# $PM_{2.5}$ sampling losses aboard the Google Street View cars in London

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## 1 Overview

As part of the Breathe London project, two instrumented Google Street View cars performed mobile measurements of $PM_{2.5}$ between September 2018 and October 2019. Earlier analysis of the mobile data revealed an apparent low bias in the mobile measurements relative to stationary data throughout London. This report summarizes assessments made so far of possible sampling losses aboard the Google cars. A goal of this exercise is to derive a correction factor (or a range of factors) that can be applied to all in-motion data to correct for sampling losses due to the layout of the sampling system in the Google cars.

## 2 Methods

Two Google cars (vehicle IDs 27522 and 27533, herein referred to as car # 1 and # 2, respectively) measured $PM_{2.5}$ using the "Palas FIDAS-100" size-resolved optical particle counter. The originally intended sampling configuration included the inlet dropping vertically through the roof of the car, which would have sampled air directly into the optical path of the FIDAS, thereby minimizing particle losses. However it was not permitted to make holes in the structure of the vehicle, so the sampling inlet entered via the rear window space introducing up to 30 degree bends into the sampling system. This curved inlet has the potential to cause particle losses. Further, due to limited electrical power availability, the sampling inlet in the cars was not heated.

When not driving, the cars continued to make measurements for extended periods while parked in the National Physical Laboratory (NPL) parking lot. During these periods, the Google cars were collocated 20 m from an identical $PM_{2.5}$ instrument operated by NPL. The Fidas in both Google cars was operated at 1 Hz time resolution, while the one in NPL was operated at 2 minute resolution. To match the Google Fidas with the NPL Fidas, the former was aggregated to a 2-minute time grid first. To assess sampling losses aboard the Google cars, I first analyzed these collocated data within a roughly 3-month period between April and July 2019. Size distribution data from this period are available (i.e., extracted to CSV format on BigQuery), and thus data from this period can also inform size-dependent losses of particles. The Fidas measures size distributions in 64 logarithmically spaced size bins between 0.1 and 10 $\mu$m. A limitation of the Fidas instrument is that it only measures particles larger than nominally 180 nm, and thus information about fresh emissions (e.g., ultrafine particles from vehicular emissions) can be lost. The NPL Fidas was operated with a heated inlet to dry the incoming sample (more details later).

Both Google cars also measured lung-deposited surface area (LDSA) of particulate matter using a "Naneos Partector". According to the user manual for this instrument, it accurately measures LDSA of particles between 10 and 400 nm in diameter. A benefit of using the Partector is that it complements the Fidas $PM_{2.5}$ measurements by measuring in this size range where the Fidas cannot. A limitation, however, is that the Partector measures in units of $\mu m^2\ cm^{-3}$ instead of $\mu g\ m^{-3}$. Thus, while the Partector can only be used to identify periods of fresh emissions, it cannot be used quantitatively to calculate mass of particles below 400 nm.

Lastly, both Google cars also measured $PM_{2.5}$ separately using a Thermo Fisher pDR-1500. Comparisons of this data with the NPL reference Fidas are shown in Figures 7 and S5.

# 3 Results

## 3.1 Comparisons between Google Car and NPL Fidas data

Figure 1 shows the precision (comparison between two Google cars) and accuracy (comparison between each Google car and the NPL reference) of the Fidas $PM_{2.5}$ measurements. A slope of 89% between the two Google cars indicates that car #2 has more losses than car #1. This difference is likely because of small differences in the inlet configuration between the two cars e.g., tubing length, bends, flow rate, etc., and/or differences in instrument calibration. In any case, the two cars' measurements are well-correlated ($R^2$ = 0.94).

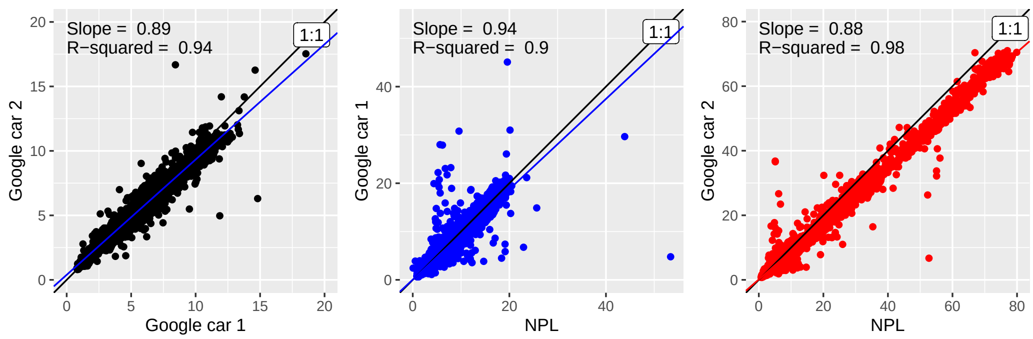


Figure 1: Precision and accuracy of the Fidas measurements aboard two Google cars. Data from April through July 2019 are used in this figure. Inter-comparison of measurements between two Google cars (left subplot) shows precision, and comparison of each Google car with the NPL measurements show accuracy (middle and right subplots; car #1 in blue, car #2 in red).

