CRC Project RW-125

Remote Sensing of Vehicle Emissions: Summary Report 1991 - 2022

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Prepared by:
M. Matti Maricq,
Forest Glen Consulting

COORDINATING RESEARCH COUNCIL, INC.
1 CONCOURSE PARKWAY • SUITE 800 • ATLANTA, GA 30328

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Executive Summary

With financial support from the Coordinating Research Council, the California Air Resources Board and others, University of Denver researchers Stedman, Bishop, and coworkers made an extensive series of Remote Sensing Device (RSD) real world emissions measurements that began in 1989 and extended to 2022. The earliest campaigns coincided with the promulgation of Tier 1 emissions standards, and the final campaigns were completed about halfway through the Tier 3 phase-in. The resulting database of emissions and ancillary vehicle data provides a valuable historical account of how motor vehicle emissions have changed since enactment of the 1990 Clean Air Act Amendments.

This review examines four topics in depth: 1) changes in fleet average emissions with time and location, 2) emissions system deterioration, 3) impact of tailpipe standards on new vehicle emissions, and 4) high emitters. The combination of strict emissions standards and aftertreatment technology development that followed from the Clean Air Act Amendments proved very effective. RSD data in Figure ES1 show exponential declines in fleet average per vehicle exhaust pollutant emissions, with ~2020 CO fleet emissions falling by a factor of 13, HC by 9 and NO a factor of 11 relative to the early 1990s. These declines are consistent across four disparate geographic areas; Chicago, Denver, Tulsa and West Los Angeles and, thus, are robust across environmental factors, such as temperature and altitude. All three pollutants decrease under Tier 1, but HCs remain flat during Tier 2.

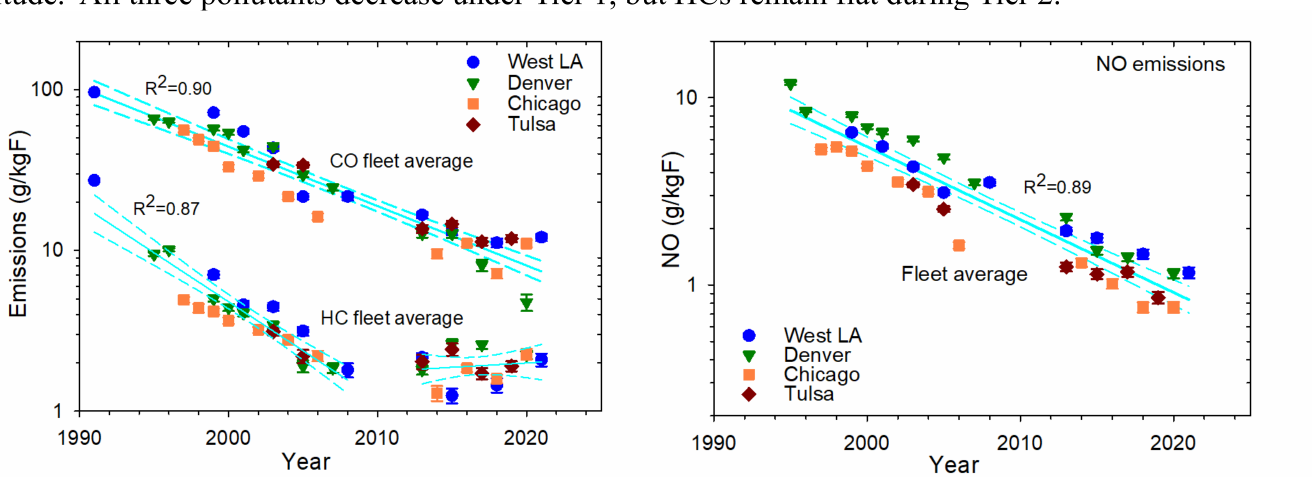

Figure ES1. Fleet average emissions from RSD. Left panel: CO and HC. Right panel: NO. Lines show regressions with 95% confidence intervals.

Although small on the scale of the thirty-year decreases, there are location dependent differences. Over much of the thirty years, Chicago emissions fall below those of the other cities, which was attributed to its younger fleet relative to the other locations. A series of 2021/2022 California campaigns measured CO emissions in Oakland and Stockton at twice the levels in Fresno and West LA likely due to the very high vehicle specific powers, greater than the US06 cycle, at Oakland and 120 F temperatures in Stockton. Inspection / maintenance (I/M) was expected to impact the fleet average trends, but there is no statistical difference between the non-I/M Tulsa fleet average emissions and those in Denver and West LA subject to long standing I/M programs.

Emissions trends with vehicle age fall into distinct groups for vehicles certified to Tier 0, 1, and 2 standards, as shown for CO and NO in Figure ES2. The positive slopes represent emissions systems deterioration with age. These improve on a g pollutant/kgF/year basis with the increasingly stringent standards owing to the progressively longer full useful life requirements. It is impressive that Tier 1 emissions remain below new Tier 0 vehicle levels for twenty years, and Tier 2 levels below new Tier 1 emissions for ten years. This confirms that emissions systems technology advances increased system robustness in addition to substantially lowering emissions levels.

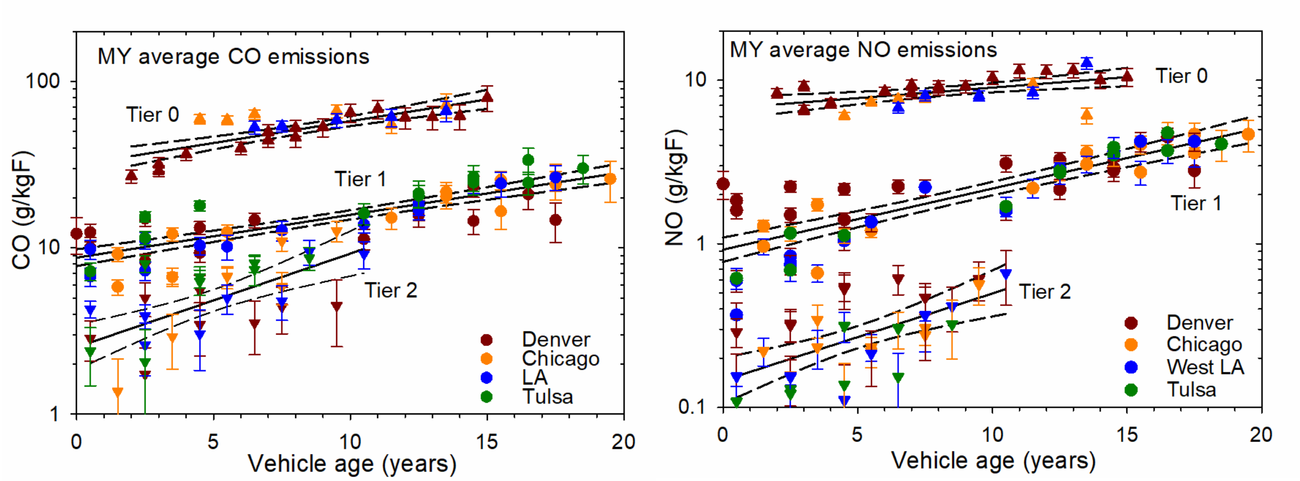

Figure ES2. Emissions versus vehicle age. Left panel: CO. Right panel: NO. Lines show regressions with 95% confidence intervals. Tier 0 – MY 1992-93, Tier 1 – MY 2000-03, and Tier 2 – MY 2010-13.

New vehicle emissions demanded by the standards are decreasing faster than the ability of the fleet to keep pace. New vehicle CO and NO emissions in Figure ES3 (bars) fall well below the fleet average (line). Fleet average emissions decline as new technology vehicles penetrate the fleet and old vehicles are discarded. This process takes nearly two decades, with fleet average emissions approaching Tier 1 technology levels as the phase-in to Tier 3 is underway. The exponential declines in both fleet average and new vehicle emissions imply diminishing marginal improvements and the increasing average age of on-road vehicles implies slower penetration of new, lower emitting, vehicles. As a result, there is no statistical indication of further improvements halfway through the Tier 3 phase-in.

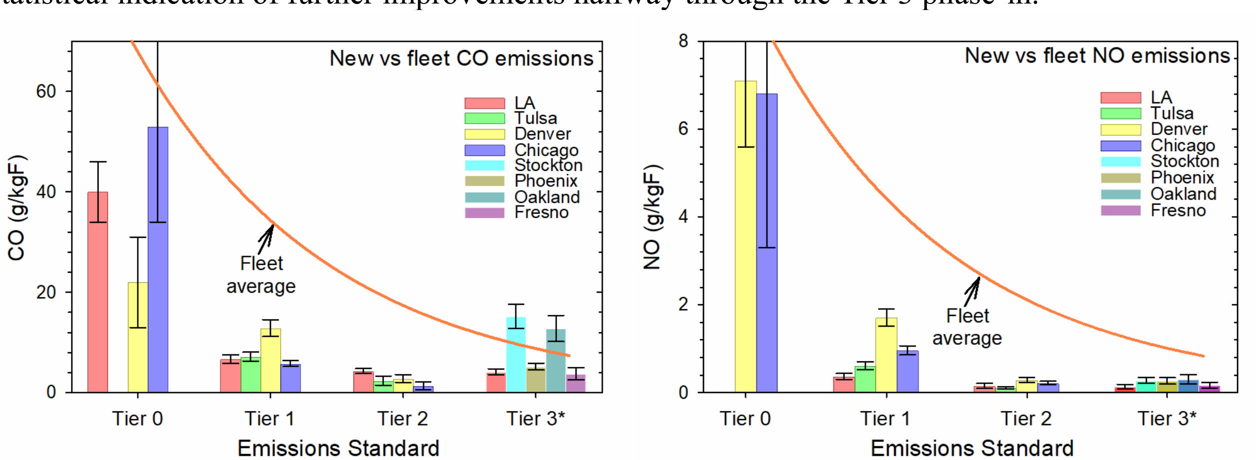

Figure ES3. New vehicle versus fleet average emissions over time / emissions standard. Left panel: CO. Right panel: NO. Bars depict new vehicle emissions. Lines show fleet average emissions.

Fleet mean 99th percentile emissions have also decreased with increasingly stringent standards, but at a significantly slower rate than the fleet average. Consequently, the air quality impact of high emitters is increasing, with the top 1% of vehicles contributing 30% of the fleet's CO and 35% of NO emissions. Removing high emitters from the fleet would be more productive for future emissions reductions than continuing to pursue the declining marginal gains afforded by lowering the standards on already clean new vehicles. I/M programs were conceived as a means to identify and remove or fix high emitters, but the thirty-year history of RSD measurements has shown that I/M programs as implemented have proven ineffective. The methodology exists to identify high emitters, however new ideas are needed to ensure that the identified vehicles receive effective, long term, repairs or are scrapped and to reduce the ease with which engine calibrations can be reflashed to pass the I/M test and then returned to high emitter operation.

RSD has proven to be a very useful tool to investigate real world motor vehicle emissions owing to its ability to make non-invasive measurements of emissions from very large number of vehicles. As vehicle emissions have declined, the RSD technology developed in the 1990s is increasingly measuring values statistically indistinguishable from zero from individual vehicles. Thus far, fleet average accuracy has not suffered owing to the ~20,000 vehicles averaged per campaign, but going forward adoption of next generation measurement technology would be beneficial. Improved sensitivity is perhaps not the most important concern. The present HC measurements required a factor of two correction to match flame ionization data and a campaign dependent offset correction that likely have a larger effect on measurement accuracy than the signal to noise limitation. The ability to differentiate total and non-methane hydrocarbons would also be helpful to better match regulatory requirements and emissions models. Finally, particulate matter measurement would be a useful addition to RSD. This, however, is a difficult challenge, especially if it is to distinguish tailpipe from non-tailpipe particulate matter.

1. Introduction

Engine exhaust aftertreatment is a present-day fact of life for motor vehicle manufacturers. Its incorporation into automobile design originated from evidence in the 1950s of the roles played by exhaust hydrocarbons and nitrogen oxides in smog formation (Haagen-Smit et al. 1953, Haagen-Smit and Fox 1954). A decade later, the California Motor Vehicle Pollution Control Board enacted the nation's first motor vehicle emissions standards for hydrocarbons (HC) and carbon monoxide (CO) in 1966 (CARB 2025). The Clean Air Act extensions of 1970 established National Ambient Air Quality Standards (NAAQS) and extended motor vehicle emissions standards to all 50 states (US EPA 1970). By the end of the 1980s, studies such as *Rethinking the Ozone Problem in Urban and Regional Air Pollution* (NAS, 1992) showed slow progress in meeting the NAAQS. This prompted the 1990 Clean Air Act Amendments (US EPA 1990), which initiated a series of increasingly stringent emissions standards that have been promulgated over the past thirty plus years in roughly ten-year increments, the Federal Tier 1, 2… series, mirrored by the California LEV I, II… series.

The requirement to meet emissions standards has seen the development of increasingly advanced exhaust aftertreatment technology in the form of catalysts, fuel injection and engine controls. To be sold, vehicles must pass dynamometer based laboratory, and in some cases on-road, emissions tests, but how well do the emissions controls work in the real world over the life of the vehicle? One approach to answering this question is by monitoring air quality. In fact, the Environmental Protection Agency's (EPA) 2023 report, *Our Nation's Air*, estimates a 79% reduction in 8-hour CO, a 62% decrease in annual NO_2 and a 55% reduction in 1-hour NO_2 since 1990 (US EPA 2023). However, these reductions derive from emissions improvements across a number of sectors, including light duty vehicles, heavy duty vehicles, power generation, and so forth. Source apportionment can help single out the light duty vehicle contribution, but direct measurement is preferable to provide a clearer view of the environmental impacts from increasingly stringent emissions standards.

To address this need, Stedman and coworkers began development of a roadside remote emissions sensing apparatus in the late 1980s (Bishop et al. 1989). The Coordinating Research Council (CRC) started supporting roadside remote sensing device (RSD) emissions measurements with its E-23 project, which began in 1997 and ran through 2007. After about a 5-year pause, CRC resumed RSD studies with a series of projects, E-106, E-119 and E-123, which continued through 2021. Together, these studies combined with RSD work sponsored by the California Air Resources Board (CARB) provide a thirty-year history of real-world tailpipe emissions at locations across the United States, in particular Chicago, Denver, Tulsa and West Los Angeles. This affords a remarkable opportunity to examine how regulations have impacted motor vehicle emissions, to learn what policies and technology innovations have worked to reduce emissions and to inform productive policy directions for the future.

The RSD measurements collected by the University of Denver researchers are publicly available at https://digitalcommons.du.edu/feat/. This website includes copies of, or links to, the many reports and publications that describe results from the various RSD campaigns. The CRC sponsored reports are listed in Appendix A and can also be found on the CRC website. These reports describe the ongoing progress in both the RSD methodology and vehicle emissions as it was happening. Having the benefit of thirty years of emissions data, the present review attempts a broader view of the interplay between emissions regulations and their real-world impacts. It builds on previous reviews, including the E-23 summary by Slott (2007) and the review of Chicago RSD measurements by Bishop and Haugen (2018). The overarching result is the better than ten-fold reduction in fleet average per vehicle CO, HC and nitric oxide (NO) emissions from the 1990s to ~2020, which is surprisingly robust across geographic region. There are, however, concerns that the rate of improvements is slowing and that the gap between fleet average and high emitter is increasing.

The copious amount of data collected by the University of Denver allows one to pose questions that delve deeper into the impacts of the increasingly tighter emissions standards. The examination of emissions from specific model year vehicles across campaigns yields trends on how emissions change with vehicle age and, thereby, emissions systems deterioration rates. The University of Denver researchers noticed early on that new vehicles were remaining cleaner longer (Pokharel et al. 2003). A subsequent examination of the West LA remote sensing data between 1999 and 2015 yielded somewhat inconsistent deterioration rates, with pre-LEV CO and HC deterioration lower than for LEV I vehicles, but comparable for NO (Zahn et al. 2020). The present review expands the deterioration analysis to also include Chicago, Denver, and Tulsa. The combined trends reveal consistent improvements in deterioration rates from Tier 0 to 2.

The regressions of emissions with vehicle age also yield emissions rates for new vehicles. How these change over time as emissions standards are lowered can be compared to the overall fleet trends. Reductions in fleet emissions occur via turnover, as new vehicles enter the fleet and old vehicles are scrapped. The promulgation rate of new standards determines how fast new emissions technology is introduced into vehicles. However, the rate of fleet emissions reductions depends additionally on how rapidly the new vehicles displace older high emitting vehicles. This depends on additional factors, such as new vehicle cost, and can lead to long delays in the fleet emissions reaching regulatory levels.

Sections 2 – 4 of the review describe the RSD method, the data analysis and how gasoline vehicle emissions are related to speed, acceleration, and vehicle specific power. These provide information relevant to interpreting RSD measurements, such as the roles of instrument noise, site to site differences, and statistical uncertainties. Sections 5 and 6 present the principal trends found in the RSD data. Section 5 describes the fleet trends, while Section 6 looks at specific model year vehicles to investigate new vehicle emissions and their deterioration rates. The final section discusses the RSD findings and its future directions. It is not necessary to read these sections in order. Readers primarily interested in the vehicle emissions trends can jump to Sections 5 - 7 and then refer to Sections 2 – 4 as needed.

2. Remote sensing of vehicle exhaust

Measurement system

Remote sensing of motor vehicle emissions employs optical absorption by the vehicle's exhaust plume to record the relative concentrations of emitted pollutants. A typical site setup is illustrated by Figure 1. The campaigns in this review used the Fuel Efficiency Automobile Test (FEAT) method developed by Stedman, Bishop and colleagues at the University of Denver (Bishop et al., 1989; Bishop and Stedman, 1996; Burgard et al., 2006). This approach utilizes infrared absorption (IR) to detect carbon monoxide (CO), carbon dioxide (CO_2) and hydrocarbons (HC), and ultraviolet (UV) light to monitor nitric oxide (NO), nitrogen dioxide (NO_2) and ammonia (NH_3).

