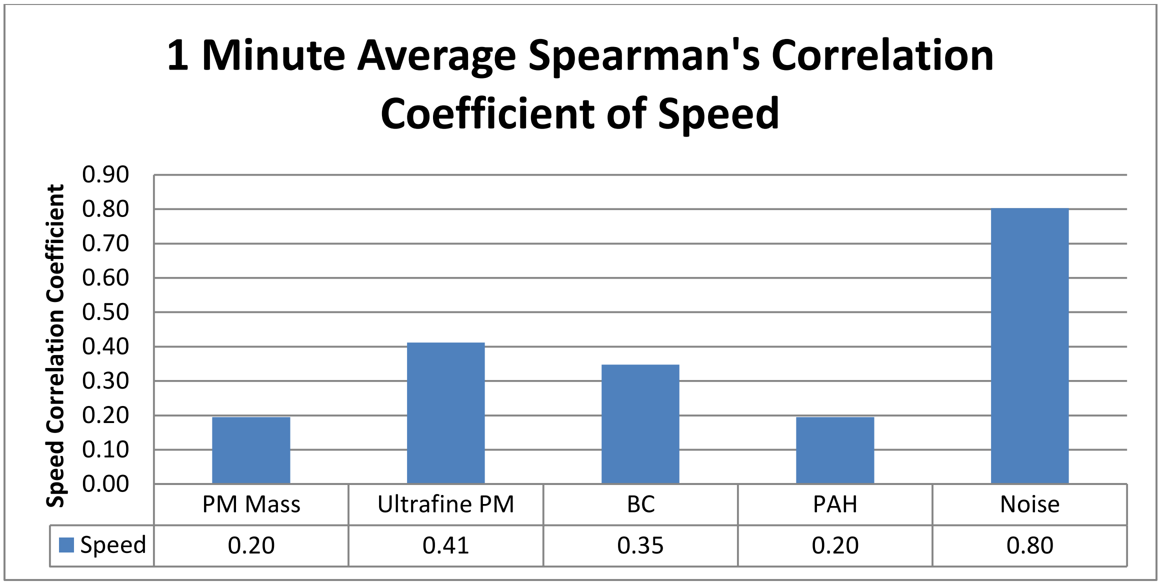


Figure 5. 1 minute average spearman's correlation coefficients of speed vs. air pollutants. All values are significant at $p < 0.05$.

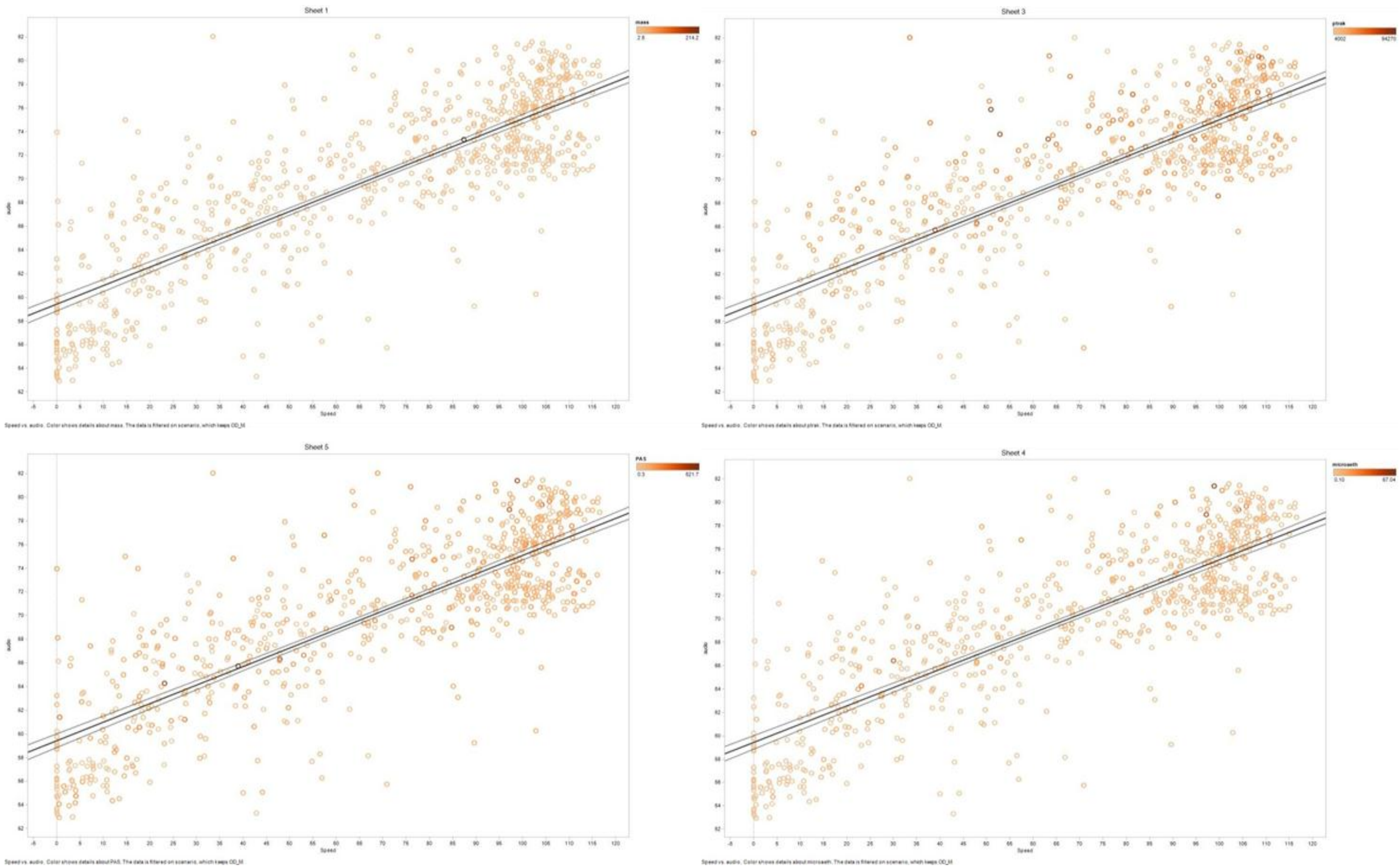


Figure 6. Scatterplot of audio vs. speed with measured pollutant