Both instruments are also individually well-correlated with the NPL reference measurements ($R^2$ = 0.90 and 0.98 for Google cars #1 and #2, respectively). The slopes of these correlations indicate an overall sampling bias during this 3-month period. Assuming both Google car Fidases were calibrated well, the sampling bias likely arises due to particle losses in the sampling lines.

An illustration of different particle loss mechanisms in sampling lines is shown in Figure S1. In theory, while small particles are prone to diffusional losses, larger particles are prone to inertial losses as the air flows around bends in the tubing. Figure 2 shows the observed size-dependence of particle losses in Google car # 1. As expected from theory (Figure S1), ratios are lower for particles smaller than 300 nm (or 0.3 $\mu$m) and larger than $\sim$ 1.5 $\mu$m. Since both the instruments on the Google car and in NPL are the same, it is reasonable to expect that this size-dependence is not a result of optical detection efficiency issues. Thus, these lower ratios can be attributed to sampling losses. However,

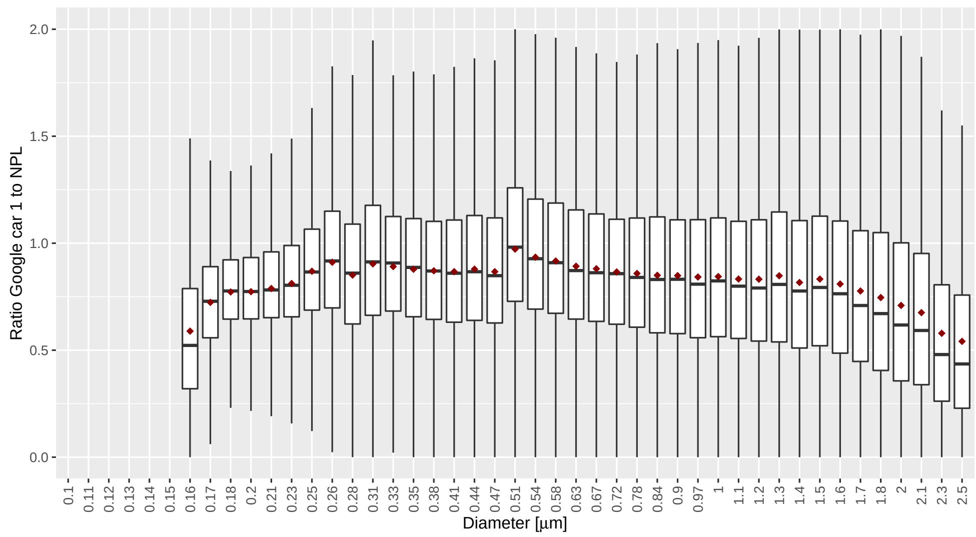


Figure 2: Ratio of Google car $PM_{2.5}$ to NPL measurements of size-resolved particle number concentrations. Data are from car #1 Fidas, when it is parked at NPL during the April - July 2019 period. Red dots are means.

it should be noted that size distributions are in units of number concentration (and not mass). Converting these ratios to mass ratios is challenging (see footnote[1]).

In addition to size-dependence, a systematic influence of other factors can be explored e.g., are sampling losses systematically higher during certain times of the day due to external factors? If such a systematic influence exists, it should be accounted for in developing correction factor(s). To investigate this dependence, I also analyzed the entire September 2018 - October 2019 dataset of the Google cars and the NPL measurements (equivalent of Figure 1 shown for full dataset in Figure S2). Figure 3 shows the ratios between the Google car and NPL measurements from this entire period.

Overall, the ranking of the two cars is consistent with the 3-month medians reported for the April - July 2019 period (Figure 1) i.e., car #2 has higher sampling losses than car #1. However, the absolute median ratios in Figure 3 are slightly ($\sim$ 3%) lower than the ratios calculated for the April - July 2019 period. Figure 4 shows 90% confidence intervals of the slopes of correlation between Google cars and NPL reference measurements. These confidence intervals are assessed by bootstrapping the Google-NPL paired dataset $10^4$ times, with each bootstrap sample drawing 1% of the total data population randomly, without replacement. For each bootstrapped sample, the linear correlation slope between the Google car and NPL is saved. Median slope (with confidence bounds in brackets) for car #1 is 0.91 (0.88, 0.94) and that for car #2 is 0.89 (0.87, 0.92). Accounting for these confidence bounds, it is seen that both cars have a 2 - 3% uncertainty around the median slope.