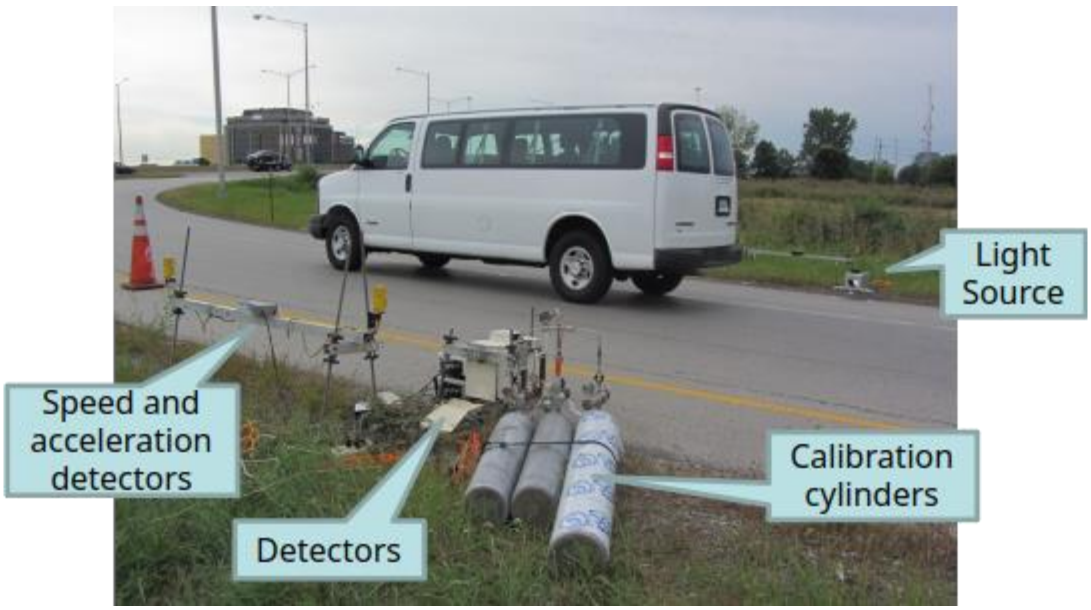

Figure 1. Typical setup of the FEAT remote sensing system.

The first generation instrument measured CO and CO_2 and subsequently added HC capability. These molecules have characteristic C-O and C-H bond stretching frequencies in the mid IR region (2170 cm^{-1} for CO, 2349 cm^{-1} for CO_2 and 2900 – 3100 cm^{-1} for HCs) that are free from interference by other atmospheric species. Infrared light is generated by thermal radiation from a silicon carbide (SiC) filament and directed across a roadway at typical tailpipe elevation (Figure 1). After passing through the exhaust plume, the light is separated into multiple paths by a rotating mirror. Each path passes through an optical bandpass filter tuned to one of the CO, CO_2 and HC absorption frequencies and then impinges onto an IR detector. A critical addition is a reference light beam, at a wavelength not absorbed by these species. This is used to compensate for any changes in light intensity between measurements of the incident and transmitted light, such as by dust or variations in refractive index.

Light absorption by pollutants in the exhaust plume decreases the transmitted intensity, which is converted to concentrations via Beer's law

$$ln(I/I_0) = -\alpha_s C_s L \tag{1}$$

I_0 is the incident light intensity, I is the transmitted intensity, α_s is the absorption coefficient of species s, C_s is the concentration of the species and L is the path length through the plume. I_0 is recorded in the absence of the exhaust plume, e.g., in front of the vehicle and the absorption coefficient is measured and calibrated in the laboratory. Unfortunately, the plume path length is not well defined, and varies with vehicle and driving condition. Therefore, instead of solving Eq. (1) for C_S, it is solved for $C_s{*}L$ for both the pollutant P and CO_2. Dividing the pollutant result with the CO_2 result yields a path length independent C_P/C_{CO2} concentration ratio. These ratios constitute the primary data collected by the remote sensing method.

HC differs from the other species measured by RSD in an important way. Whereas the IR absorptions by CO and CO_2 are specific to these species, all HCs absorb in the 2900 – 3100 cm^{-1} region, with absorption strengths that vary from one HC to another. As a result, the HC measurement represents some unknown weighted average of the hydrocarbons present in vehicle exhaust. The RSD HC channel is calibrated in the laboratory against propane, but when this is used to record vehicle exhaust, the RSD measurement is found to be a factor of two below the value obtained with the regulatory flame ionization method (Singer et al. 1998). Thus, in practice the raw HC/CO_2 concentration ratios are scaled up by a factor of two to give the propane equivalent HC emissions.

Later generations of the FEAT instrument added nitrogen compound capability (Popp et al. 1999). NO, NO_2 and NH_3 are detected via electronic absorptions in the UV at 227 nm, 438 nm and 210 nm, respectively. A xenon arc lamp generates broadband UV light, which is collimated and sent across the roadway. The arriving light is dispersed through two monochromators, one for NO and NH_3 and the other for NO_2 and recorded by photo-diode arrays. The captured absorption spectra are compared to calibration spectra and the corresponding values of $C_P{*}L$ are determined using Beer's law.

The details of how RSD measurements are made provide useful insight for interpreting the data. The IR and UV light intensities are continually monitored. When a vehicle is detected, the last 20 pre-vehicle values are kept to calculate an average value for I_0. Then fifty 10 ms measurements are made of the light absorbed by the vehicle exhaust plume. A least squares regression of the fifty $C_P{*}L$ versus $C_{CO2}{*}L$ data pairs yields the desired C_P/C_{CO2} concentration ratio. The important point here is that RSD measurements capture ½ seconds of vehicle emissions as compared to a Federal Test Procedure (FTP) drive cycle lasting ~2000 s.

The FEAT method includes numerous quality assurance steps. Detector responses with the light beams blocked are monitored to determine any zero offsets, and the light intensity measurements are corrected accordingly. Puffs of gas are released on site from certified gas mixture bottles to verify laboratory calibrations and provide adjustment factors for the C_P/C_{CO2} ratios as needed. The pre-vehicle CO_2 channel is monitored for any indication of possible interference from the preceding vehicle. The post-vehicle CO_2 measurements are checked to ensure an adequate plume exists (e.g., the tailpipe may be too high, or the vehicle might be battery electric). Appendix B lists the data validity criteria. The measurement campaign reports by Stedman and Bishop provide more detail regarding these criteria (cf. Bishop, 2020).

The fact that combustion stoichiometrically converts hydrocarbon fuels to CO, CO_2 and HCs allows rewriting the C_P/C_{CO2} concentration ratios in the more meaningful units of grams of emissions per kg of fuel. The result is

$$grams\ Pollutant/kgF = \frac{MW_P \cdot (CO/CO_2) \cdot 860}{(1 + CO/CO_2 + 6 \cdot (HC/CO_2)) \cdot 12} \quad (2)$$

where MW_P is the pollutant's molecular weight. In the case of HCs, the molecular weight of propane is doubled to 88 g/mole to account for the factor of two discrepancy between RSD and flame ionization measurements. These fuel-based emissions factors represent the data used for the trends analyses presented in this review.

Measurement uncertainties

Detector noise and lamp intensity fluctuations constitute the principal noise sources for laboratory measurements of optical absorption. Making such measurements in the field introduces a number of additional noise sources. Mechanical shifts in optical alignment over time can lead to small shifts in apparent light intensity. Variations in temperature over the day can similarly affect the measurement via shifts in alignment or detector response. Changes in wind velocity and direction can alter the background levels of CO_2 and pollutants.

Noise often exhibits an approximately normal distribution. In the case of remote sensing, however, a Laplace distribution provides a better fit. Figure 2 illustrates two examples of remote sensing NO_2 measurements, one from Tulsa in 2019 and the other from West LA in 2021. The fleet average over ~20,000 vehicles is zero within statistical uncertainty for Tulsa, and slightly negative for West LA. The symmetry indicates that vehicle NO_2 emissions are effectively zero, although there may be a small negative bias in the West LA case in spite of the care taken in laboratory and field calibration. Maximum likelihood statistics provide best fit parameters for both Laplace and normal distributions, indicated by the solid and dashed lines. Clearly, the Laplace distribution gives a much better fit of RSD noise than a normal distribution. Note that the width of the noise distribution and, hence measurement error, varies from one RSD measurement campaign to another.

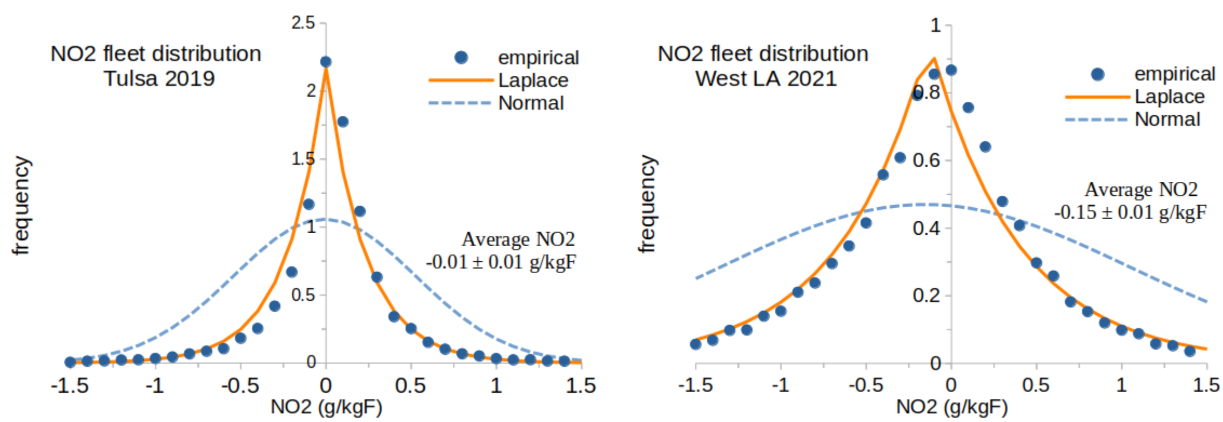

Figure 2. RSD measurement noise. Left panel: Tulsa 2019. Right panel: West LA 2021. Points represent the empirical distributions and lines represent fits to a Laplace versus normal distribution.

When emissions are present, the distribution of RSD measurements across the fleet is the result of both measurement and vehicle-to-vehicle variability. Figure 3 illustrates this in the case of CO measurements made in the 2019 Tulsa campaign. The presence of emissions, which are only positive, results in an asymmetric distribution. This distribution, h(x), is the convolution of the emissions and noise distributions, that is,

$$h(z) = \int_{-\infty}^{\infty} g\,(x) f(z-x) dx \qquad (3)$$

where g(x) represents the emissions distribution across vehicles and $f(x) = \frac{1}{2b} exp(-|x-\mu|/b)$is the Laplace noise distribution. When z is negative, the fact that the exponential of a sum is the product of the exponentials allows us to rewrite Eq. (3) in the form

$$h(z) = const \cdot exp(z/b) \tag{4}$$

Eq. (4) assumes that the average noise is zero, i.e., μ=0, sets the lower limit of integration to zero, since emissions are non-negative, and defines $const = \frac{1}{2b}\int_0^\infty g\,(x)exp(-x/b)dx$. Fitting the negative RSD measurements to the exponential decay in Eq. (4) yields the Laplace scale factor b and the noise standard deviation, $\sigma_{noise} = 2^{½}\, b$, as shown in Figure 3.

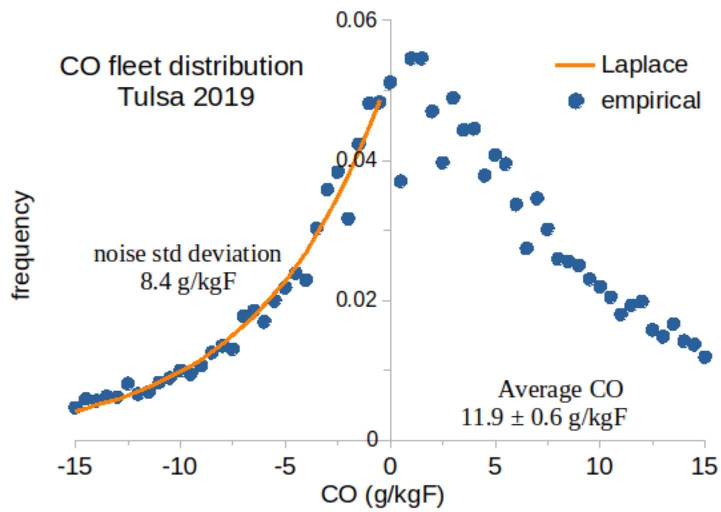

Figure 3. RSD signal plus noise for CO. Points represent the empirical distribution. The line is a fit of the Laplace distribution to the negative data points.

It is evident from Figure 2 that measurement noise levels vary from site to site. This is due to environmental and instrument setup differences. Noise standard deviations are in the 6 – 14 gCO/kgF range for CO, 3 – 11 gHC/kgF for HCs, 0.2 – 0.8 gNO/kgF for NO, ~0.3 gNO_2/kgF for NO_2 and 0.05 – 0.15 gNH_3/kgF for NH_3. Note that these represent the uncertainties in individual vehicle measurements. As discussed in the next section, errors in statistical metrics can be much smaller; for example, the 2σ confidence interval for fleet average CO in Tulsa, 2019, is ±0.6 gCO/kgF compared to the σ = 6 – 14 gCO/kgF measurement noise.

3. Statistical methods

The comprehensive database of remote sensing emissions measurements collected by the University of Denver group provides an invaluable opportunity to examine how vehicle emissions have evolved over the course of roughly thirty years. This section describes the statistical tools used to analyze these data. The primary quantities of interest include fleet averages, mean 99th percentiles, and trends in these statistics.

Fleet averages

Individual RSD measurements are of limited value. Any vehicle will exhibit a wide array of emissions behaviors for a 0.5 s measurement depending on its instantaneous speed, acceleration, power, catalyst state and A/F ratio control. Repeated 0.5 s measurements for a single vehicle would yield an average emissions rate comparable to that of a drive cycle with speeds, accelerations and VSPs representative of the RSD site. Extending this to a large sample of vehicles yields an emissions rate averaged over both the range of vehicles in the local fleet and the driving conditions at the measurement site.

The sample average also provides a statistical benefit. By the central limit theorem, the average of N samples converges with large N to a normal distribution, independent of the underlying population distribution (DeGroot 1975). Specifically, this implies that the fleet average will have a standard deviation of $\sigma_{avg} = \sigma_{sample}/N^{½}$, and thereby that the fleet average emissions will have a 95% confidence interval of $\pm 2\sigma_{sample}/N^{½}$. These confidence intervals allow us to decide if changes in fleet average emissions over time, or from one location to another, are statistically significant or not. σ_{sample} includes both vehicle-to-vehicle variability and measurement noise. The large number of vehicles measured, with N ~ 20,000 for a typical RSD campaign, leads to tight confidence intervals. In particular, the impact of measurement noise on the fleet average is roughly 140 times smaller than the RSD system noise discussed in Section 2.

High emitters

High emitting vehicles are of interest because of their disproportionate impact on air quality; for example, many states have inspection / maintenance (I/M) programs in an effort to help ensure that owners keep their vehicles' emissions systems in good working order. Here we apply extreme value theory (EVT) (Coles 2001) to analyze the RSD data for high emitters. The basis for this approach is that the maximum in a sample of size N approaches with large N a trio of distributions, Fréchet, Gumbel and Weibull, independent of the underlying distribution of vehicles emissions. These have the following cumulative distribution functions: Fréchet: $F(x) = exp(-\left(\frac{b_N}{x-a}\right)^{\varepsilon})$, Gumbel: $F(x) = exp(-exp\left(\frac{-(x-a_N)}{b}\right))$ and Weibull: $F(x) = exp(-\left(\frac{a-x}{b_N}\right)^{\varepsilon})$ with shape $\varepsilon > 0$, location a_N and scale parameter b_N. Note that the latter two parameters can vary with sample size.

Details about the EVT analysis of high emitters are given in previous work (Maricq and Bishop 2025). It proceeds by randomizing the emissions data from a given campaign and partitioning the data into blocks of size N, i.e., groups of N vehicles from the total sampled in the campaign. The emissions maxima from these blocks are used to construct maximum likelihood statistics for the shape and scale parameters of the Fréchet and Weibull distributions and for the scale and location parameters of the Gumbel distribution. Physical constraints on vehicle emissions are used to assign values for the Fréchet and Weibull location parameters. The location parameter serves as a lower bound for the Fréchet distribution, so we set $a = 0$ as the lower bound for emissions.

The location parameter represents an upper bound in the Weibull case; thus, its value varies with pollutant. As a rough approximation, gasoline has a chemical formula CH_2, in which case 2 kg of CO is the maximum possible from combustion of a kg of fuel. In practice it is unlikely that an engine operating this rich can power a vehicle to the RSD site, so *a* is set to 1600 gCO/kgF for CO high emitters, which is consistent with the highest emissions found in the entire University of Denver RSD database. Similarly, the highest possible HC emissions per kg of fuel is 1 kg. Since no fuel is burned under this condition, an upper limit of $a = 700$ gHC/kgF is adopted for hydrocarbon emissions.