concentrations represented by color intensity. Higher measured pollutant concentration are reflected by darker color shades.

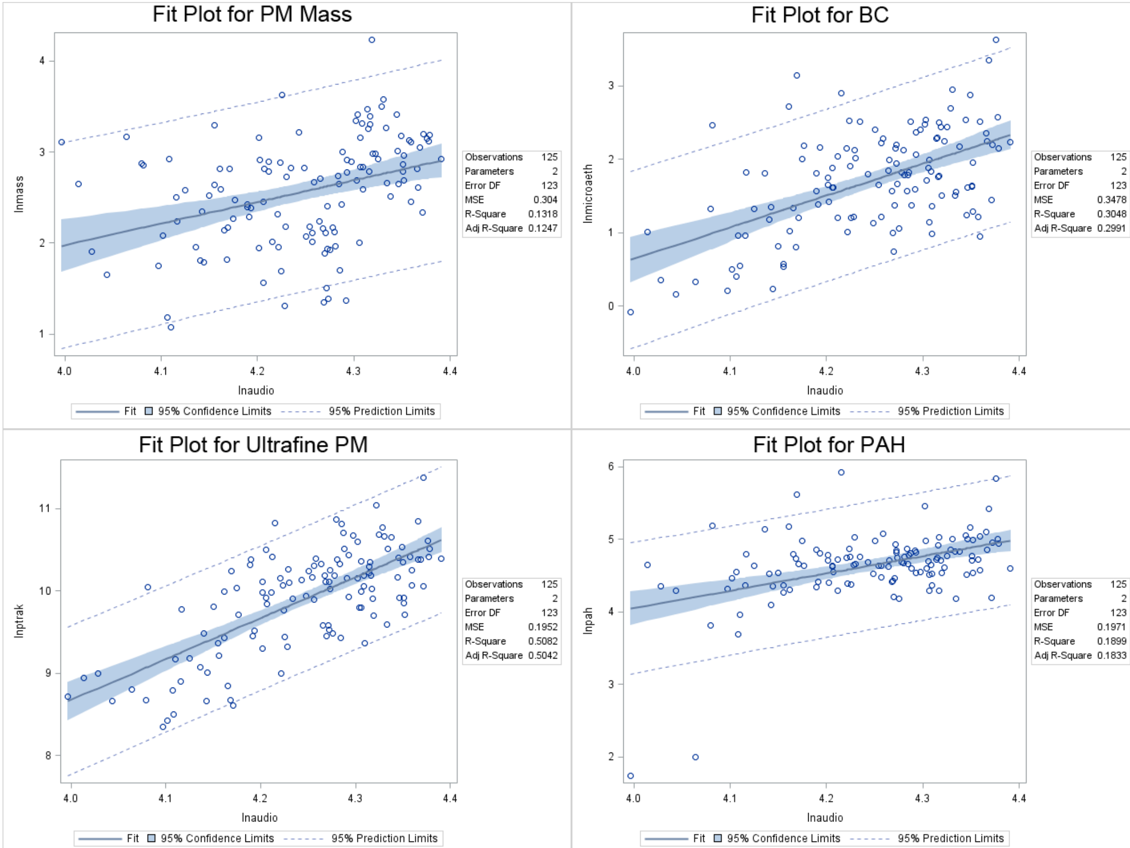


Figure 7. Noise vs. air pollutant exposures for moving in-vehicle sampling scenario based on 5 minute averages.