Figure 3 also shows a diurnal pattern in the ratio between Google car and NPL Fidas

[1]Theoretically, converting number concentrations to mass concentrations is straightforward, given some basic assumptions about particle density and shape factor. In fact, since the fundamental property measured by the Fidas is particle count (and not mass), all $PM_{2.5}$ values reported by this instrument inherently rely on such assumptions. However, the proprietary algorithm used by this instrument to calculate $PM_{2.5}$ also uses an empirical approach wherein different size distributions are treated as having different composition (e.g., smaller particles are assumed to be fresh vehicular emissions of lower density, while larger particles are assumed to be aged with higher density), and thus composition-dependent density and shape factor are used to calculate $PM_{2.5}$.

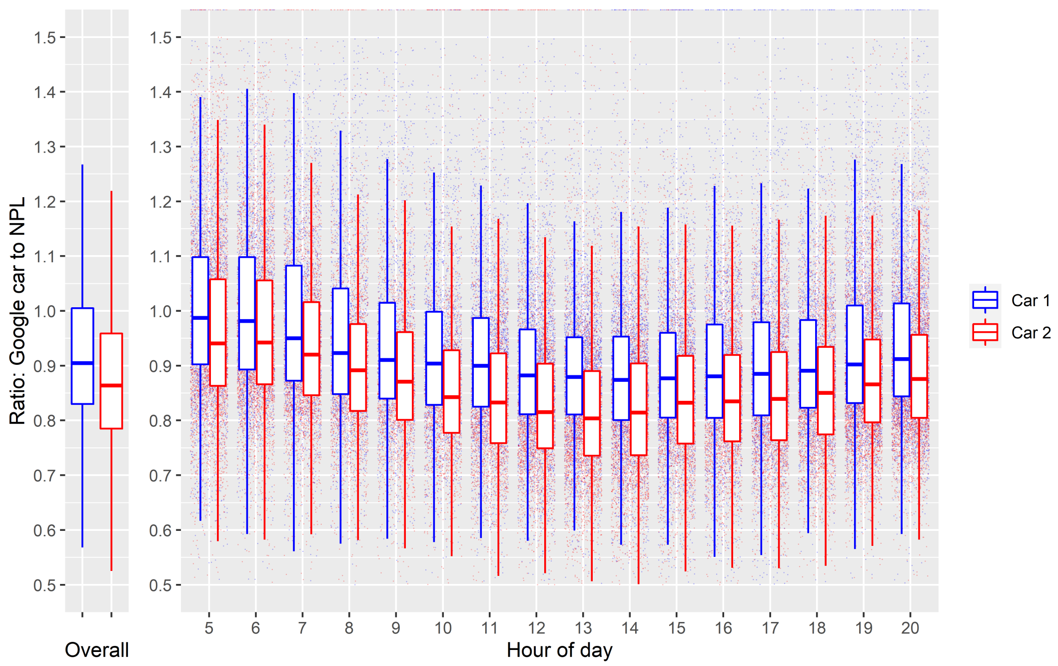


Figure 3: Ratio of Google car $PM_{2.5}$ to NPL measurements. Data are from when the cars are parked at NPL during the entire September 2018 - October 2019 period. Overall median ratio is 0.91 for car #1 and 0.89 for car #2. Diurnal pattern is limited to daytime hours.

measurements. The ratios are typically higher ($\sim$ 6% higher than respective median) at 5 AM, reduce smoothly till 1 PM, and then begin to increase again. There are two possible explanations behind this systematic diurnal pattern:

1. **Size-dependence:** it is possible that sampling inlet losses aboard the Google cars are higher during daytime, because of fresh emissions of smaller particles. To characterize size-dependence of particle mass loss, I analyzed the Naneos LDSA measurements.

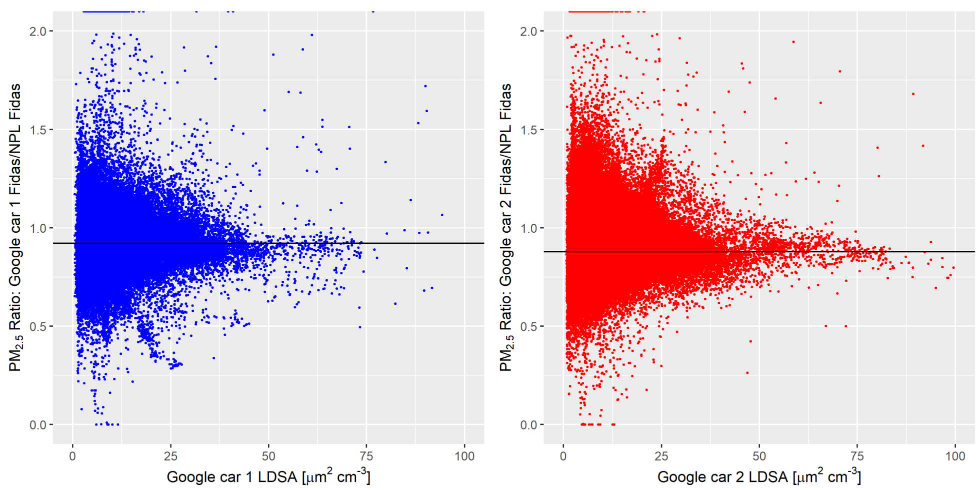


Figure 5: Ratio of Google car $PM_{2.5}$ to NPL measurements and its dependence on lung-deposited surface area (LDSA) of sub-300 nm particles. Horizontal lines are median ratios.