The value chosen for location parameter affects the best fit values for shape and scale, but has limited impact on quantities of interest, such as the mean 99th percentile emitter. Upper bounds for nitrogen species emissions are difficult to estimate, so these are set based on the largest values observed in the database; thus, $a = 200$ gNO/kgF for NO, $a = 20$ gNO_2/kgF for NO_2 and $a = 20$ gNH_3/kgF for NH_3. In practice, the Weibull distribution plays a limited role in describing high emissions of nitrogen species, which generally follow the Gumbel distribution. In those cases where the Weibull distribution gives a better fit of the empirical data, it generally remains within the 95% confidence range of the best fit Gumbel distribution and, thus, the distinction is not statistically significant.

Once the shape, scale and location parameters are determined, one can find the high emitter cumulative distribution function (CDF), $F(x) = P(X \leq x)$, for the probability that the highest emissions in a group of N vehicles is less than or equal to x g/kgF. The left panel of Figure 4 illustrates CO block maxima CDFs in Chicago, 2014, for three block sizes, $N = 200$, 500, and 1000. While these are all Gumbel distributions, they appear distinct because the location parameter varies with sample size; namely, $a_N = a_0 + b \cdot \ln(N)$. However, if we invert the CDF to $P = F^{-1}(x)$ and plot the emissions level, x, against $-N/ln(P)$, the separate CDFs collapse onto the common exceedance level in the right panel of Figure 4.

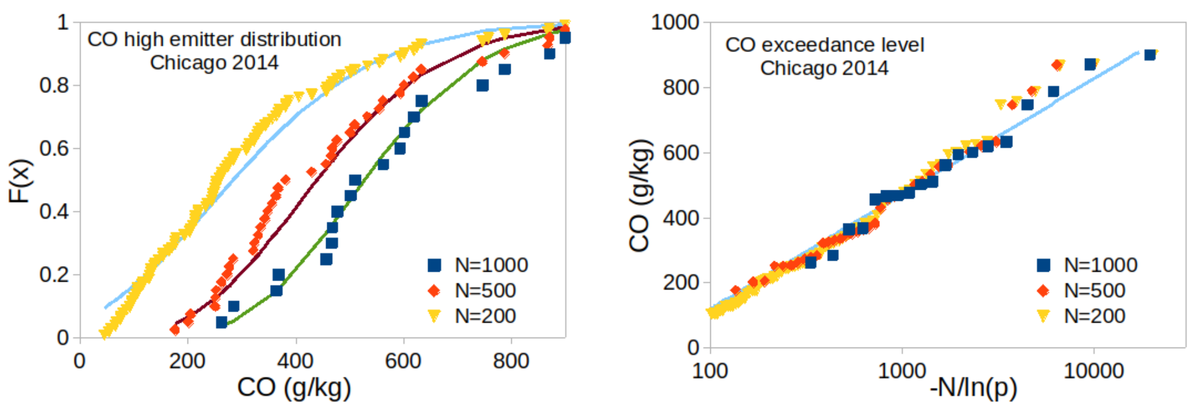

Figure 4. Relationship between CDF and exceedance level. Left panel: CDFs for three block sizes. Right panel: Corresponding exceedance level. Points represent empirical distributions and lines the maximum likelihood fits.

The same applies to Fréchet and Weibull distributions, except that the location parameter remains constant and the scale parameter varies as $b_N = b_0 N^{(1/\varepsilon)}$ and $b_N = b_0 N^{(-1/\varepsilon)}$, respectively. The term "exceedance" reflects the fact that if the maximum emitter in a group of N vehicles emits less than a specified level, then all the vehicles in the group have emissions below this level. Exceedance plots can be looked at in two ways: One is to fix N, which gives the probability that no vehicle in a group of this size emits above the level. The other is to fix P, which shows how exceedance level varies with the number of vehicles in a sample. It is sometimes easier to characterize these distributions via their means. In this case, it is convenient to choose N=100, which corresponds to the mean 99th percentile emitter.

The high emitter distributions represent three distinct tail behaviors of vehicle emissions, i.e., how fast the probability of finding a vehicle with emissions higher than x g/kgF falls off with increasing x. As Figure 5 demonstrates, the corresponding exceedance levels have distinct shapes. The convex shape of the Weibull exceedance level arises because this distribution represents the case where emissions have a finite upper bound. In principle no vehicle can emit an infinite level of pollutants, and so there is always some upper bound. In practice it applies to CO and HC emissions from Tier 0 and 1 vehicles, which can reach significant fractions of the upper limits available from a kilogram of fuel. In the remaining cases, the upper bound is sufficiently high as to appear infinite.

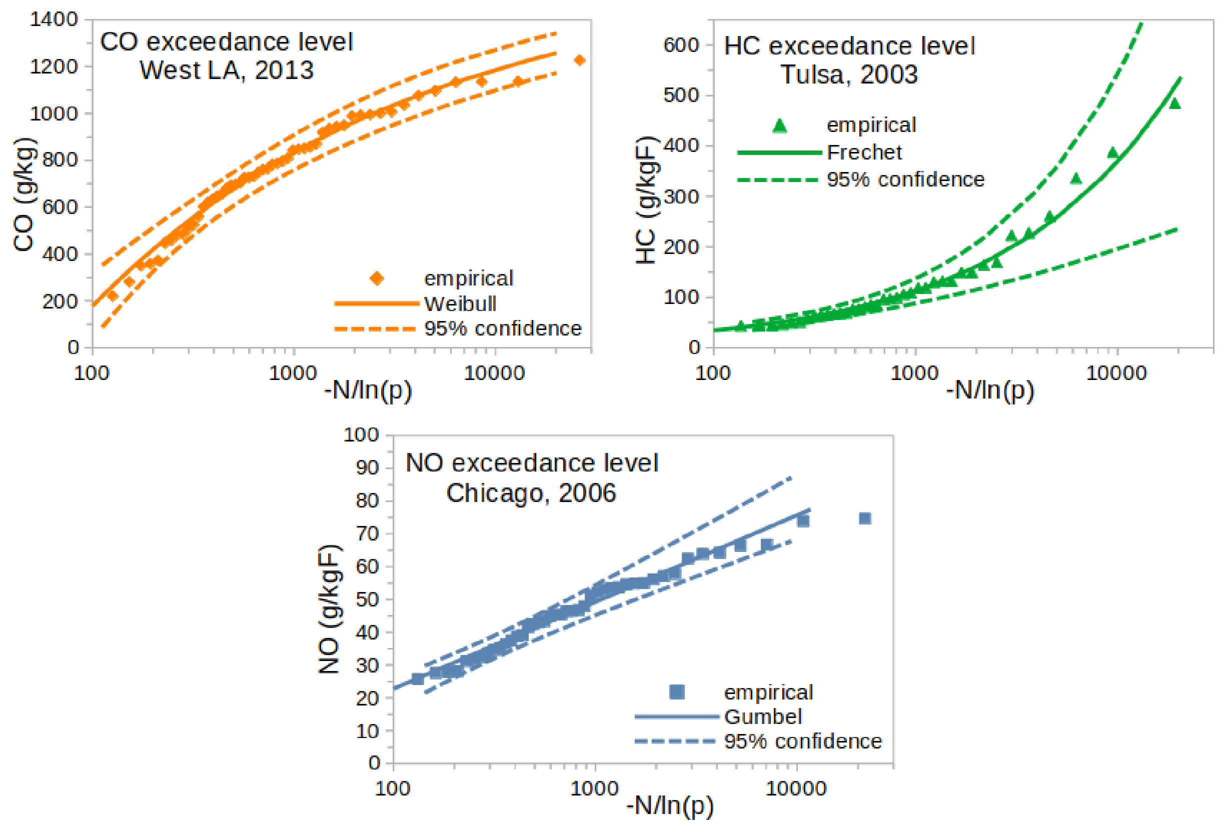

Figure 5. Emissions exceedance levels. Top left: Weibull distribution. Top right: Fréchet distribution. Bottom: Gumbel distribution. Points represent empirical distributions, solid lines are maximum likelihood fits to the distributions and dashed lines show 95% confidence intervals.

The Gumbel distribution represents the case where the distribution of vehicles in the overall population has an exponential tail. Mathematically, the emissions are not bound, but the probability of finding a vehicle emitting above x g/kgF decreases exponentially. In this case, the exceedance curve increases linearly with $-N/ln(P)$. The Fréchet exceedance level describes high emitters from a vehicle population with a long tail, namely one where finding a vehicle with emissions above x g/kg decreases as x^q, for some power q. This gives the Fréchet exceedance its characteristic upward curvature.

Trend analysis

Statistics such as fleet average emissions and 99th percentile emissions provide a convenient means to characterize a vehicle fleet at a given location and time. The breadth of the University of Denver RSD database affords the opportunity to investigate trends in these quantities over time and between locations. Regression analysis represents a quantitative approach to ascertain statistical trends (DeGroot 1975). Specifically, the present report applies linear regression to investigate emissions trends over time and over vehicle specific power (VSP). This is in some cases applied directly to the emissions and in others to the logarithm of emissions.

Given a set of emissions, y_i over a set of years or VSP values x_i, one can determine a least squares best fit slope, m, and intercept b. The slope and intercept are themselves statistical quantities and are described by Student's t distributions with n-2 degrees of freedom, where n is the number data points y_i. These distributions allow the determination of 95% confidence intervals for the slope and intercept, as well as for predicted emissions $m \cdot x_i + b$.

The 95% confidence intervals describe the statistical uncertainties in best fit slope and intercept, but not necessarily how well the model predicts emissions. The R^2 value provides a measure to ascertain the quality of fit. This is defined as

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - mx_i - b)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{5}$$

R^2 represents the ratio of "explained" to total variance, i.e., $R^2 = 1$ implies the model explains the variation of measured values, y_i. A value of zero implies that the data variation arises for some other reason. One possibility is random measurement uncertainty. But a slope of $m = 0$ also leads to $R^2 = 0$, since in this case the data do not depend on the values of x_i. Since R^2 depends not only on measurement uncertainty, but also on the best fit slope, overall confidence in the trend analysis rests both on this value and the 95% confidence intervals.

4. Spark ignition vehicle emissions basics

Transient nature of exhaust emissions

The typical RSD site is a curved, slightly uphill, highway ramp (Bishop and Haugen 2018). The curved roadway limits the speed and acceleration of the passing vehicles, the uphill ensures that the vehicles will mostly be under modest load, and the highway location allows time for the vehicles to warm up. This leaves room for a wide variety of driver behaviors during the 0.5 s emissions measurement time, with some maintaining speed while others accelerate or brake. Thus, it is helpful to examine how vehicle emissions vary during a typical drive.

The city, hot start and US06 phases of the Federal Test Procedure (FTP) and Supplemental FTP drive cycles shown in Figure 6 demonstrate modern warmed-up gasoline vehicle tailpipe emissions behavior. The instantaneous CO, HC and NO_x emissions are plotted in fuel-based units to match RSD data. The emissions exhibit very dynamic behavior over the drive cycle. In general, the timing of emissions coincides with accelerations and decelerations, and this is consistent from one drive to the next and between vehicles. However, the heights of the emissions peaks vary considerably between drives of the same vehicle as well as between vehicles. Gasoline vehicle emissions depend not only on the instantaneous engine conditions, but also on their history. This adds to the second-by-second variability and renders it impossible to map emissions simply from vehicle speed, load and accelerator position.

The traces in Figure 6 demonstrate that random 0.5 s emissions snapshots from the drive cycle can differ by more than an order of magnitude. The emissions transients often occur during accelerations, presumably from the sudden influx of fuel perturbing the steady state combustion that is normally very clean for stoichiometric air / fuel mixtures. The size of the transients tends to increase when accelerations occur at higher engine load owing to larger fuel sprays and more difficulty in maintaining tight air / fuel control. Emissions also occur during decelerations as the oxygen sensor and catalyst adjust to the sudden changes in exhaust oxygen concentration.

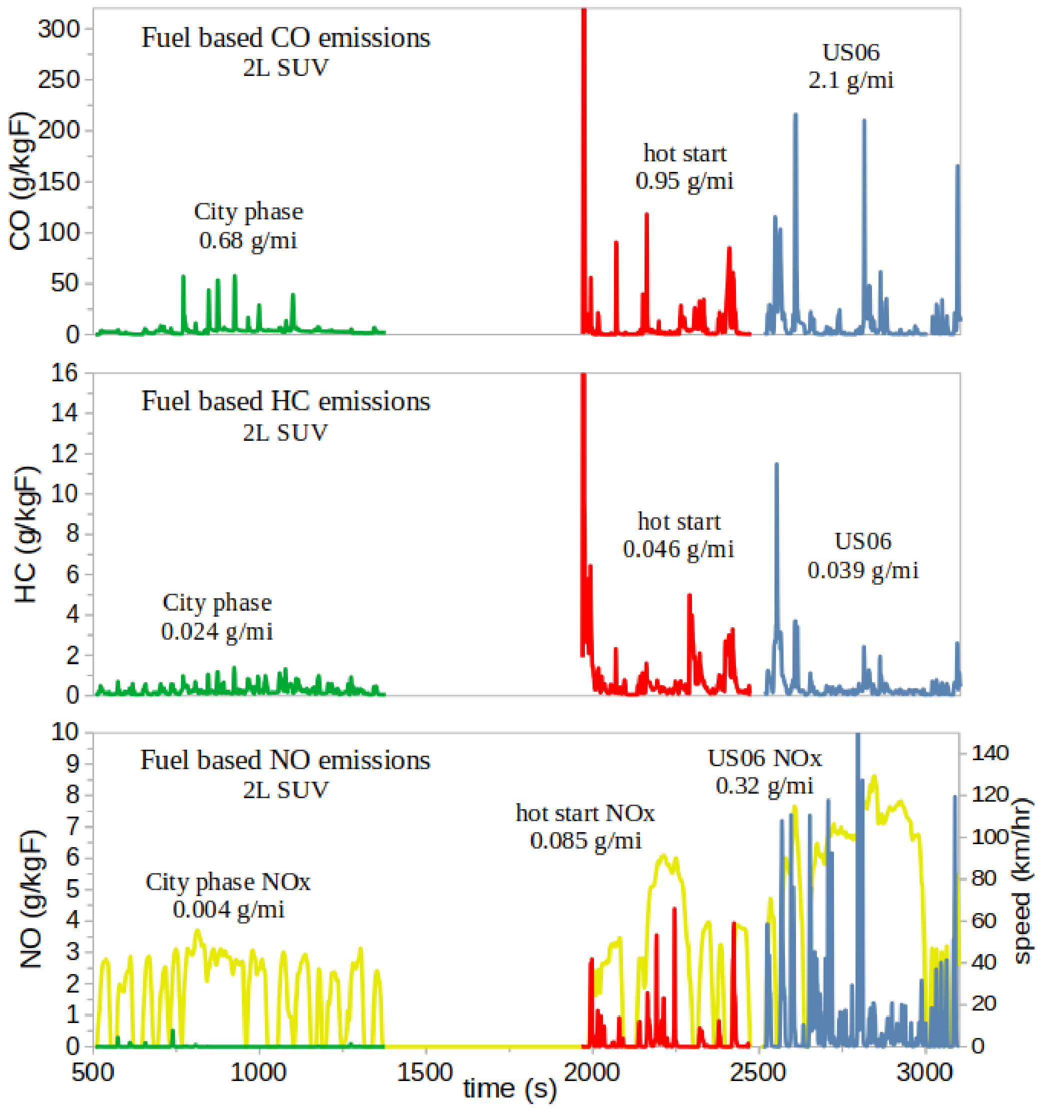

Figure 6. Transient fuel-based tailpipe emissions from a Tier 2 compliant vehicle over the FTP city and hot start phases and the US06 cycle. Top: CO, Middle: HC and Bottom: NO. The bottom panel also shows the speed trace.

Relationship between emissions and VSP

Vehicle specific power (VSP) is a measure of engine power scaled by vehicle mass, which is often used in emissions models, such as EPA's motor vehicle emissions simulator (MOVES) (US EPA, 2010). The University of Denver RSD campaigns (e.g., Bishop 2019, 2020a, 2020b, 2021) calculate VSP from vehicle speed, acceleration and road grade via (Jimenez et al. 1999)

$$VSP = 4.39\ v\ sin(s) + 0.22\ v\ a + 0.0954\ v + 0.0000272\ v^3 \qquad (6)$$

Here v is vehicle speed in mph, a is acceleration in mph/s and s is the road slope in degrees. The terms from left to right account for the work against gravity, inertia, friction, and air drag.

Figure 7 displays a variety of VSP distributions. The solid lines represent distributions from various RSD sites, whereas the symbols show the distributions for the hot start + city portion of the FTP cycle and the US06 drive cycle. The Fresno and West LA VSP distributions are typical of RSD sites, whereas those in Stockton and Oakland are the highest two of the RSD campaigns examined in the present review. The VSP distribution recorded at West LA, 2021 is nearly identical to the one for the FTP hot start + city drive. In contrast, the Stockton, 2021, distribution coincides with the US06 VSP distribution. Surprisingly, the VSPs recorded at the Oakland, 2022, site exceed those of the US06 drive cycle. The high VSPs at Stockton and Oakland are likely a consequence of the sites being located along straight uphill sections of roadway.

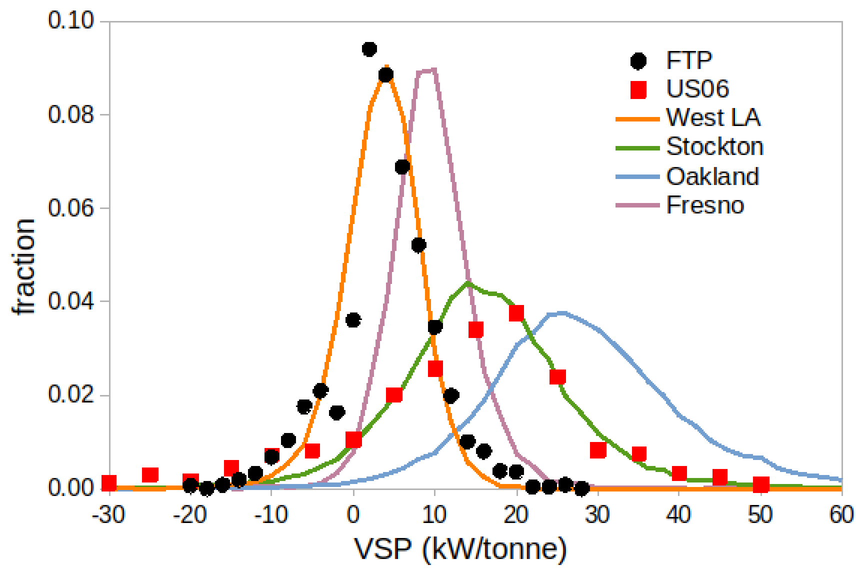

Figure 7. VSP distributions at various RSD sites and over regulatory drive cycles.