Ln Transformed Combined Scenario For 1 Minute Averages						
Pollutant Type	Observations	Intercept Estimate	Slope Estimate	Model P-Value	R^2 value	
PM Mass	1950	-2.53 (-3.29,-1.78)	1.14 (-1.78,1.50)	<.0001	0.1	
Ultrafine PM	1950	-3.49 (-4.20,-2.79)	3.08 (2.91, 3.25)	<.0001	0.4	
Black Carbon	1950	-8.72 (-9.65, -7.80)	2.38 (2.16, 2.60)	<.0001	0.19	
PAH	1950	-5.68 (-6.76, -4.61)	2.28 (2.03, 2.54)	<.0001	0.14	
Ln Transformed Outdoor Stationary Scenario For 1 Minute Averages						
Pollutant Type	Observations	Intercept Estimate	Slope Estimate	Model P-Value	R^2 value	
PM Mass	676	-1.07 (-2.70, 0.57)	1.03 (0.65, 1.41)	<.0001	0.04	
Ultrafine PM	676	-5.31 (-8.56, -2.07)	3.45 (2.70, 4.21)	<.0001	0.11	
Black Carbon	676	-4.22 (-8.17, -0.26)	1.28 (0.36, 2.20)	0.0063	0.01	
PAH	676	8.61 (-13.68, -3.55)	2.88 (1.70, 4.05)	<.0001	0.03	
Ln Transformed Indoor Stationary Scenario For 1 Minute Averages						
Pollutant Type	Observations	Intercept Estimate	Slope Estimate	Model P-Value	R^2 value	
PM Mass	676	-13.96 (-15.17, -12.75)	4.18 (3.89, 4.48)	<.0001	0.53	
Ultrafine PM	676	-1.89 (-3.34, -0.44)	2.67 (2.32, 3.04)	<.0001	0.24	
Black Carbon	676	-10.08 (-12.22, -7.95)	2.72 (2.19, 3.25)	<.0001	0.13	
PAH	676	-0.38 (-2.70, 1.94)	0.94 (0.37, 1.51)	0.0013	0.02	
Ln Transformed Indoor Moving Scenario For 1 Minute Averages						
Pollutant Type	Observations	Intercept Estimate	Slope Estimate	Model P-Value	R^2 value	
PM Mass	598	-6.53 (-8.50,-4.55)	2.14 (1.67, 2.60)	<.0001	0.12	
Ultrafine PM	598	-6.59 (-8.41, -4.78)	3.88 (3.45, 4.31)	<.0001	0.35	
Black Carbon	598	-13.28 (-15.82, -10.73)	3.51 (2.91, 4.11)	<.0001	0.18	
PAH	598	-6.61 (-8.82, -4.39)	2.63 (2.11, 3.15)	<.0001	0.14	
Ln Transformed With Interaction Term For 1 Minute Averages						
Pollutant Type	Observations	Intercept Estimate	Slope Estimate	Interaction Estimate	Model P-Value	R^2 value
PM Mass	1950	-0.91 (-1.56, -0.26)	1.10 (0.94, 1.25)	-0.09 (-0.09, -0.08)	<.0001	0.35
Ultrafine PM	1950	-4.68 (-5.34, -4.03)	3.24 (3.09, 3.40)	0.06 (0.06, 0.07)	<.0001	0.50
Black Carbon	1950	-9.81 (-10.7, -8.91)	2.53 (2.32, 2.74)	0.06 (0.05, 0.07)	<.0001	0.26
PAH	1950	-7.78 (-8.73, -6.82)	2.56 (2.34, 2.79)	0.11 (0.10, 0.12)	<.0001	0.34
Ln Transformed Combined Scenario For 5 Minute Averages						
Pollutant Type	Observations	Intercept Estimate	Slope Estimate	Model P-Value	R^2 value	
PM Mass	406	-2.18 (-3.87, -0.48)	1.23 (0.83, 1.64)	<.0001	0.08	
Ultrafine PM	406	-4.14 (-5.58, -2.71)	3.24 (2.90, 3.58)	<.0001	0.46	
Black Carbon	406	-9.02 (-10.93, -7.10)	2.47 (2.01, 2.93)	<.0001	0.22	
PAH	406	-5.51 (-7.51, -3.51)	2.26 (1.79, 2.74)	<.0001	0.18	
Ln Transformed Outdoor Stationary Scenario For 5 Minute Averages						