Figure 5 shows the relation between the Google car/NPL $PM_{2.5}$ ratio (as measured by Fidas) and the LDSA concentration. If size-dependent sampling losses were significantly affecting the $PM_{2.5}$ reported by the Google car Fidas, this effect would be apparent as a downward trend of the points in Figure 5 i.e., during periods of high LDSA concentrations (fresh emissions), the Google car Fidas would be expected to measure lower $PM_{2.5}$ than the NPL Fidas, thereby lowering the Google car to NPL ratio. However, Figure 5 shows that this ratio has no dependence on LDSA concentration. In other words, while sampling losses are certainly larger for smaller particles (as shown in Figure 2), this loss only affects the *number* concentrations, but does not significantly affect the $PM_{2.5}$ *mass* concentrations.

2. **Temperature-dependence:** Unlike the Google cars, the NPL Fidas used a drying unit upstream of sample entrance into instrument. This may have introduced two counter-acting artefacts in the comparison between the Google car and NPL Fidas data: a) due to lack of drying, the Google car Fidas measurements may be biased high, especially during periods of high relative humidity, as condensed water is miscounted as particle mass; b) because the drying unit in the NPL Fidas heats the incoming air, the NPL measurements may be biased low due to evaporative loss of semi-volatile species e.g., nitrate. This drying unit uses a dewpoint-based feedback loop for controlling the heating of the sample, and thus the amount by which the sample is heated depends on ambient humidity.

   Both these artefacts depend on ambient humidity, and thus the magnitude of their combined effect would be expected to track the typical diurnal pattern of humidity at the NPL site. This would explain the diurnal pattern of the Google car to NPL ratio shown in Figure 3.

## 3.2 Comparisons between Google Car and AQMesh Pods data

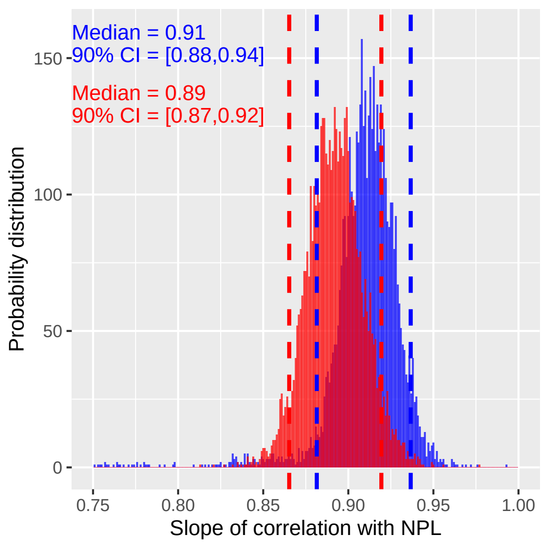


Figure 4: Probability distribution of slopes of correlation between Google cars and NPL reference instrument, derived by resampling data from the April-July 2019 period. Vertical dashed lines are $5^{th}$ and $95^{th}$ percentiles of the distributions. Car #1 is in blue, car #2 in red.

Instead of comparing Google car data to NPL, I also performed a similar comparison of Google car with the stationary AQMesh Pods (which do not use a heated inlet). All in-motion Fidas measurements recorded within 100 m of an AQMesh Pod are captured and compared against the Pod's measurement. Because the Pods report measurements at 1 minute resolution, the median of all 1 Hz in-motion data within a 100 m buffer of the Pod was used for comparison.

Figure 6 shows the comparison of in-motion measurements by the Google car Fidas with nearby stationary AQMesh Pods. Overall, the ranking of the two cars is consistent with findings presented earlier in Figure 3: car #2 has higher sampling losses than car #1. However, unlike the comparisons with NPL, there is no clear diurnal pattern in the ratios between Google car and AQMesh Pods. There is a slight increase in the ratio during morning and evening rush hours, but this is likely due to different size detection efficiencies of the Fidas and the AQMesh Pods, and/or higher number of samples collected during these periods (Figure S3). This further shows that the diurnal pattern observed in the ratio between Google car and NPL Fidases is likely because of sampling inlet differences (i.e., heated inlet in NPL) biasing Google car measurements high and/or NPL measurements low.