Regardless of the complex relationship between exhaust emissions and engine / catalyst conditions, there remains the general perception that emissions increase with VSP. This is in some sense true, but the relationship is not predictive. Figure 8 displays emissions versus VSP scatter plots for the four locations in Figure 7. The average VSPs range from about 2 – 27 kW/tonne. Besides the average, the VSP standard deviation also varies from site to site, with Fresno and West LA exhibiting tight distributions as compared to the broad counterparts found in Stockton and Oakland.

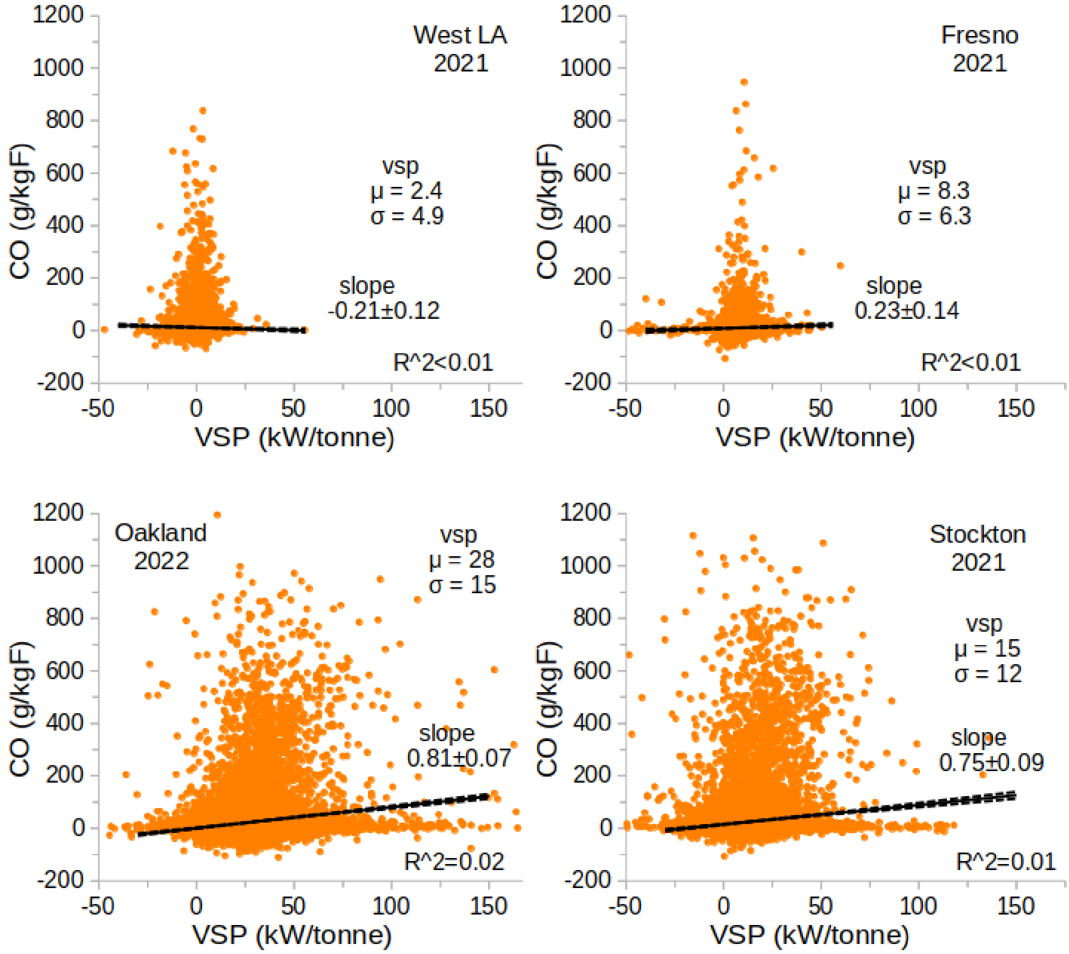

Figure 8. Regression of CO emissions against VSP. Top left: West LA. Top right: Fresno. Bottom left: Oakland. Bottom right: Stockton. Solid lines represent best linear fits. Dashed lines show 95% confidence bands.

The solid lines in each panel display best fit linear regressions, three of which show CO emissions to increase with VSP, whereas the slope for West LA is negative. The barely discernible dashed lines display very tight 95% confidence intervals for the fits. Yet they clearly do a poor job at predicting CO emissions from VSP. This is confirmed by the very low R^2 statistics, which are 0.02 or below. The tight confidence bounds result from the large number of vehicles and not from the accuracy of the emissions predictions. Emissions are not directly related to VSP. Steady state engine operation at high VSP typically has low emissions. Instead, the positive slopes in Figure 8 likely arise because higher VSPs lead to higher emissions during engine and catalyst transients on average, even though the emissions intensities themselves are poorly correlated with VSP.

5. RSD view of gasoline vehicle emissions trends

Data sets

The database of RSD emissions measurements conducted by the University of Denver includes numerous locations in the United States and abroad and extends from 1989 to 2022. The data are publicly available from the FEAT database at https://digitalcommons.du.edu/feat/. The present report concentrates on RSD campaigns in Chicago, Denver, Tulsa and West Los Angeles (Bishop 2019, 2020a, 2020b, 2021). The Chicago, Denver and West LA sites include measurements from the mid 1990s to 2021, with a brief hiatus between about 2008 and 2013. Phoenix was originally in the list of long-term study locations but was abandoned after 2006 due to a highway modification that eliminated the ramp used as the measurement site. Tulsa was added in 2003 to represent a non-inspection / maintenance (I/M) location. It was chosen based on the criteria that it had never had an I/M program and was distant from areas that had programs and might be sources of non-I/M compliant vehicles.

The roughly thirty-year time span allows a detailed examination of how vehicle emissions have evolved over the progressively more stringent standards from Tier 0 to Tier 3. The latest iteration of emissions standards completed its phase-in in 2025, whereas the last campaigns performed at the long-term locations are 2019 in Tulsa, 2020 in Chicago and Denver and 2021 in West LA. Therefore, the additional recent studies in 2021 Fresno, Stockton and Phoenix and in 2022 Oakland are included in the present analysis to increase the amount of Tier 3 relevant RSD emissions data. Furthermore, this permits an examination of how the most recent fleet emissions vary across a set of eight locations.

RSD provides a good approximation to a random sample of vehicle emissions measurements from a given metropolitan area. The use of highway ramps as measurement sites guarantees a large number of vehicles and reduces the likelihood that they originate from a limited geographical area. The sampling is not ideal, however. While random sampling admits the possibility of repeat measurements, the numbers of repeats found in RSD campaigns are larger than expected; for example, 20% of the measurements were repeats in Denver, 2020 (Bishop 2020b), and 47.1% were repeats in Tulsa, 2019 (Bishop 2020a). There are two reasons, however, to expect that this does not adversely affect the quality of the dataset. First, there is no reason to expect a bias in the repeat vehicles in terms of their emissions. Second, the fact that the driver likely drives differently from one pass through the RSD site to another, means that the 0.5 measurement interval records repeat emissions measurements under different vehicle operating conditions.

The FEAT database lists records that include both valid emissions measurement and vehicle registration data. The data reduction process and validation criteria to arrive at these records are described in each of the measurement campaign final reports (e.g., Bishop 2019, 2020a, 2020b, 2021) and are reproduced in Appendix B for convenience. The present analyses use this data without additional modification, with two minor exceptions. First, there were a few instances where a single vehicle contributed three of the highest emissions recorded during a campaign, and the repeats were removed. This improved the statistical fits but did not qualitatively alter any trends or conclusions. Second, records associated with a vehicle speed of zero were omitted from any VSP analysis; because a zero speed is not possible, it is assumed that a valid speed / acceleration measurement was not obtained.

The FEAT database includes two sets of HC data: measured and corrected. An offset in HC values was first noticed by Pokharel et al. (2001) in their year 2 campaign of RSD measurements in the Los Angeles area. While the cause has not been definitively identified, the HC data are corrected by identifying the subset of make and model vehicles with the lowest median and mean HC values, setting these to zero based on the assumption that their HC emissions are negligible, and adjusting emissions from the remaining vehicles accordingly. This report uses the corrected HC data.

The present section on long term SI vehicle emissions trends selects non-diesel vehicles from the FEAT database. This means that hybrid and flex-fuel vehicles, which have increasingly entered the light duty fleet are included. The non-diesel selection also includes a very few compressed natural gas vehicles, but their numbers are too small to impact the results. Section 6 on emissions deterioration specifically selects gasoline vehicles. The reason is to focus on emissions systems and avoid potential interference from any impact of hybrid technology on the deterioration. Checks done for selected campaigns indicate that selection by non-diesel versus gasoline fuel types has negligible impact on the subsequent statistical analyses.

Day of week variation in RSD data

One example of the random nature of RSD measurements is demonstrated by the day of week comparisons in Figure 9. While the University of Denver campaigns were generally conducted on weekdays, the 2013 and 2018 campaigns in West LA included Saturday and Sunday emissions measurements. Day to day variations in CO and NO emissions are within, or close to, the 95% confidence limits of the fleet averages, indicating that these emissions are independent of when they are measured. To the extent that weekend versus weekday vehicle population differences exist, for example in average age, they do not have a statistically meaningful impact on fleet average emissions. In the case of HCs, some statistically significant differences are visible, but they do not appear to be associated with any particular day. It is possible that they arise from the HC correction mentioned above, if the HC offset varies from day to day.

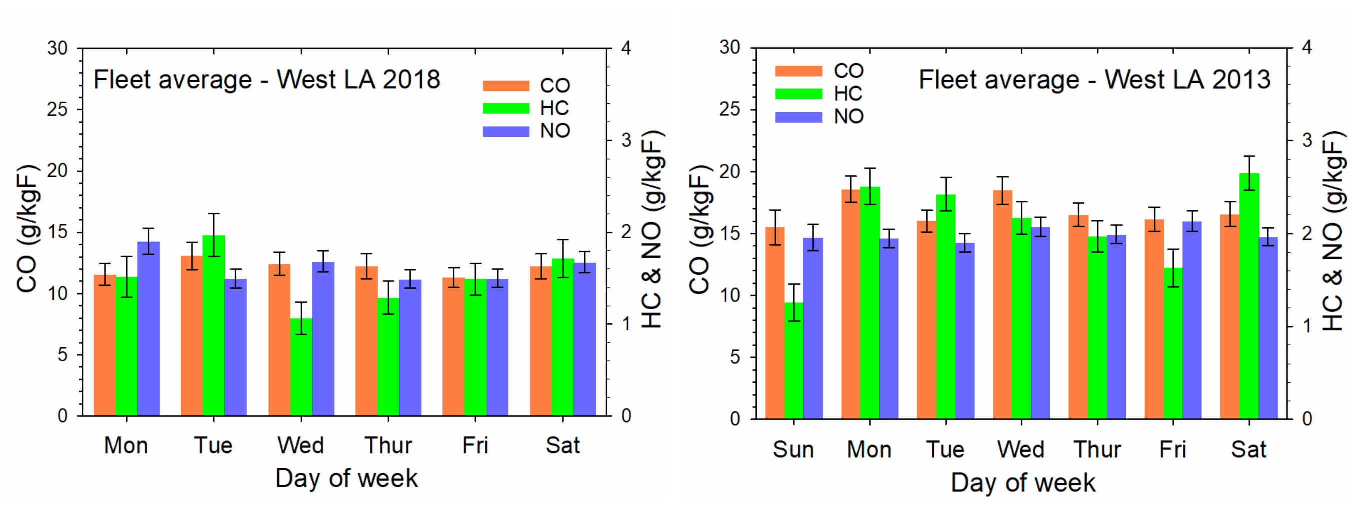

Figure 9. Day to day variations in fleet average CO, HC, and NO emissions. Left: West LA, 2018. Right: West LA, 2013. Error bars are $\pm 2\sigma_{avg}$

Fleet average and high emitter trends over time

This section condenses a great deal work by the University of Denver group into a brief history of gasoline vehicle emissions in the US that stretches from 1991 to 2021. The emissions trends for CO, HC, NO, NO_2 and NH_3 are presented in graphical form. The details are provided in Tables 1 – 4 in

Appendix C, including the fleet average and mean 99th percentile high emitter emissions as well as the best fit EVT distribution shape, scale and location parameters.

Figure 10 displays fleet average and mean 99th percentile CO emissions from Chicago, Denver, Tulsa and West LA. The fleet average and mean 99th emissions exhibit exponential declines over approximately thirty years, with high R^2 values in each case. The fleet average emissions decline by a factor of 13, which demonstrates a substantial benefit to air quality from the progressively more stringent emissions standards and the improvements in engine / aftertreatment technology to meet those standards. The declines in g/mi emissions predicted by the MOVES5 model agree very well, falling within the 95% confidence interval of the RSD regression. The model results come from car and light duty truck data reported by the Bureau of Transportation Statistics (Bureau Transport. Stat.), which are combined as a weighted average using EPA's light duty fleet composition data (US EPA 2024). The mean 99th percentile emissions show a substantial reduction but declining at half the fleet average rate they are becoming a progressively larger burden on air quality.

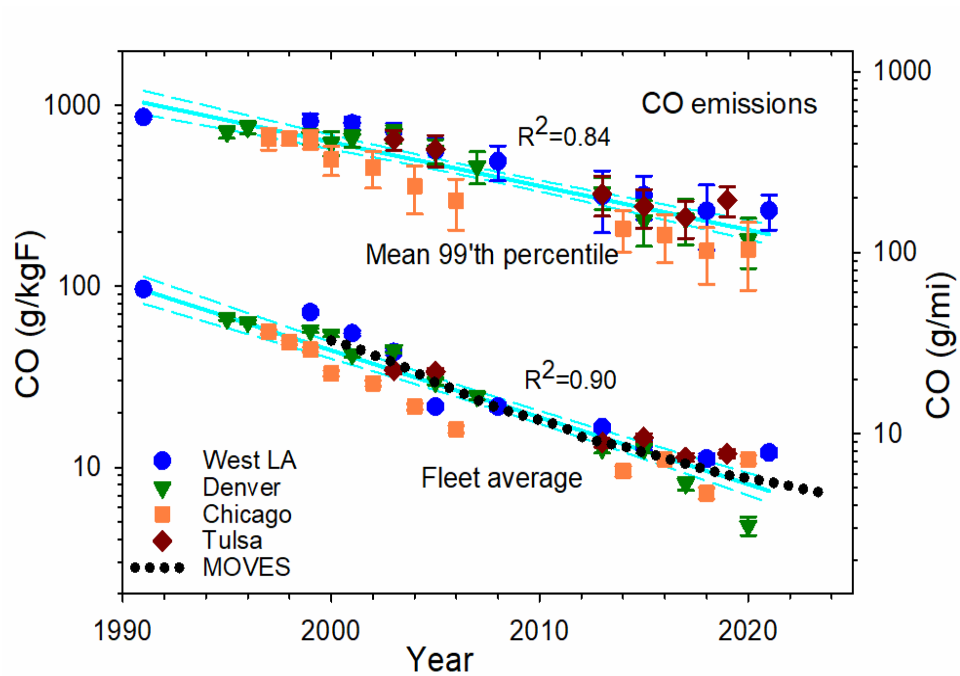

Figure 10. CO emissions over time. Symbols represent the data. Error bars show 95% confidence intervals, many of which are smaller than the symbol size. Solid lines are least squares fits. Dashed lines show 95% confidence bands. Dotted line displays MOVES5 emissions rates on the right axis.

All four locations exhibit the same basic fleet and mean 99th percentile emissions trends. Closer inspection reveals a few small differences. The Chicago values appear systematically lower than those in the other three cities. These differences are mostly within the 95% confidence intervals for the mean 99th percentile emissions but are statistically significant for the fleet averages. Bishop (2020c) points out that Chicago has the youngest fleet of the four locations and suggests that this may account for the lower emissions. However, a number of other factors could contribute, such as differences in weather or VSP distribution. The divergence in fleet average CO emissions between 2019 and 2021 represents another small discrepancy in trends. This is discussed in broader terms in the next section by including four additional cities.

HC fleet average emissions in Figure 11 also show dramatic improvement, falling ninefold between 1991 and 2008. But then they remain flat through 2021. The MOVES model predictions accurately describe the decline to 2008 but miss the leveling off seen in RSD data and continue to fall exponentially past 2020. The mean 99th percentile emissions exhibit a smaller threefold improvement from 1991 to ~2008 and also remain flat after that. The fleet average decrease is well described by an exponential decay, $R^2 = 0.87$, but owing to the larger data scatter, the exponential fit to the 99th percentile has a lower statistical significance of $R^2 = 0.38$. As with CO, the fleet average and mean 99th HC emissions have diverged over time, with the high emitters contributing an increasing burden to adverse air quality, approximately 25% by the top 1% in 2020.