Pollutant Type	Observations	Intercept Estimate	Slope Estimate	Model P-Value	R^2 value	
PM Mass	139	-2.00 (-5.55, 1.56)	1.24 (0.42, 2.07)	0.0035	0.06	
Ultrafine PM	139	-6.12 (-12.26, -0.06)	3.66 (2.24, 5.08)	<.0001	0.16	
Black Carbon	139	0.40 (-8.93, 9.73)	0.23 (-1.94, 2.39	0.8376	0.00	
PAH	139	-8.85 (-17.34, -0.36)	2.95 (0.98, 4.93)	0.0036	0.06	
Ln Transformed Indoor Stationary Scenario For 5 Minute Averages						
Pollutant Type	Observations	Intercept Estimate	Slope Estimate	Model P-Value	R^2 value	
PM Mass	142	-13.78 (-16.57, -10.99)	4.14 (3.46, 4.83)	<.0001	0.50	
Ultrafine PM	142	-2.08 (-5.03, 0.86)	2.73 (2.01, 3.46)	<.0001	0.28	
Black Carbon	142	-12.66 (-16.94, -8.38)	3.37 (2.32, 4.43)	<.0001	0.22	
PAH	142	-1.66 (-5.95, 2.64)	1.28 (0.22, 2.34)	0.0179	0.04	
Ln Transformed Indoor Moving Scenario For 5 Minute Averages						
Pollutant Type	Observations	Intercept Estimate	Slope Estimate	Model P-Value	R^2 value	
PM Mass	125	-7.53 (-12.16, -2.90)	2.38 (1.29, 3.47)	<.0001	0.13	
Ultrafine PM	125	-11.20 (-14.91, -7.50)	4.97 (4.10, 5.84)	<.0001	0.51	
Black Carbon	125	-16.64 (-21.58, -11.69)	4.32 (3.16, 5.48)	<.0001	0.30	
PAH	125	-5.46 (-9.18, -1.73)	2.38 (1.50, 3.26)	<.0001	0.19	
Ln Transformed With Interaction Term For 5 Minute Averages						
Pollutant Type	Observations	Intercept Estimate	Slope Estimate	Interaction Estimate	Model P-Value	R^2 value
PM Mass	406	-0.40 (1.85, 1.05)	0.98 (0.64, 1.32)	-0.09 (-0.10, -0.07)	<.0001	0.35
Ultrafine PM	406	-5.44 (-6.73, -4.14)	3.43 (3.12, 3.73)	0.06 (0.05, 0.07)	<.0001	0.58
Black Carbon	406	-10.23 (-12.07, -8.38)	2.64 (2.21, 3.08)	0.06 (0.04, 0.07)	<.0001	0.30
PAH	406	-7.79 (-9.44, -6.14)	2.59 (2.20, 2.98)	0.11 (0.09, 0.12)	<.0001	0.46

Ln Transformed Combined Scenario For 1 Minute Averages With 1 Minute Lag					
Pollutant Type	Observations	Intercept Estimate	Slope Estimate	Model P-Value	R^2 value
PM Mass	1936	-2.58 (-3.34, -1.82)	1.33 (1.15, 1.51)	<.0001	0.10
Ultrafine PM	1936	-3.25 (-3.98, -2.53)	3.03 (2.85, 3.20)	<.0001	0.38
Black Carbon	1936	-8.72 (-9.65, -7.79)	2.38 (2.16, 2.60)	<.0001	0.19
PAH	1936	-5.32 (-6.41, -4.24)	2.20 (1.94, 2.45)	<.0001	0.13
Ln Transformed Outdoor Stationary Scenario For 1 Minute Averages With 1 Minute Lag					
Pollutant Type	Observations	Intercept Estimate	Slope Estimate	Model P-Value	R^2 value
PM Mass	670	1.05 (-2.69, 0.59)	1.02 (0.64, 1.41)	<.0001	0.04
Ultrafine PM	670	-3.87 (-7.17, -0.57)	3.12 (2.35, 3.89)	<.0001	0.09
Black Carbon	670	-3.80 (-7.79, 0.19)	1.19 (0.26, 2.12)	0.012	0.01
PAH	670	-6.50 (-11.62, -1.38)	2.39 (1.20, 3.58)	<.0001	0.02
Ln Transformed Indoor Stationary Scenario For 1 Minute Averages with 1 Minute Lag					