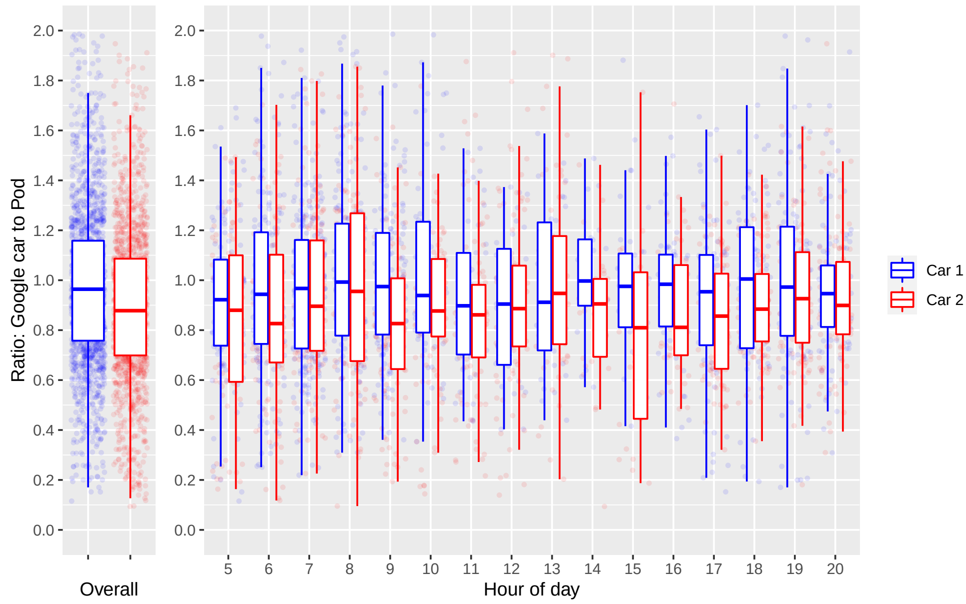


Figure 6: Ratio of Google car $PM_{2.5}$ to AQMesh Pods measurements. Data are from when the cars are within a 100 m of any Pod, and during daytime hours.

Comparing in-motion measurements with those from a network of stationary monitors can introduce other errors e.g., additional losses aboard the Google cars due to non-isokinetic sampling while in motion, and location of Pods with respect to road. However, Figure S4 shows that these factors did not have a detectable effect on the ratio between in-motion and stationary measurements.

## 3.3 Comparisons between Google car Thermo-Fisher pDR and NPL data

As mentioned earlier, both Google cars also measured $PM_{2.5}$ using a Thermo Fisher pDR instrument. Figure 7 shows a comparison between the pDR measurements and the NPL Fidas measurements, while the cars were parked at NPL. Overall, both cars' pDR measurements appear to be biased high by 18% and 43% relative to the NPL Fidas. This bias could be due to multiple types of differences between the Google car pDR and the NPL Fidas: a) instrumental detection efficiency, b) moisture interference in the pDR, c) pDR calibration errors, d) different algorithms used by the pDR and Fidas instruments for converting light scattering signal into particle mass values.

Figure S5 shows that the ratio of Google car's pDR to NPL Fidas measurements has a diurnal pattern similar to the one shown in Figure 3. This further confirms that this diurnal pattern is likely a combination of two counter-acting artefacts: lack of drying may have introduced moisture interference (positive bias) in the Google car measurements, while heated drying may have introduced evaporative losses (negative bias) in the

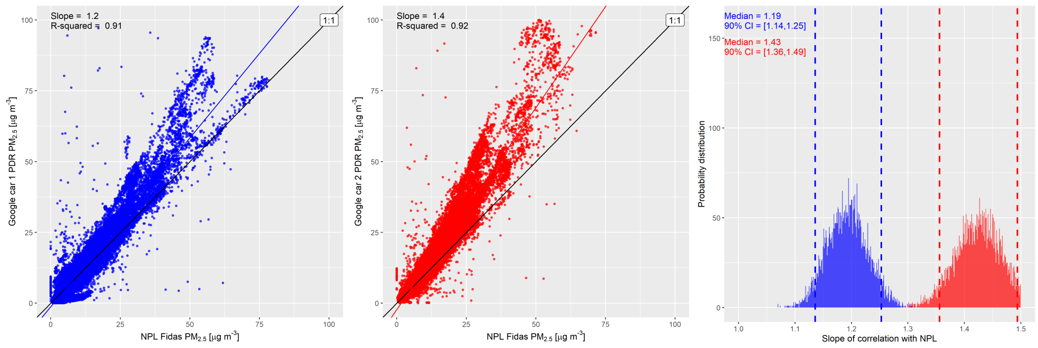


Figure 7: Ratio of Google car $PM_{2.5}$, measured by the Thermo Fisher pDR, to NPL $PM_{2.5}$, measured by the Fidas. The left and middle subplots show the comparisons for cars # 1 and # 2, respectively. The right subplot shows confidence intervals of the correlation slopes for each car, derived using the same resampling procedure as used for Figure 4.

NPL measurements. However, according to the Thermo Fisher pDR user manual, the instrument's algorithm corrects its reported $PM_{2.5}$ for humidity interferences.