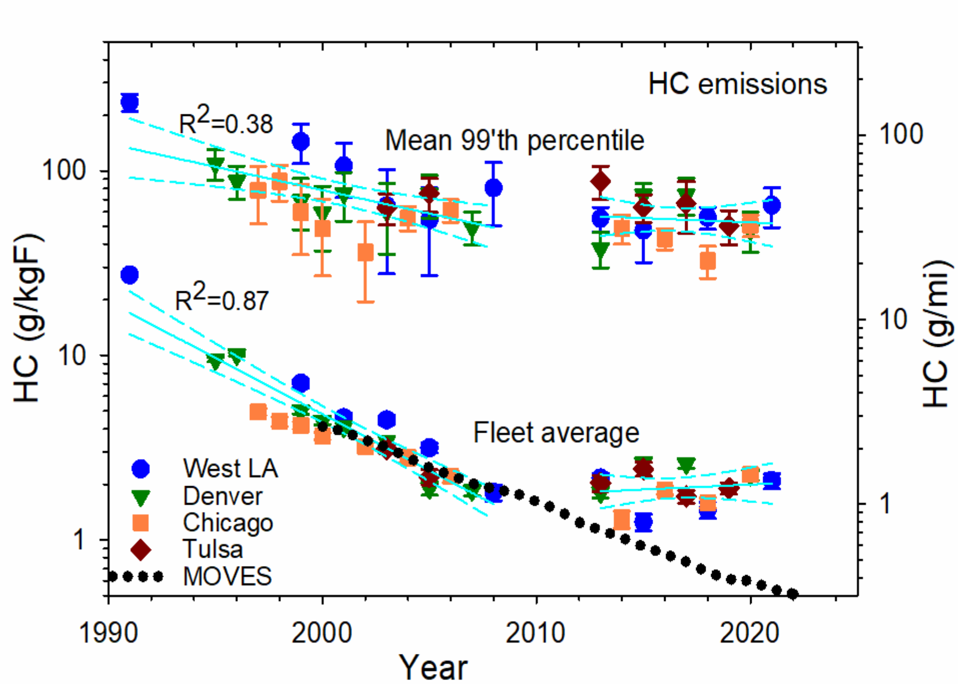

Figure 11. HC emissions over time. Symbols represent the data. Error bars show 95% confidence intervals, many of which are smaller than the symbol size. Solid lines are least squares fits. Dashed lines show 95% confidence bands. Dotted line displays MOVES5 emissions rates on the right axis.

Why HC emissions improvements cease after Tier 1 is unclear. One possibility is that further improvements after 2008 are obscured by the low signal to noise ratio of HC measurements and the process used to correct for offsets, namely setting the cleanest new make and model HC emissions to zero. While this is a plausible explanation for flat fleet average emissions, it does not explain why the mean 99th percentile emitters, with ~25 times higher signal/noise, exhibit the same behavior.

Just as with CO and HCs, fleet average NO emissions in Figure 12 exhibit an impressive eleven-fold reduction over the 1995 to 2021 time period. This decrease follows an exponential decay ($R^2 = 0.89$), which extends continually over the ~25 year period, unlike for HCs. The decline in MOVES emissions rates follows the RSD trend well until about 2012, after which it decreases faster than the measured fleet average. The mean 99th percentile emissions remain close to flat, decreasing only by a factor of ~1.5 over 25 years. The R^2 value for the fit, 0.38, is lower than for the fleet average, in spite of similar data scatter, because even when data is tightly scattered around a horizontal line, the "explained" variation in Eq. (5) goes to zero (i.e., the emissions do not depend on the independent variable).

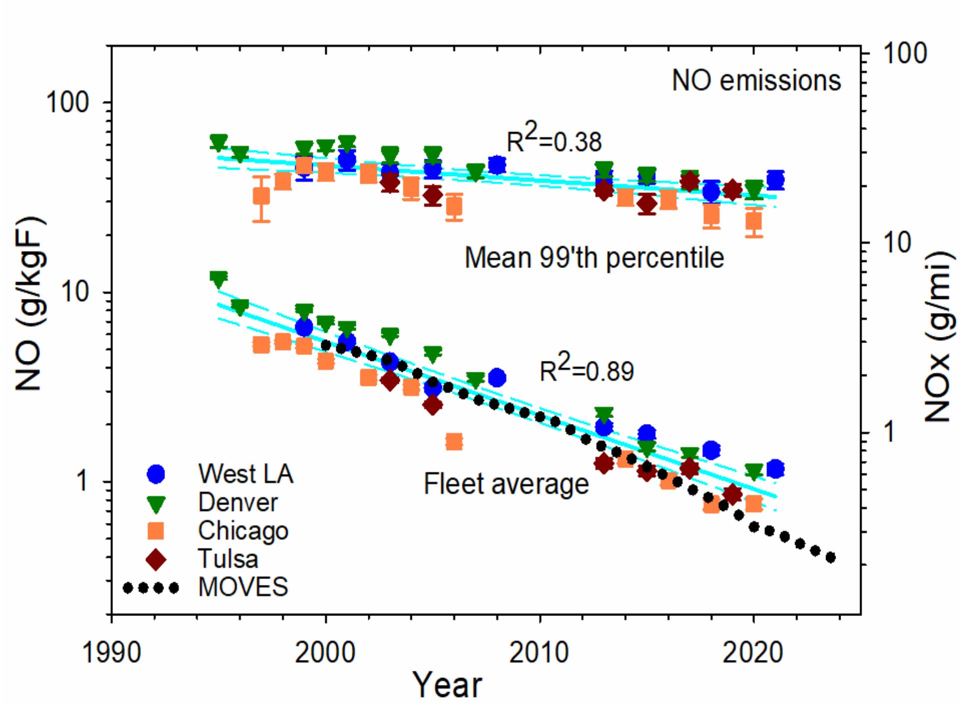

Figure 12. NO emissions over time. Symbols represent the data. Error bars show 95% confidence intervals, many of which are smaller than the symbol size. Solid lines are least squares fits. Dashed lines show 95% confidence bands. Dotted line displays MOVES5 emissions rates on the right axis.

The divergence between mean 99th percentile and fleet average emissions is particularly noticeable in the case of NO, with their ratio increasing from about 6 in the mid 1990s to ~35 in 2020. This means that high emitters have gone from contributing 6% to 35% of the gasoline vehicle fleet's NO emissions. Clearly, removing high emitters from the fleet will be a much more productive avenue for future NO emissions reductions than the declining marginal gains available from lowering the fleet average.

When looking over the thirty-year time frame of RSD emissions measurements, the trends in CO, HC and NO emissions look remarkably similar across the diversity of locations. The geography is different, with Denver at about 5000 ft elevation and Chicago and West LA near sea level. There are seasonal differences; Chicago and Tulsa RSD campaigns occurred in September, West LA Campaigns in March, May, October and November, whereas Denver RSD campaigns took place in January and February. Yet these factors do not have a major impact on the overall trends. There are site to site differences in the vehicle speed and acceleration distributions that along with environmental factors and fleet composition may explain some of the scatter in fleet average and mean 99th percentile emissions across locations.

One factor that according to these long-term trends does not play a role in real world emissions is I/M. These programs are designed to identify high emitting vehicles and have them repaired to their emissions certification levels. However, there is no statistically significant difference between emissions measured in Tulsa, which has never had an I/M program, and those recorded in Denver and West LA, which have had I/M programs for many years. The emissions measured in Chicago are below those in Tulsa, but they are also below those in Denver and West LA; thus, the reason must be something other than I/M. Given the simple premise of identifying and fixing high emitters, it is unclear why I/M appears to be ineffective. One weak point may be the implicit assumption that the identified high emitters actually receive effective long-term repairs.

Because NO_2 and NH_3 FEAT measurement capability only became available in the mid 2000s, trends in these species only cover the reduced time span from 2008 and 2005 to 2021, respectively. The fleet average NO_2 emissions displayed in Figure 13 are very low and do not change over time. In fact, there are negative values that do not appear on this semi-log plot, but can be found in Tables 1 – 4 in Appendix C. The fuel-based mass NO_2 emissions are an order of magnitude below the lowest NO fleet average emissions, before scaling by the NO_2/NO molecular weight ratio required when calculating NO's contribution to NO_x emissions. Even the mean 99th percentile NO_2 emissions are only comparable to Tier 2 fleet average NO emissions and remain flat across the 2008 – 2020 time frame. Thus, RSD measurements indicate that gasoline vehicle NO_2 emissions are essentially zero and make a negligible contribution to ambient NO_x levels.

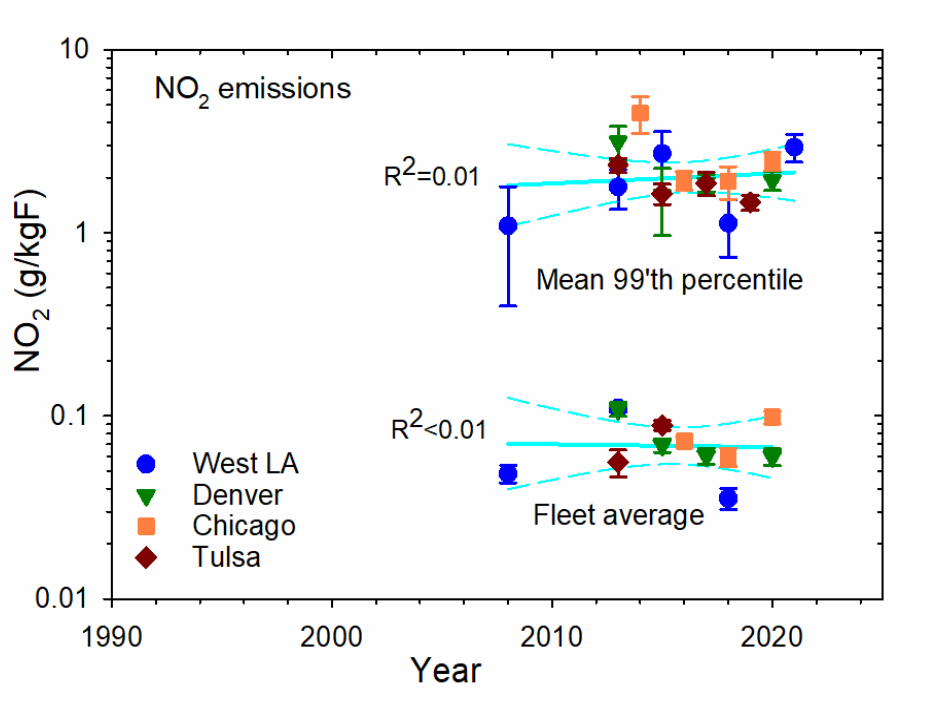

Figure 13. NO_2 emissions over time. Symbols represent the data. Error bars show 95% confidence intervals. Dashed lines show 95% confidence bands.

Ammonia is not an engine-out emission, but rather an undesired pathway in catalytic NO_x reduction that occurs under some catalyst operating conditions. As seen in Figure 14, NH_3 emissions have declined slightly on average, by about 30%, between 2005 and 2020, although the difference between this and a 0% decrease is not statistically significant at 95% confidence. NO fleet average emissions have fallen more steeply over the same time, by a factor of four; thus, the NH_3 fraction of nitrogen species emissions has risen from roughly 15% to 35% by mass, while the total emissions have decreased by about 70%. The mean 99th percentile emissions are flat over time within statistical uncertainty. They are about ten times higher than the fleet average, as compared to 20 – 30 times higher in the case of NO emissions. This, and the fact that NH_3 is not an engine-out species, suggest that these high emissions arise more from catalyst control than emissions system malfunctions.

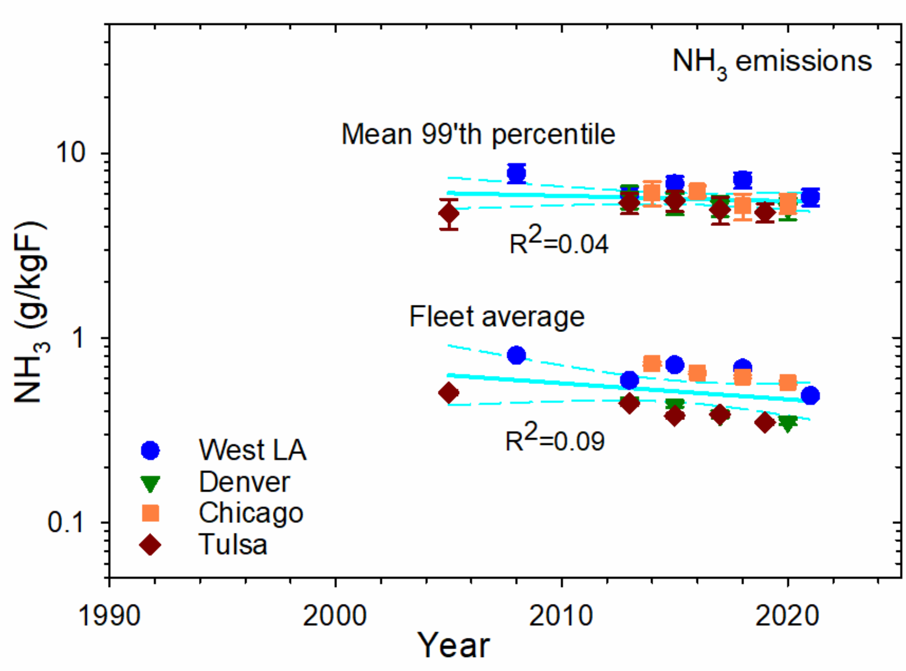

Figure 14. NH_3 emissions over time. Symbols represent the data. Error bars show 95% confidence intervals. Dashed lines show 95% confidence bands.

Location dependence of vehicle emissions circa 2020

A flurry of emissions measurement during 2019 – 2022 included eight RSD campaigns: Tulsa, 2019; Chicago and Denver, 2020; Fresno, Phoenix, Stockton and West LA, 2021 and Oakland, 2022. This provides an opportunity to examine location dependent emissions variations as they existed about halfway through the Tier 2 to 3 phase-in. Figure 15 compares the fleet average and mean 99th percentile CO, HC and NO emissions recorded across these locations, with CO values shown on the left axes and HC and NO values on the right axes (the values are listed in Table 5 of Appendix C). With linear and expanded vertical axes, significant differences appear between locations in these graphs that are less visible in Figures 10 to 12. Surprisingly, the largest differences are in CO emissions; the fleet averages are approximately two times higher in Oakland and Stockton and half as high in Denver as compared to the other five locations. The same pattern is observed for the mean 99th percentile emissions. HC emissions, in contrast, are close to indistinguishable at the 95% confidence level. Fleet average and mean 99th percentile NO emissions exhibit some statistically significant location differences, but these are smaller than for CO. The similarity between the pattern of fleet average versus 99th percentile emissions variations with location derives, at least in part, from the high emitters' contributions to the fleet averages.

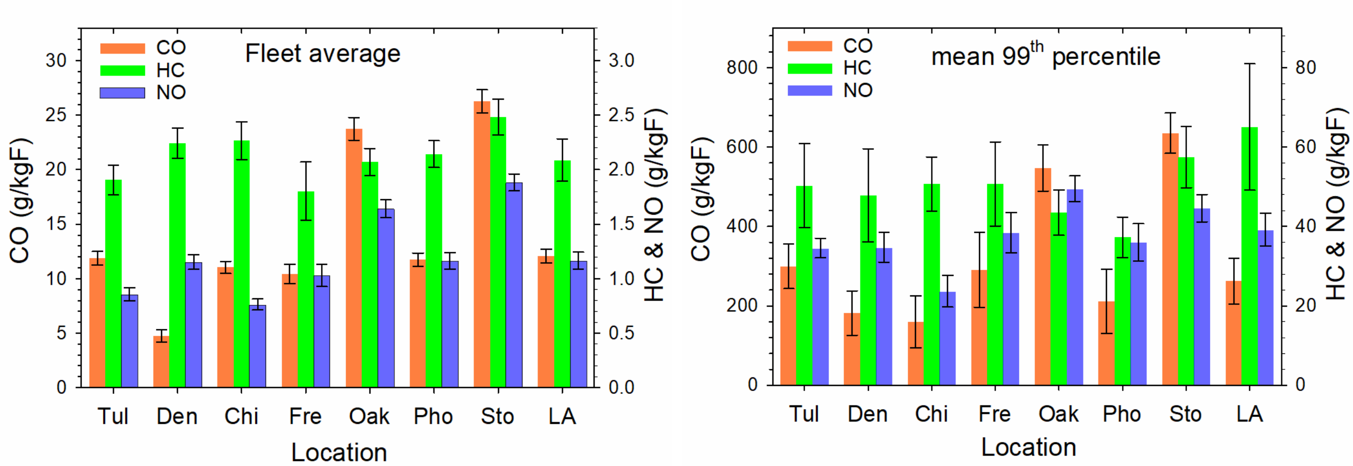

Figure 15. Variations in circa 2020 emissions across location. Left panel: fleet average. Right panel: mean 99th percentile. Error bars show 95% confidence intervals.

At least four types of variables can in general contribute to location dependent emissions factors: site differences that influence vehicle operating conditions, environmental factors, fleet composition and policy/behavioral factors. Figure 16 plots the CO emissions in Figure 15 against the average VSPs at the eight locations. Both the fleet average and mean 99th percentile emissions exhibit positive correlations with site average VSP at respectable R^2 values near 0.5. As demonstrated by Figure 8, the direct correlation between emissions and VSP is poor. The correlations in Figure 16 arise indirectly. Higher VSPs, with their larger associated fuel injection volumes exacerbate emission formation during engine transients. Thus, measurement sites with higher average VSPs tend statistically to result in higher fleet average and mean 99th percentile emissions, which explains at least partly the site-to-site differences in Figure 15.