Pollutant Type	Observations	Intercept Estimate	Slope Estimate	Model P-Value	R^2 value
PM Mass	671	-13.35 (-14.61, -12.10)	4.03 (3.72, 4.34)	<.0001	0.49
Ultrafine PM	671	1.17 (-2.65, 0.32)	2.50 (2.13, 2.87)	<.0001	0.21
Black Carbon	671	-9.09 (-11.24, -6.93)	2.47 (1.94, 3.00)	<.0001	0.11
PAH	671	-0.02 (-2.34, 2.30)	0.85 (0.28, 1.43)	0.0035	0.01
Ln Transformed Indoor Moving Scenario For 1 Minute Averages with 1 Minute Lag					
Pollutant Type	Observations	Intercept Estimate	Slope Estimate	Model P-Value	R^2 value
PM Mass	595	-7.46 (-9.44, -5.49)	2.36 (1.89, 2.82)	<.0001	0.14
Ultrafine PM	595	-5.58 (-7.48, -3.68)	3.64 (3.20, 4.09)	<.0001	0.30
Black Carbon	595	-13.79 (-16.35, -11.23)	3.64 (3.03, 4.24)	<.0001	0.19
PAH	595	-4.51 (-6.81, -2.22)	2.14 (1.60, 2.68)	3.6351	0.09
Ln Transformed Combined Scenario For 5 Minute Averages With 5 Minute Lag					
Pollutant Type	Observations	Intercept Estimate	Slope Estimate	Model P-Value	R^2 value
PM Mass	393	-2.29 (-4.03, -0.56)	1.26 (0.85, 1.67)	<.0001	0.08
Ultrafine PM	393	2.96 (-4.56, 1.37)	2.96 (2.58, 3.34)	<.0001	0.37
Black Carbon	393	8.29 (-10.31, -6.26)	2.30 (1.81, 2.78)	<.0001	0.18
PAH	393	4.99 (-7.09, -2.90)	2.14 (1.64, 2.64)	<.0001	0.15
Ln Transformed Outdoor Stationary Scenario For 5 Minute Averages With 5 Minute Lag					
Pollutant Type	Observations	Intercept Estimate	Slope Estimate	Model P-Value	R^2 value
PM Mass	134	-2.22 (-5.86, 1.41)	1.30 (0.45, 2.14)	0.0029	0.07
Ultrafine PM	134	-3.64 (-10.00, 2.73)	3.07 (1.59, 4.55)	<.0001	0.11
Black Carbon	134	0.52 (-9.12, 10.16)	0.20 (-2.05, 2.44)	0.8621	0.00
PAH	134	-6.86 (-15.74, 2.01)	2.49 (0.43, 4.56)	0.0182	0.04
Ln Transformed Indoor Stationary Scenario For 5 Minute Averages with 5 Minute Lag					
Pollutant Type	Observations	Intercept Estimate	Slope Estimate	Model P-Value	R^2 value
PM Mass	137	-11.32 (-14.50, -8.13)	3.53 (2.75, 4.32)	<.0001	0.37
Ultrafine PM	137	-2.21 (-1.08, 5.51)	1.67 (0.86, 2.48)	<.0001	0.11
Black Carbon	137	-9.05 (-13.61, -4.49)	2.48 (1.36, 3.60)	<.0001	0.12
PAH	137	0.29 (-4.14, 4.71)	0.80 (-0.29, 1.89)	0.1482	0.02
Ln Transformed Indoor Moving Scenario For 5 Minute Averages with 5 Minute Lag					
Pollutant Type	Observations	Intercept Estimate	Slope Estimate	Model P-Value	R^2 value
PM Mass	122	-10.41 (-14.99, -5.82)	3.05 (1.98, 4.13)	<.0001	0.21
Ultrafine PM	122	-5.92 (-10.49, -1.35)	3.73 (2.65, 4.80)	<.0001	0.28
Black Carbon	122	-13.32 (-18.77, -7.87)	3.54 (2.26, 4.82)	<.0001	0.20
PAH	122	-2.12 (-6.26, 2.01)	1.59 (0.62, 2.56)	0.0016	0.08

Table 5. Simple linear regression statistics and values for modeling noise exposures relationship with vehicular air pollutants. Performed log transformations to normalize data.