# 4 Conclusions

I present the following conclusions from my assessment of $PM_{2.5}$ sampling losses aboard the Google cars:

- Car #1 (vehicle ID 27522) has a median $PM_{2.5}$ sampling loss of 9% (determined from the overall median ratio in Figure 4), with a 90% confidence interval between 6% and 12%. Car #2 (vehicle ID 27533) has a median sampling loss of 11%, with a 90% confidence interval between 8% and 13%.

- Accounting for these sampling losses, I recommend that correction factors of 1.09 and 1.11 be applied to the in-motion $PM_{2.5}$ measurements by the Fidas on Google car #1 and #2, respectively. The distributions around the median bias shown in Figure 4 can be used as inputs for further statistical analyses (e.g. probability of exceedance) on the in-motion $PM_{2.5}$ measurements.

- Sampling loss with respect to NPL reference measurements exhibits a diurnal pattern, with larger losses during daytime. This could imply that daytime particles (which tend to be freshly emitted, and thus smaller in diameter) are not efficiently measured in the Google cars. However, Figure 5 shows that this does not appear to be the case i.e., on a mass basis, $PM_{2.5}$ sampling losses are not significantly affected by losses in the capture rate of smaller particles typically present in fresh emissions.

- In-motion sampling is not significantly affected by vehicle speed, as shown in Figure S4.

- Comparing $PM_{2.5}$ measured by the Google cars' Fidas with AQMesh Pods shows similar bias in the in-motion measurements, but without a clear diurnal pattern of this bias.

- Comparing $PM_{2.5}$ measured by the Google cars' Thermo Fisher pDR with the NPL Fidas shows that the pDR measurements are biased high by roughly 18% in car #

1 and 43% in car # 2. Further, these biases also have a diurnal pattern similar to the one observed in the Google car Fidas w.r.t. NPL Fidas. This again shows that sampling inlet differences between the Google cars and NPL (i.e., heated inlet in the latter) likely had an effect on the bias.

# References

S.-L. von der Weiden, F. Drewnick, and S. Borrmann. Particle Loss Calculator – a new software tool for the assessment of the performance of aerosol inlet systems. *Atmospheric Measurement Techniques*, 2(2):1099–1141, 2009. ISSN 1867-8610. doi: 10.5194/amtd-2-1099-2009.

# Supplemental information

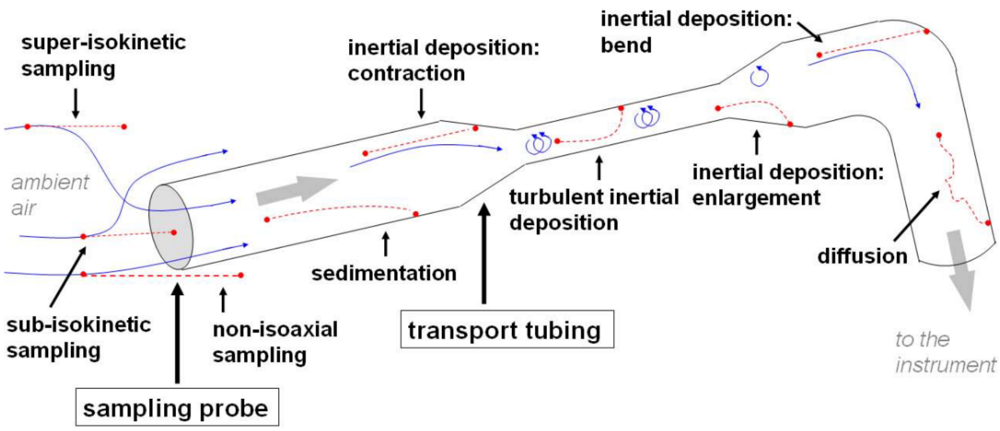


Figure S1: Figure from von der Weiden et al. [2009]: mechanisms occurring during aerosol sampling and transport in a sampling probe and a transport tube. Two important mechanisms are diffusion (which causes smaller particles to be lost in tubing), and inertial deposition (which causes larger, heavier particles to escape sharply bending fluid streamlines and get lost).