Environmental factors, such as ambient temperature and altitude are in principle important factors in tailpipe emissions levels. Cold ambient temperature has the biggest impact during vehicle cold start, where it increases the time required for the engine and catalyst to warm up to proper operating temperature; thus, it is expected to have minimal impact at a highway ramp RSD site where vehicles have presumably had sufficient warm-up time. High altitude reduces the intake oxygen concentration, but this is accounted for by the oxygen sensor and engine controller in properly functioning modern engines. The fact that both the fleet average and mean 99th percentile CO emissions recorded during winter in Denver are below those in Oakland and Stockton, suggests that temperature and altitude do not explain the location dependent emissions differences.

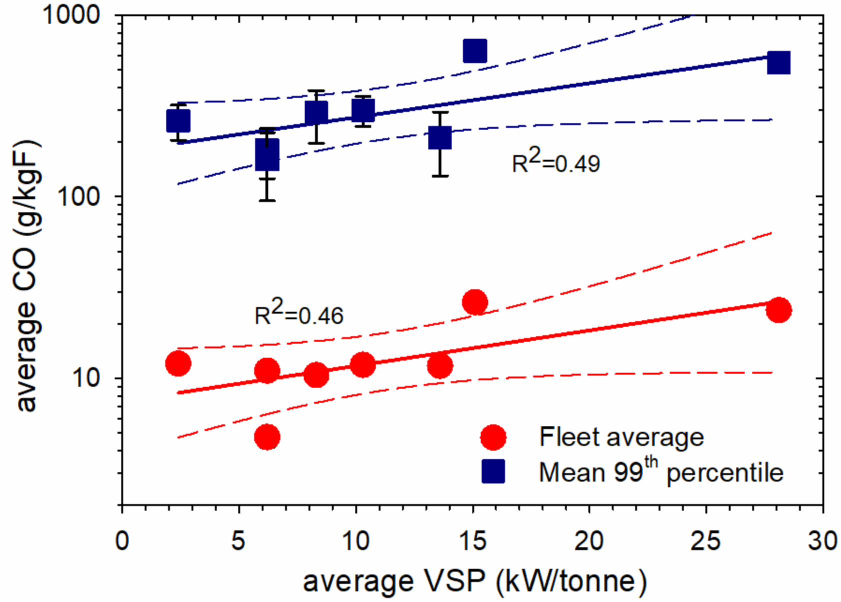

Figure 16. Fleet average and mean 99th percentile CO emissions versus average VSP at the eight locations in Figure 15. Solid lines show least squares fits and dashed lines the 95% confidence limits.

Fleet composition can vary from one location to another. For example, economically disadvantaged areas might have an older fleet with higher emissions. To investigate this possibility, Figure 17 compares fleet average CO emissions from 2020/21 model year (MY) vehicles recorded in 2021/22 Fresno, Oakland, Phoenix, Stockton and West LA. These emissions exhibit the same pattern seen in Figure 15 of approximately two to three times higher emissions in Oakland and Stockton than in the other three locations. NO emissions are likewise higher, though by less than a factor of two. The fact that the fleet average and new vehicle average emissions exhibit the same location dependence suggests that this is not a fleet age issue.

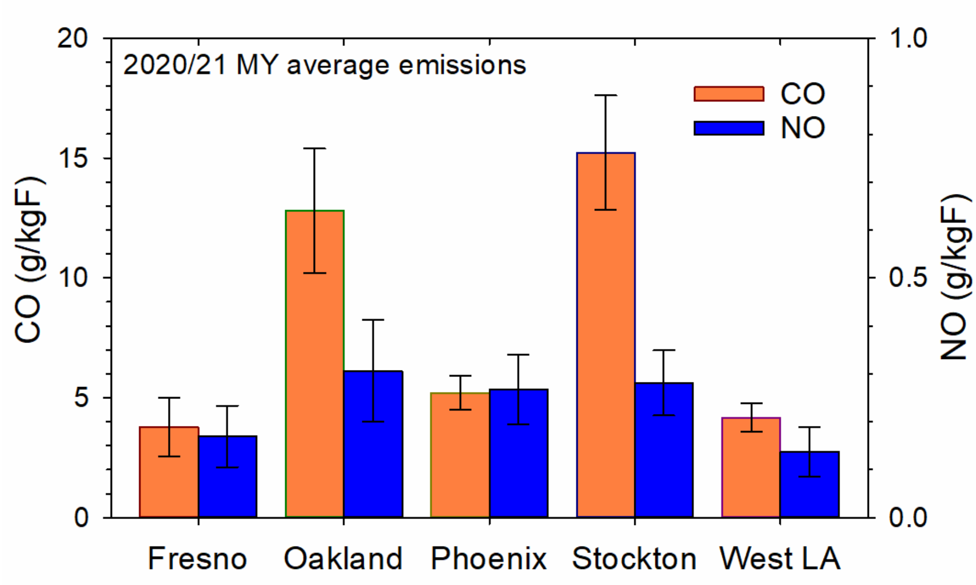

Figure 17. Average new vehicle emissions versus location. Error bars show 95% confidence intervals.

Malfunctions and tampering are other potential explanations for high emissions. However, the vehicles in Oakland and Stockton are subject to the same I/M program as those in West LA and Fresno. Thus, this explanation is only viable if for some reason the I/M program is substantially less effective in Oakland and Stockton than the other California locations. Anecdotal data from these two sites may provide the best explanations (Bishop 2026). The Oakland site was situated at a straight, versus curved, section of highway interchange and, thus, incurred a number of wide open throttle events, which is consistent with the very high vehicle specific power distribution in Figure 7. The Stockton sight was very hot, with the temperature reaching 120 F on a number of days. The wide open throttle events and high temperatures likely led to emissions control exception conditions. These enrich combustion to reduce the exhaust temperature and protect the catalyst but substantially increase CO emissions.

6. Model year specific vehicle emissions

Emissions deterioration

In any given RSD campaign, the fleet includes vehicles with a wide range of ages and certified to various emissions standards. To address the important question of how regulations impact the improvement of emissions systems, this section investigates emissions from select model year (MY) vehicles as they age from one campaign to the next at the Chicago, Denver, Tulsa and West LA locations. Model years are selected that fall between emissions standards phase-in periods so that they reflect engine and aftertreatment technologies developed to meet a specific exhaust emissions standard rather than a mix of technologies associated with the phase-in of new standards. In general, two consecutive model years are combined to increase the numbers of vehicles and, thereby, the statistical power of the trends analyses. The exceptions are Denver Tier 0 and 1 vehicles, which serve as a check that combining successive model years does not introduce any inconsistencies. MY 1992/93 is chosen to represent Tier 0 vehicles, MY pairs 2000/01 and 2002/03 represent Tier 1 and MYs 2010/11 and 2012/13 represent Tier 2. No Tulsa data appear in the Tier 0 vehicle analysis since RSD campaigns did not commence there until 2003. Tier 3 implementation concluded in 2025, after the final University of Denver RSD campaigns; thus, the determination of Tier 3 vehicle emissions deterioration is not feasible. The analysis of MY specific NO_2 trends is omitted, because the fleet averages were found above to be negligible. Finally, the emissions trends data presented in the figures below are reproduced in tabular form in Tables 6 – 8 of Appendix D.

Figure 18 (left panel) displays MY year average CO emissions as a function of RSD campaign year minus model year, i.e., as a function of vehicle age. CO levels from vehicles representing the three standards are clearly distinct. Tier 1 vehicles emissions rates are roughly a third of those for Tier 0, and Tier 2 vehicle emissions are about a third of Tier 1. The average CO emissions increase with vehicle age at all three emissions standards. The slope, which on the logarithmic scale in Figure 18 represents the fractional deterioration rate, is approximately the same for Tier 0 and 1, but increases under Tier 2. The vehicle age trends are consistent across the four locations within the data scatter. The apparent increase in data scatter from Tier 0 to Tier 2 is at least partly due to plotting emissions on a logarithmic scale, which is done to display emissions data from the three standards on the same graph.

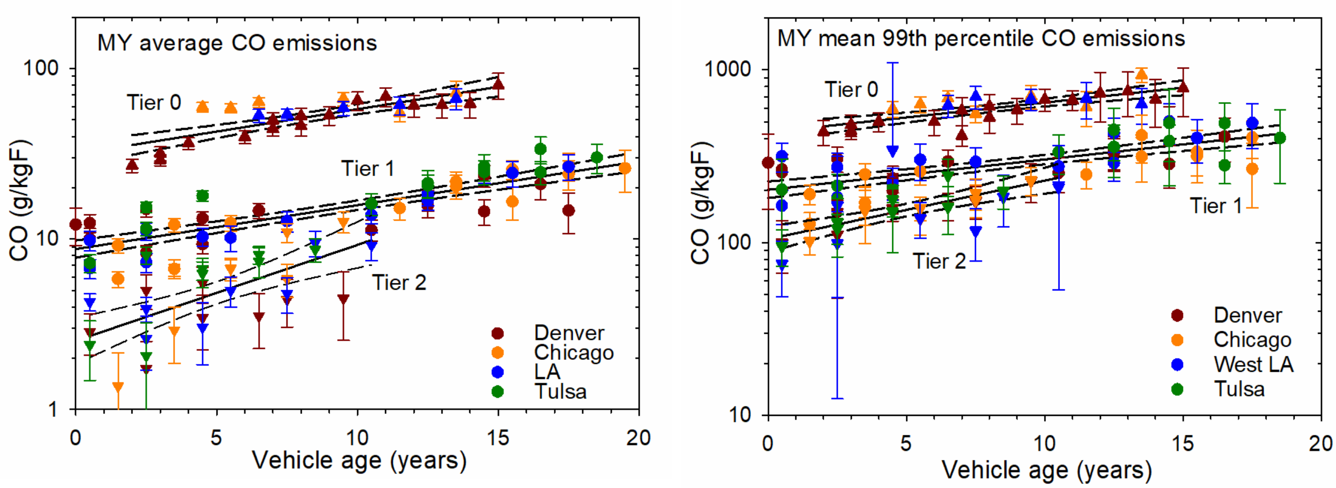

Figure 18. CO emissions versus vehicle age. Left panel: MY average. Right panel: mean 99th percentile. Symbols represent RSD averages. Solid lines display least squares fits. Dashed lines show 95% confidence intervals.

Model year specific mean 99th percentile CO emissions in the right panel of Figure 18 exhibit the same pattern as observed for the MY averages. The mean 99th emissions are roughly a factor of 10 times higher than the MY averages. There are again consistent drops in the high emitter CO emissions from Tier 0 to Tier 1 and Tier 2, but these are smaller than the MY average decreases. The fractional deterioration rates in mean 99th percentile emissions are roughly parallel to those for the MY averages. They are the same for Tier 0 and Tier 1, but steeper for Tier 2.

The story for HC emissions is a bit different. In this case, Figure 19 shows a clear decrease in MY average HC emissions from Tier 0 to Tier 1, but Tier 2 MY average HC emissions are statistically indistinguishable from Tier 1. The Tier 0 HC regression does not include the 2-4 year old Denver vehicles, since these 1995/96 campaigns did not make an offset correction and these points appear to be inconsistently high. Tier 1 emissions remain below new Tier 0 vehicle HC emissions even up to 20 years of age. There is large data scatter in HC emissions from Tier 1 and 2 vehicles less than six years old, particularly in Denver and West LA. This is partly due to the HC emissions levels being largely below the S/N capability of the HC measurement but may be exacerbated by the HC offset correction.

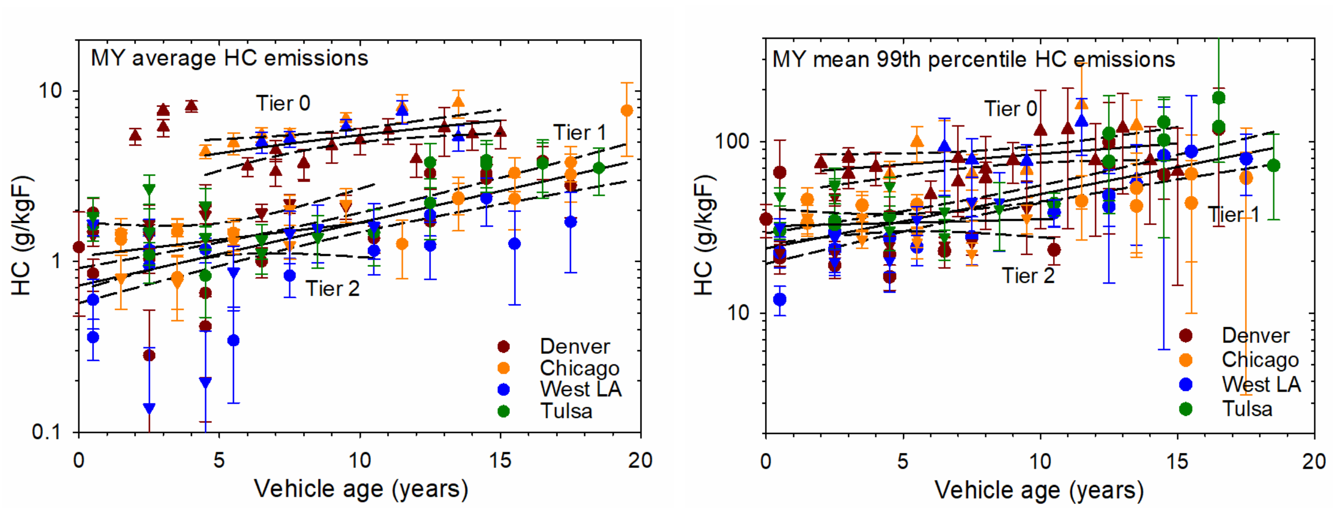

Figure 19. HC emissions versus vehicle age. Left panel: MY average. Right panel: mean 99th percentile. Symbols represent RSD averages. Solid lines display least squares fits. Dashed lines show 95% confidence intervals.

As with CO, the mean 99th percentile HC emissions in Figure 19 (right panel) follow the same pattern as the MY average emissions, but with relatively smaller distinctions between the different emissions standards. At a given vehicle age, high emitter HC emissions from Tier 0, 1 and 2 vehicles are often statistically indistinguishable. Tier 0 and 1 regressions, which represent data aggregated across roughly 15 years, are statistically different at 95% confidence, but those for Tier 1 and 2 are not. The lack of a statistically significant distinction for either the MY average or mean 99th percentile emissions between Tier 1 and Tier 2 vehicles is consistent with the HC fleet emissions trends in Figure 11, becoming flat after about 2010.

Model year average NO emissions exhibit the clearest distinctions between Tier 0, 1 and 2 vehicles, as demonstrated in the left panel of Figure 20. The emissions fall by a factor of 4 – 5 from Tier 0 to 1 and then by another factor of 4 – 5 from Tier 1 to 2. The average emission fractional deterioration rates increase from Tier 0 to 2, but 20 year old Tier 1 emissions remain below new Tier 0 emissions, and Tier 2 vehicles up to 10 years old have lower emissions on average than new Tier 1 vehicles.

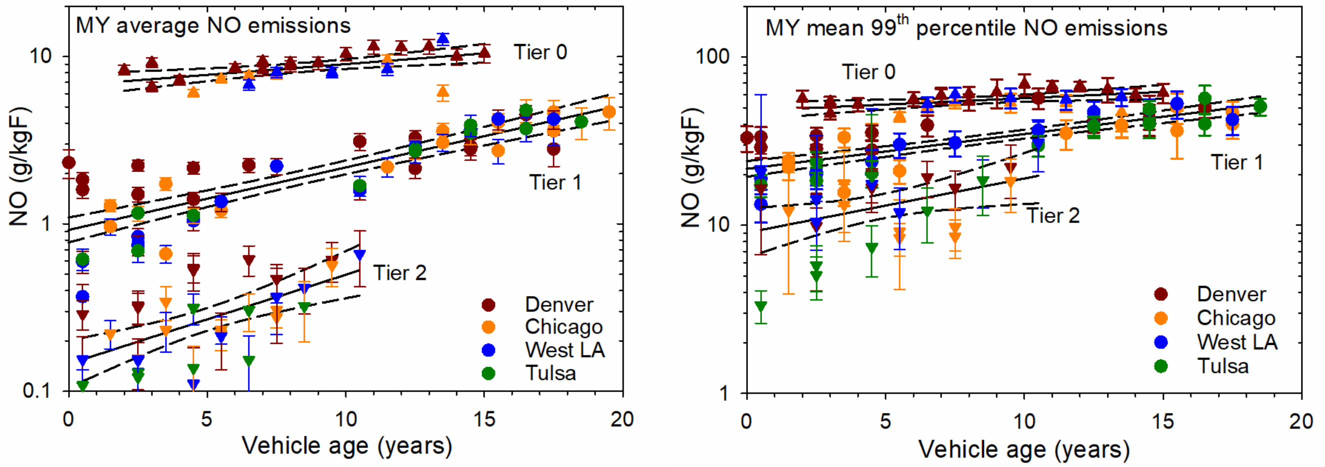

Figure 20. NO emissions versus vehicle age. Left panel: MY average. Right panel: mean 99th percentile. Symbols represent RSD averages. Solid lines display least squares fits. Dashed lines show 95% confidence intervals.

The mean MY 99th percentile NO emissions follow the same pattern as the average emissions, as seen in Figure 20, but with smaller differences between the certification standards. The high emitter emissions decrease only about a factor of two from Tier 0 to 1 and from Tier 1 to 2. Again, the fractional deterioration rates increase with successive emissions standards, but it takes 15 years for Tier 1 high emitter levels to reach those of new Tier 0 vehicles, and 10 years for Tier 2 high emitters to reach Tier 1 high emitter levels.