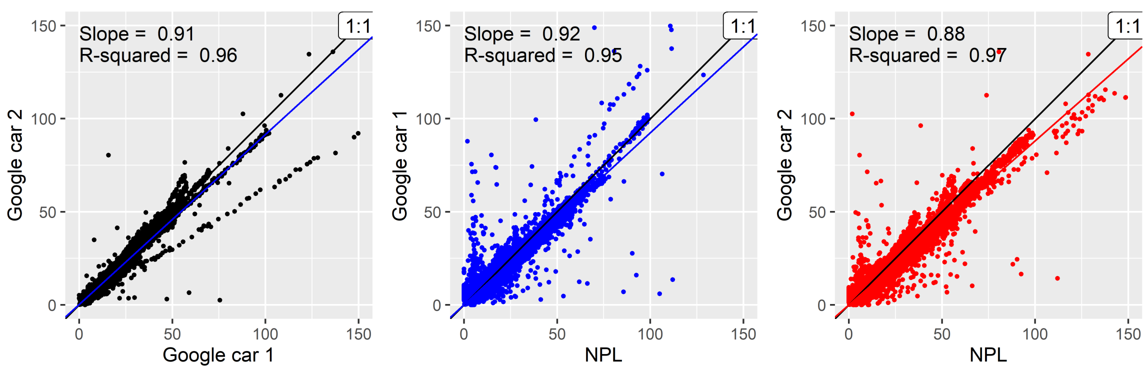


Figure S2: Precision and accuracy of the Fidas measurements aboard two Google cars. Data from entire 13 month period (September 2018 to October 2019) are used in this figure. Inter-comparison of measurements between two Google cars (left subplot) shows precision, and comparison of each Google car with the NPL measurements show accuracy (middle and right subplots; car #1 in blue, car #2 in red)

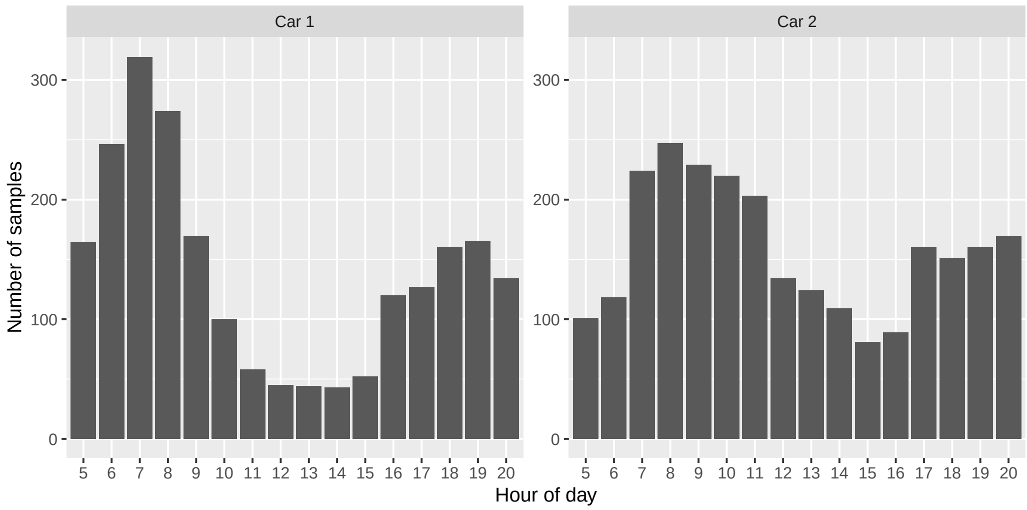


Figure S3: Number of in-motion samples captured within 100 m of AQMesh Pods. Note: 1 sample = 1 unique minute for which there is a measurement by the AQMesh Pod (which measures at 1 min resolution), and a median of anywhere between 1 and 60 measurements by the Fidas (which measures at 1 sec resolution).