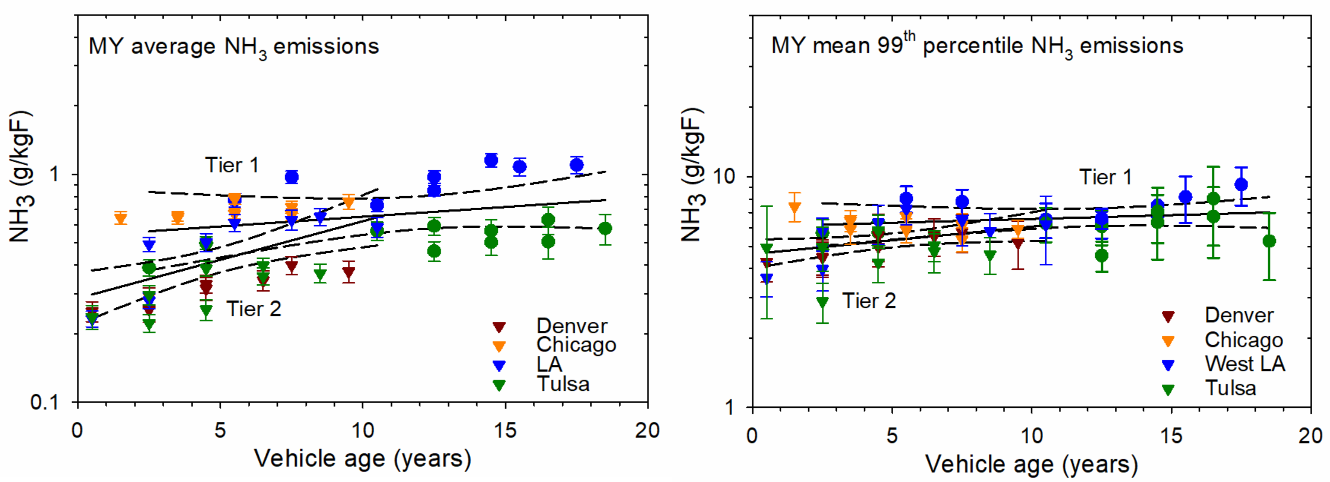

Figure 21. NH_3 emissions versus vehicle age. Left panel: MY average. Right panel: mean 99th percentile. Symbols represent RSD averages. Solid lines display least squares fits. Dashed lines show 95% confidence intervals.

Figure 21 displays model year specific average and mean 99th percentile NH_3 emissions. Tier 0 data do not appear, because RSD measurement of NH_3 only began in 2005. Tier 2 new vehicle emissions are about 50% lower than those of new Tier 1 vehicles, for both the model year average and mean 99th percentile. The Tier 2 deterioration rates, however, are higher and, thus, Tier 1 and 2 emissions rates become indistinguishable for vehicles 8 years or older.

The plots of log-emissions against vehicle age in figures 18 – 21 are fit well by linear regressions within the data scatter. The regressions represent the combined data across the four measurement locations to reduce statistical uncertainties. It turns out that if the emissions are instead plotted on a linear vertical scale, the resulting age trends remain well described by linear regressions. This is true because the yearly increases in emissions are small. In effect, the exponential dependence is approximately linear, at least within the statistical ability to distinguish otherwise. Figure 22 presents the best fit slopes (left panel) and intercepts (right panel) for the regressions of emissions on a linear scale versus vehicle age. The slopes, in units of g/kgF/year, yield the emissions deterioration rates, while the intercepts give the new, zero year old, vehicle fuel-based emissions factors. The regression parameters, as well as the R^2 values, are provided in Table 9 of Appendix D.

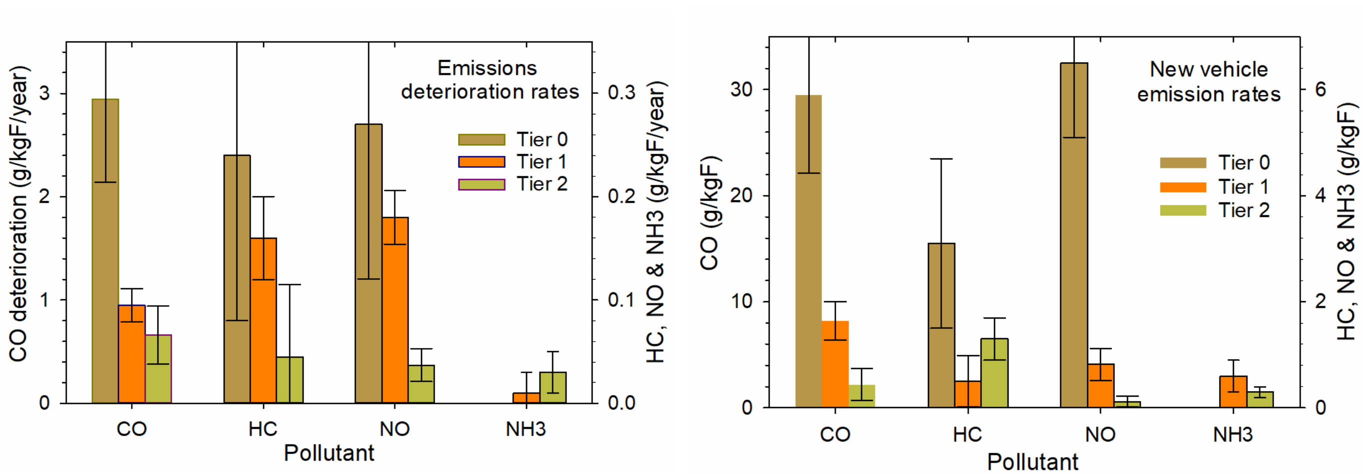

Figure 22. Left panel: Emissions deterioration rates. Right panel: New vehicle emissions. Error bars show 95% confidence limits.

The CO, HC and NO emissions deterioration rates in Figure 22 (left panel) decrease from Tier 0 to 2. The NH_3 deterioration rate increases from Tier 1 to 2, but the increase is not statistically significant. The improvements observed across successive emissions standards refer to the absolute year-to-year increases in grams of pollutant per kg of fuel, as opposed to the fractional increases in Figures 18 - 21. The conclusion is that as emissions standards have become more stringent the deterioration rates have improved on an absolute basis, but not as a fraction of the standard.

New vehicle emissions

Figure 22 (right panel) shows that new vehicles meeting increasingly stringent emissions standards exhibit on average statistically significant decreases in CO and NO emissions from Tier 0 to Tier 1 and again from Tier 1 to Tier 2. HC emissions fall from Tier 0 to 1 but then remain statistically indistinguishable between Tier 1 and 2, and NH_3 emissions fall slightly from Tier 2 to 3. The data in Figure 22 are averaged over location. This section takes a more detailed look at new vehicle emissions and partly extends the analysis to Tier 3. The fact that the HC offset correction is based on new vehicle emissions leads to a potential bias in the corrected values for these vehicles. Therefore, the discussion focuses on new vehicle CO, NO and NH_3 emissions.

The University of Denver RSD campaigns do not extend to the completion of the Tier 3 phase-in period in 2025. The last five campaigns were conducted in 2021 and 2022. This and the desire to combine two model years lead to the choice of 2020/21 MY vehicles to represent a partially implemented Tier 3 fleet. To denote this distinction, these vehicles are labeled Tier 3*. At the time of the RSD campaigns, MY 2020/21 vehicles were 0 – 2 years old; thus, this defines "new". Model years 2020/21 fall about halfway through the 2017-2025 phase-in period that leads from Tier 2 CO and NMOG+NOx light duty standards of 4.2 g/mi and 0.16 g/mi, respectively, to the Tier 3 standards of 1.0 g/mi and 0.03 g/mi that are about four times as stringent. Thus, one might expect to see CO and NO emissions from the 2020/21 Tier 3* fleet that are roughly half of Tier 2 new vehicles.

The new vehicle CO emissions in Figure 23 (bars) show decreases from Tier 0 to 1 and from Tier 1 to 2 in West LA, Tulsa, Denver and Chicago, most of which are statistically significant (see also Table 10, Appendix D). These new vehicle emissions rates are well below the fleet average from Figure 10 (orange line). Tier 3* new vehicle emissions, in contrast, are mostly higher than those for Tier 2, even discounting the anomalously high Oakland and Stockton values. Thus, there is no evidence yet of an impact from the Tier 3 phase-in, even for the subset of 0-2 year old vehicles.

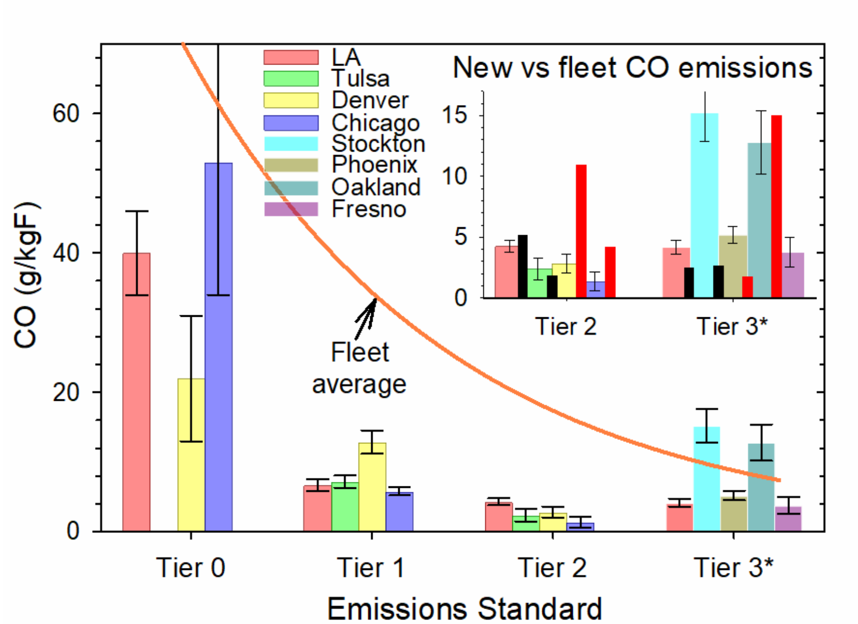

Figure 23. New vehicle versus fleet average CO emissions. The horizontal axis is time labeled by emissions standard instead of campaign year. The solid line is the fit to the fleet average from Figure 10. The inset superimposes FTP (black) and US06 (red) fuel-based emissions.

Comparing the results in Figure 23 to CO emissions over the FTP and US06 drive cycles can help provide context. Imagine that instead of a random sample of vehicles passing past the RSD site, a single vehicle drives by multiple times, each time at a random point on the FTP or US06 speed trace. The average over many such measurements would reproduce the average instantaneous fuel-based emissions factor for the drive cycle recorded in a dynamometer test.

Chassis dynamometer fuel based CO emissions from two Tier 2 and two Tier 3 compliant test vehicles are superimposed on the bar graph in the inset to Figure 23, with thin black bars for the hot start + city portion of the FTP cycle and thin red bars for the US06 emissions from four test vehicles (listed in Table 11, Appendix D). The Tier 2 FTP fuel based CO emissions agree with the Tier 2 RSD levels within their uncertainties, whereas those based on the US06 cycle are higher. In the Tier 3 comparison, the FTP based CO emissions fall below those for the Tier 3* vehicles in Figure 23, but the higher of the two test vehicles' US06 emissions matches those from Stockton and Oakland. Although FTP / US06 data from four vehicles is very limited, the comparison suggests that new vehicle emissions factors recorded by RSD are consistent with regulatory standards.

New vehicle NO emissions, displayed in Figure 24 (also Table 10), show substantial, roughly factor of four, statistically significant decreases with progressively more stringent emissions standards. Tier 0 new vehicle emissions are slightly below the fleet average at the time, but Tier 1 and 2 new vehicle emissions fall well below the corresponding fleet levels. The stark location differences seen in the Tier 3* new vehicle CO emissions are not reproduced by NO. As evident in the inset to Figure 24, there is location to location variability in the Tier 3* new vehicle NO emissions, but this is comparable to the location variability exhibited by the Tier 2 emissions. The Tier 3* and Tier 2 emissions are nearly the same within the 95% confidence limits; thus, for NO as well there is no evidence of emissions reductions as of about halfway through the Tier 3 phase-in.

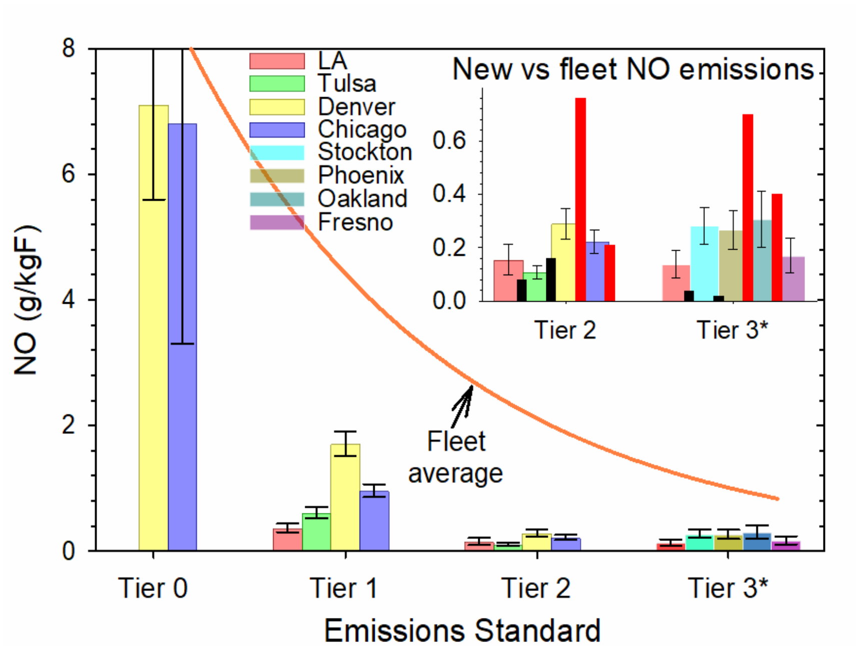

Figure 24. New vehicle versus fleet average NO emissions. The horizontal axis is time labeled by emissions standard instead of campaign year. The solid line is the fit to the fleet average from Figure 12. The inset superimposes FTP (black) and US06 (red) fuel-based emissions.

The inset to Figure 24 includes average NO fuel-based emissions for the hot start + city FTP and the US06 cycle (listed in Table 11). For Tier 2, these are comparable to the RSD measured new vehicle emissions. In the case of Tier 3, the FTP values are well below the RSD results, whereas the US06 values are somewhat higher, but this comparison is complicated by the fact that the Tier 3* fleet is roughly half Tier 2 and half Tier 3.

Figure 25 compares new vehicle versus fleet NH_3 emissions. The first RSD NH_3 emissions were made in Tulsa in 2005, and then more widely in 2008. As a result, the "new" Tier 1 vehicles for NH_3 measurements are on average three years old as compared to one year for the CO and NO measurements above and the Tier 2 and 3* NH_3 measurements. The new vehicle emissions from Tier 1 to 3* appear to mirror the 30% fleet average decline (orange line) in spite of the variability between RSD locations. In general, Tier 1 and 2 new vehicle NH_3 emissions are closer to the fleet average than for CO and NO.

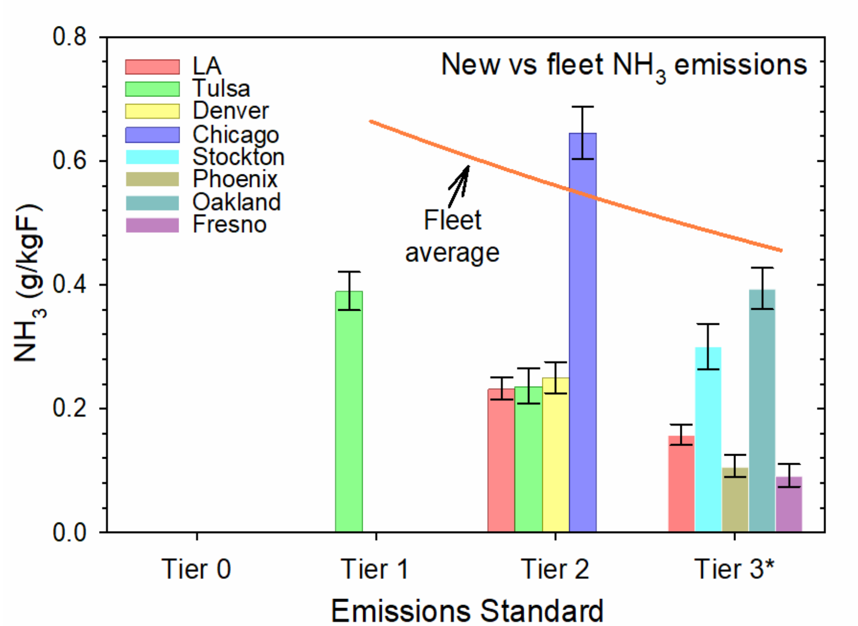

Figure 25. New vehicle versus fleet average NH_3 emissions. The horizontal axis is time labeled by emissions standard instead of campaign year. The solid line is the fit to the fleet average from Figure 14.

Next, we examine how the 99th percentile emissions by new vehicles changed with the introduction of progressively tighter tailpipe standards. One way to address this is by looking at their exceedance levels. Figure 26 displays the results for CO. The new vehicle exceedance curves exhibit both quantitative and qualitative changes in the progression from Tier 0 to Tier 3*. Except for Oakland and Stockton, the levels fall and slopes decrease as emissions standards are tightened. However, the shapes also change from the Gumbel to Fréchet domain. In the Gumbel domain, the highest emissions in a sample of N vehicles scale as log (N), whereas in the Fréchet domain the maximum emissions increase more steeply as a power law, $N^{1/\varepsilon}$. In other words, as technology improvements reduce high emissions, it becomes progressively harder to ensure those improvements across a large fleet of vehicles and a wide range of operating conditions.