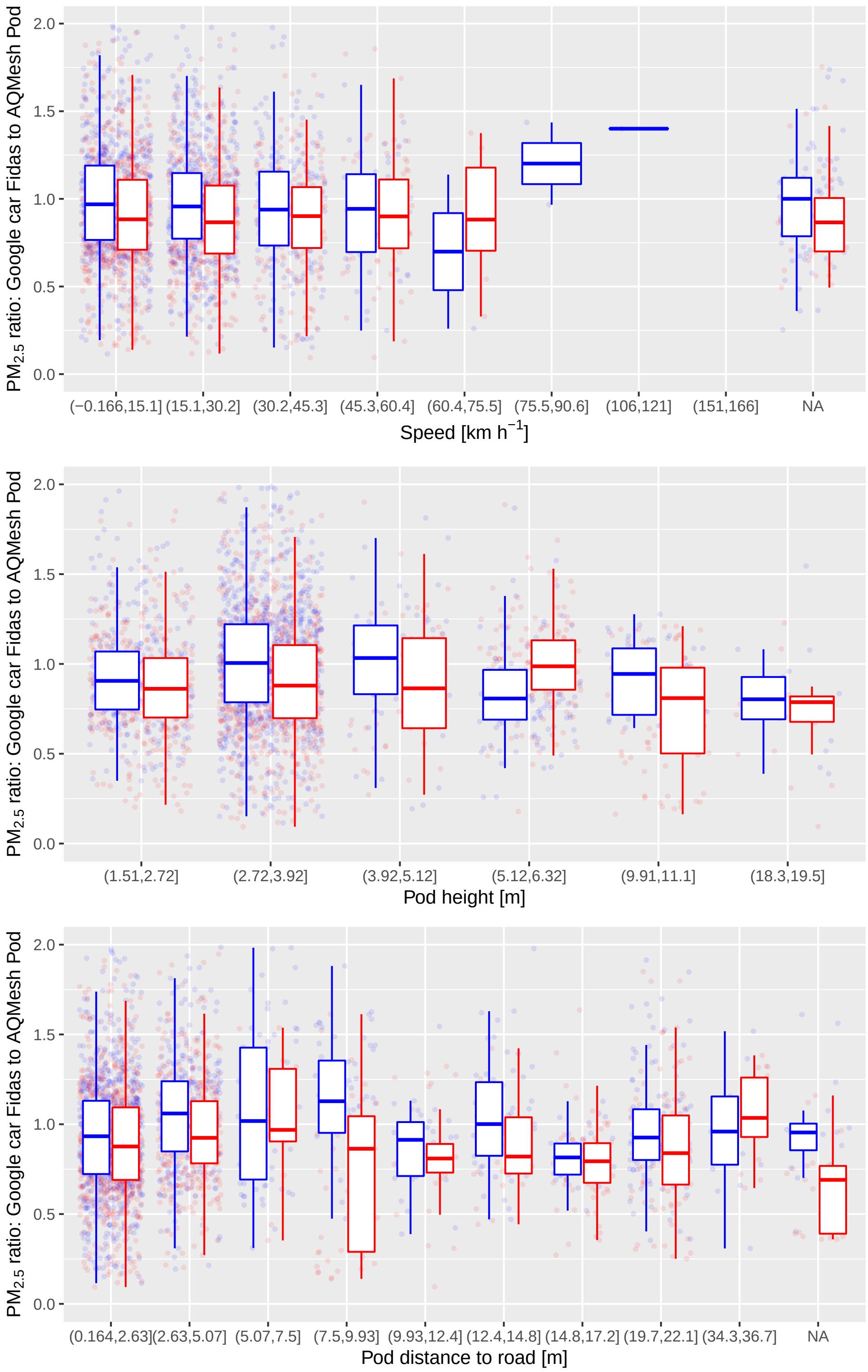


Figure S4: Ratio of Google car $PM_{2.5}$ to AQMesh Pods measurements plotted against different variables: *(top)* vehicle speed, *(middle)* Pod height with respect to road, and *(bottom)* distance of Pod from road. Consistent with previous figures in this document, blue color represents car # 1, and red represents car # 2.

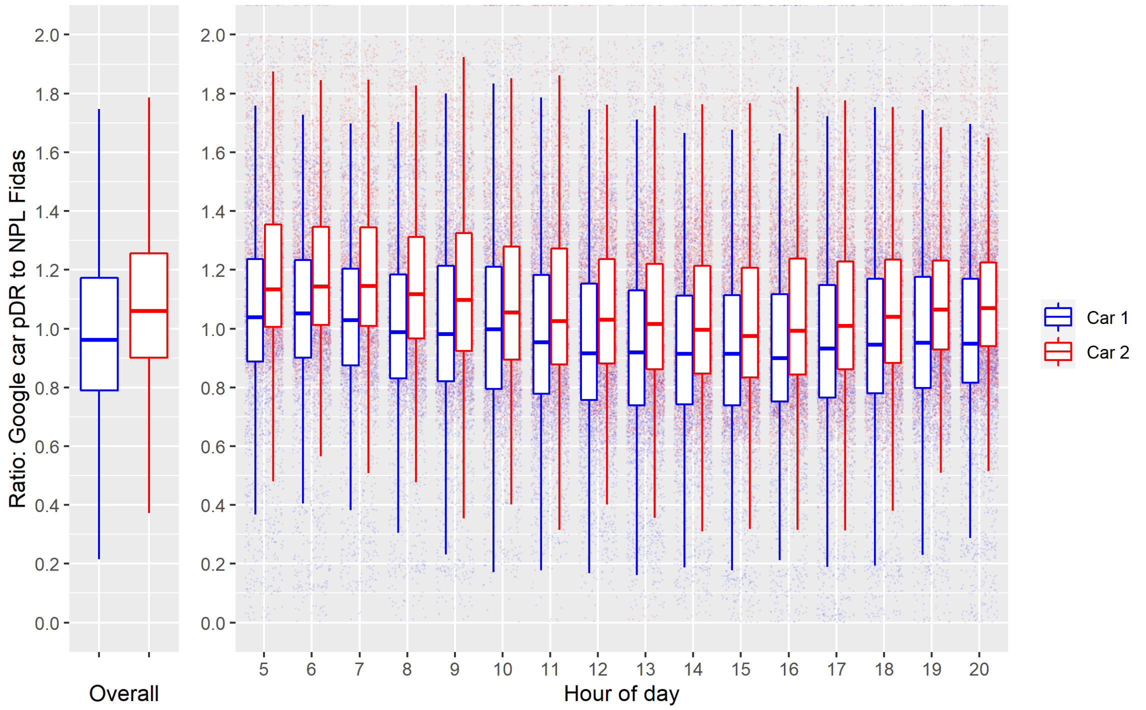


Figure S5: Ratio of Google car $PM_{2.5}$, measured by the Thermo Fisher pDR, to NPL $PM_{2.5}$, measured by the Fidas.