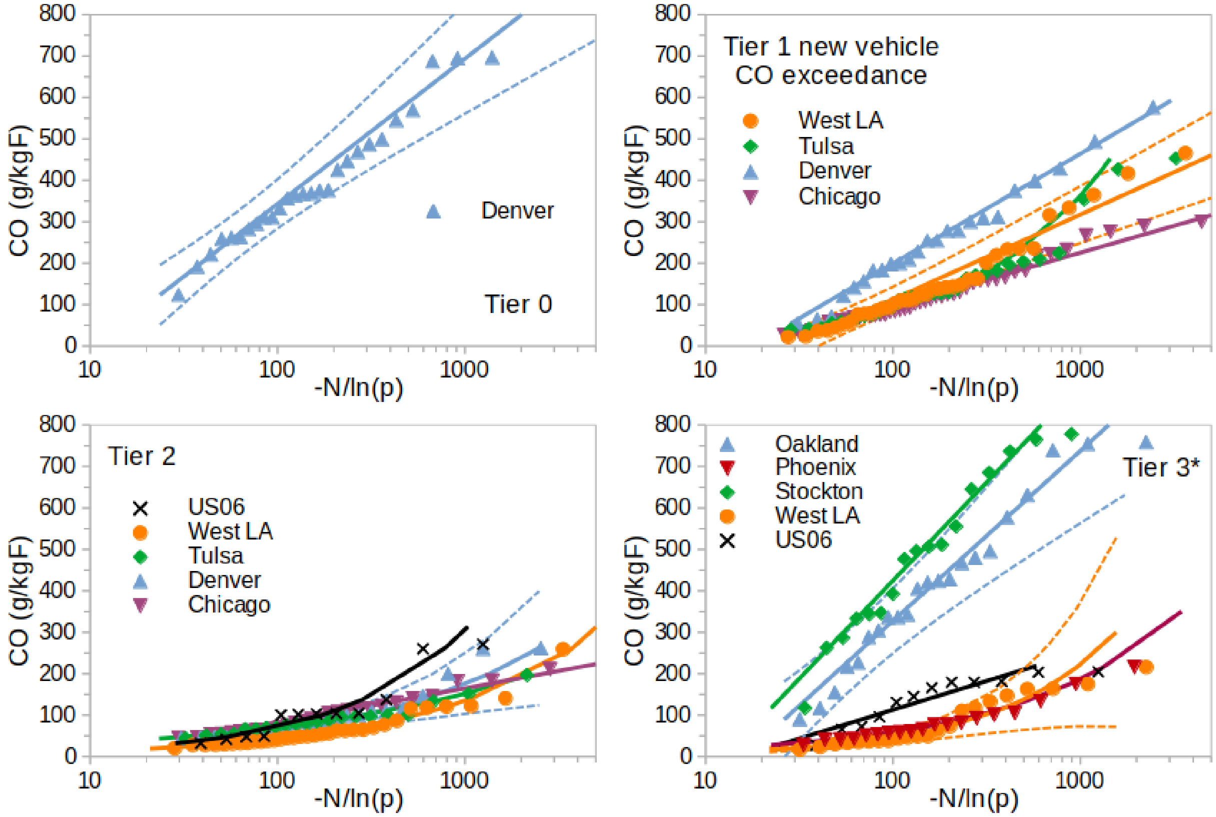

Figure 26. New vehicle CO exceedance levels. Top left: Tier 0. Top right: Tier 1. Bottom left: Tier 2. Bottom right: Tier 3*. Symbols represent empirical distributions, solid lines are fits to EVT distributions and dashed lines illustrate 95% confidence limits. US06 derived exceedance levels are included for Tier 2 and 3*.

Figure 26 also compares new vehicle RSD exceedance levels to those determined from test vehicles run on the US06 test cycle. It is notable that the exceedance levels from Tier 2 and 3 certified vehicles can exceed real world RSD values. This suggests that that RSD measurements can register high emissions from randomly catching properly functioning vehicles under US06-like operating conditions. In effect, the short RSD observations make it difficult to distinguish malfunctions from unlikely operating conditions with high emissions.

The fact that the US06 derived exceedance levels for Tiers 2 and 3 fall well below those from new vehicles in Oakland and Stockton, however, indicate that the anomalously high CO emissions found at these locations (Figures 15 & 17) do not derive solely from the properly functioning vehicles operating at US06-like VSP distributions. Some additional factor must play a role, possibly air/fuel enrichment for catalyst protection, wide open throttle operation, or aftertreatment tampering.

New vehicle NO exceedance levels in Figure 27 likewise exhibit both quantitative reductions and a qualitative transition from Gumbel to Fréchet domain with increasingly stringent emissions standards. For NO, the trend is consistent across all locations, including Oakland and Stockton. The change in shape again reflects the progressively harder task of ensuring that the emissions improvements apply equally across a large vehicle population. As with CO, US06 based NO exceedance levels can be comparable to, or exceed, those from RSD measurements. Thus, for NO as well, the short RSD observation times make it difficult to distinguish malfunctioning vehicles from those momentarily caught under a high emitting operating point. The consistency of Oakland and Stockton new vehicle exceedance levels with the other sites in the case of NO, but not CO suggests that the anomalously high CO levels more likely arise from enrichment or wide open throttle operation than catalyst malfunctioning or tampering.

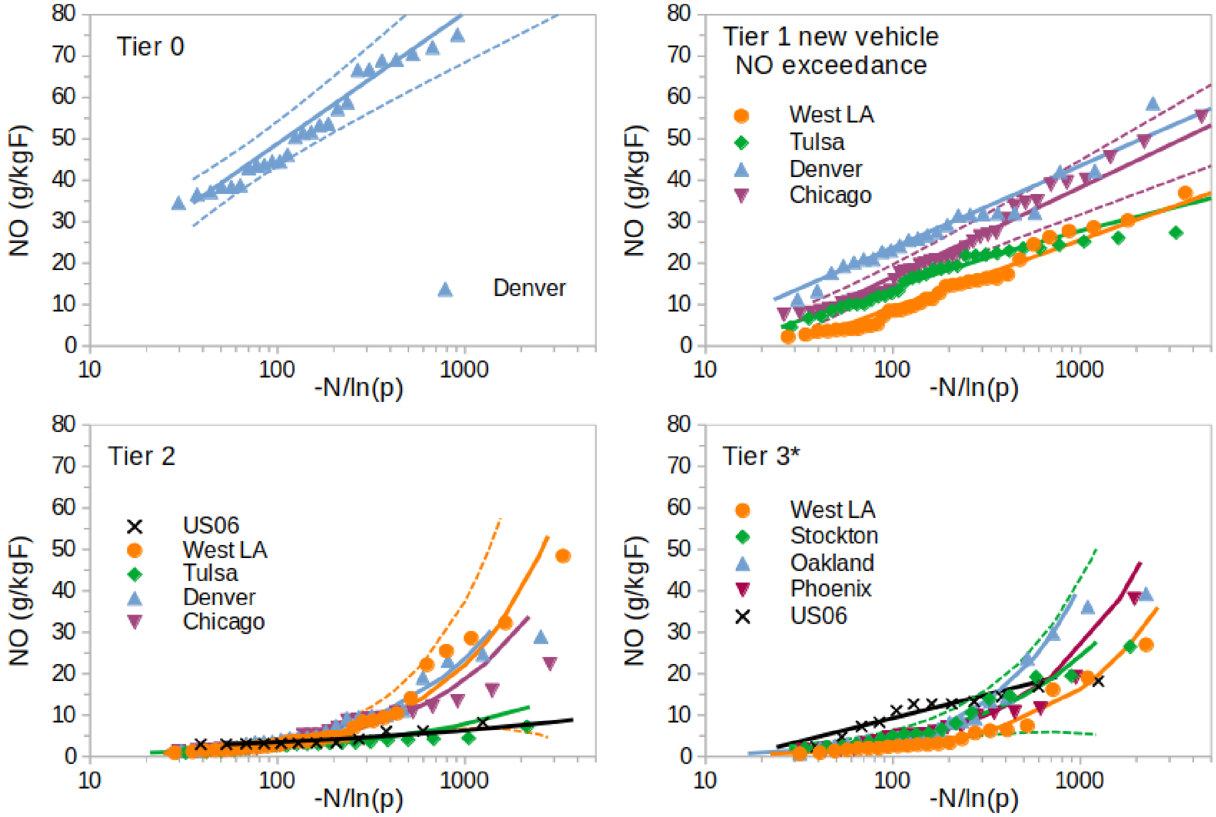

Figure 27. New vehicle NO exceedance levels. Top left: Tier 0. Top right: Tier 1. Bottom left: Tier 2. Bottom right: Tier 3*. Symbols represent empirical distributions, solid lines are fits to EVT distributions and dashed lines illustrate 95% confidence limits. US06 derived exceedance levels are included for Tier 2 and 3*.

7. Discussion

Lessons from 30 years of RSD emissions measurements

The thirty years of University of Denver RSD campaigns coincided with a series of increasingly stringent tailpipe emissions standards, which were met by improvements in engine, catalyst and controls technology. Various experimental approaches exist to investigate the resultant impacts on emissions, each with advantages and disadvantages. RSD has the unique ability to record emissions from a very large sample of vehicles, typically tens of thousands, and thereby capture a snapshot of real-world emissions characteristic of a particular location and time. These campaigns repeated over time map a history of fleet emissions from which one can learn valuable lessons about the impact of emissions regulation policy on real world emissions.

The RSD approach has limitations. It affords limited ability to control experimental conditions. The vehicles operate over a distribution of speeds, accelerations and engine power. The observation period is very short, 0.5 seconds. The instrumentation has reduced sensitivity compared to laboratory or portable emissions measurement systems (PEMS). These appear to pose a serious handicap to the utility of RSD data. However, the very large numbers of measurements collected in a typical campaign overcome these issues. A laboratory, or PEMS, test is also a collection of measurements over a distribution of speeds, loads and engine power associated with a particular drive cycle. RSD and laboratory measurements are then comparable to the extent that the engine operating points recorded at the RSD site mimic a particular laboratory or PEMS drive. The benefit of RSD is that the average extends over both vehicles and operating conditions, whereas a laboratory / PEMS measurements pertain to a single vehicle. Furthermore, cancellation of random measurement error from averaging circa 20,000 data points alleviates the reduced RSD instrument signal to noise.

There remains an inherent difference between laboratory and RSD emissions data. RSD measures the instantaneous grams of pollutant per kilogram of fuel and then averages these. Laboratory and PEMS tests, in contrast, report milligrams emitted per mile driven, which can be converted to average milligrams per kilogram of fuel based on the vehicle's fuel economy. This differs from the RSD results, since the order of taking the ratio and average are reversed. However, the laboratory data can also be analyzed in the same manner as RSD data, as shown in Figure 6, to allow comparisons such as those in Figures 23, 24, 26 and 27.

Fleet average data provide an overview of emissions behavior over time and geographic region. Changes over time result from regulatory policy and technology advances to meet the policy demands. Variations with location arise from environmental and economic conditions and differences in local emissions policies. The major observation from historical RSD data is the large, exponential, decreases in CO, HC and NO gasoline vehicle tailpipe emissions over time. There are location dependent differences in these trends, but these are second order effects. Average CO emissions in Chicago, Denver, Tulsa, and West LA decreased by a factor of 13 between 1991 and 2021. The average HC emissions across these four locations fell ninefold between 1991 and 2008 but have not fallen further since. NO emissions decreased by a factor of eleven from 1995 to 2021. The fact that new standards phase in periods and fleet turnover occur over many years makes these decreases look smooth as opposed to coinciding with regulatory changes.

Closer inspection reveals location dependent differences. The two principal examples are Chicago and Oakland / Stockton. Over much of the thirty-year span, Chicago fleet average CO and NO emissions are the lowest of the four RSD locations (Figures 10 and 12). The higher altitude and wintertime RSD campaigns in Denver may plausibly account for why emissions there are higher than in Chicago, but this argument does not explain why emissions in Tulsa and West LA are also higher. VSP differences are unlikely to explain the lower Chicago emissions levels, since the Chicago site VSP distribution is very similar to those in the other three locations, slightly higher than in West LA and slightly lower than in Denver and Tulsa. Thus, other factors, such as average vehicle age, vehicle mix, or local fuel composition may explain the lower Chicago emissions.

Environmental conditions seem unlikely to explain the high CO emissions observed on Oakland, 2022, and Stockton, 2021, which substantially exceed those in locations as diverse as Denver and Phoenix. The fact that 2020 / 2021 MY vehicles in Oakland and Stockton exhibit similarly excessive CO emissions as the corresponding overall fleet renders economic considerations and deterioration as unlikely explanations. The high VSP distributions in these two locations likely do contribute to the high emissions recorded by RSD; however, the fact the CO exceedance levels exceed those obtained from US06 drives of Tier 2 and 3 compliant vehicles indicates that VSP alone is not the explanation. The likely explanations are wide open throttle operation and enrichment due to the straight roadway at the Oakland site and the 120 F temperatures at Stockton.

New vehicle emissions and deterioration

The analysis of model year specific exhaust emissions versus vehicle age yields fuel-based emissions of vehicles when they were new as well as their deterioration rates. MY average CO emissions by new Tier 2 compliant vehicles are a factor of fourteen below new Tier 0 vehicles (MY average intercept, Table 9), which is larger than the fleet average decrease from 1991 to 2021. MY 2020/2021 average CO emissions from the 2021 – 2022 RSD campaigns (Table 10) are similar to, or exceed, Tier 2 new vehicle emission, thus, no impact is thus far observed from Tier 3 standards. Average new vehicle NO emissions fell by more than a factor of twenty from Tier 0 to 2, which greatly exceeds the factor of eleven observed for the 1991 to 2021 fleet average reduction. However, model year 2020/2021 new Tier 3^ emissions are again indistinguishable from those of new Tier 2 vehicles. New vehicle HC emissions saw a factor of four decrease from Tier 0 to 1, but then showed no significant change for Tier 2, and, if anything, an increase for Tier 3*, which is consistent with the fleet HC emissions remaining constant after about 2010. Thus, Tier 1 standards led to statistically significant reductions in CO, HC and NO emissions by new vehicles, whereas Tier 2 did so only for CO and NO, and as of 2020/2021 Tier 3 has shown no impact an any emissions. For CO and NO, the new vehicle emissions decreases are outpacing the fleet's ability to keep up. People are keeping vehicles longer, which reduces new vehicle penetration and increases the impacts of emissions deterioration.

In addition to new vehicle emissions, average deterioration rates (MY average slope, Table 9) have also improved with the promulgation of stricter emission standards. For CO and NO, average Tier 1 vehicle emissions remain lower than those form a new Tier 0 vehicle for about twenty years, while Tier 2 emissions remain below those of new Tier 1 vehicles for roughly 10 years. The improvements are roughly proportional to the new vehicle emissions decreases, as seen from the close to parallel regressions in Figures 18 and 20. Twenty year old Tier 1 vehicle HC emissions likewise remain largely below those of new Tier 0 vehicles; however, emissions from Tier 1 and 2 cannot be distinguished. Thus, the aftertreatment technologies developed to meet the progressively more stringent standards have shown robustness with vehicle aging for ages up to twenty years. These impressive results presumably result from the extended full useful life requirements included in the emissions standards.

High emitters

The EVT approach adopted to analyze high emissions is predicated on the probability distribution for the maximum in a random sample of size *N* having a limiting distribution belonging to the Weibull, Gumbel or Fréchet domain. The sample in the present application is taken from a population of short, 0.5 s, emissions measurements. Three types of samples have been considered. The first is the regional gasoline vehicle fleets at the various RSD sites. The second consists of the subsets of specific model years within these fleets. And the third is the sample of vehicle operating points of a single vehicle driven according to a drive cycle.

The interpretation of "high emitter" differs for these three cases. In the single properly operating vehicle case, the mean 99th percentile refers to the speed, load and VSP operating points that on average produce the highest emissions. It reflects the tail distribution of high emitting engine / catalyst operating points. The mean 99th percentile emissions for specific model year vehicles are vehicle age dependent. To the extent that new vehicles are free from malfunctions, it reflects the distribution of the vehicle's high emitting operating points, but in this case averaged over many different vehicles. For older vehicles it also includes aftertreatment deterioration and a greater likelihood of malfunctions and tampering. Finally, the mean 99th percentile emissions for the overall fleet include all causes: high emitting operating points, deterioration, malfunctions, and tampering.

Figure 28 compares mean 99th percentile emissions by new Tier 0, 1 and 2 vehicles (see Table 9) to those of the fleets at Chicago, Denver, Tulsa and West LA. In the case of CO, 1991 to 2000 fleet mean 99th percentile emissions are two to three times higher than those of new Tier 0 vehicles, and only reach comparable levels after about 2005, roughly 10 years after implementation of Tier 1 standards. This indicates that the fleet high emissions result largely from deterioration, malfunction, or tampering, as opposed to high emitting operating points. Fleet mean 99th percentile CO emissions between 2013 and 2021 lie between those of new Tier 0 and 1 vehicles, even as Tier 3 implementation began, again showing that the high emitters primarily represent deteriorated, malfunctioning or tampered vehicles.

The fleet versus new vehicle comparisons for HC and NO reveal the same story. With few exceptions, mean 99th percentile fleet NO emissions are comparable to those of new Tier 0 vehicles up to 2008. And mean 99th percentile HC emissions remain comparable to Tier 0 new vehicle emissions up to 2021 (the new vehicle Tier 1 to 2 increase is not statistically significant). These observations clearly indicate that the mean 99th percentile fleet emissions identified via the EVT analysis predominantly result from vehicles not meeting the applicable emissions standards, and not from properly functioning vehicles captured at high emitting operating points.

The case of NH_3 is different. Here, fleet 99th percentile emissions are indistinguishable from new Tier 1 and 2 vehicles at the 95% confidence level. The Tier 1 and 2 difference itself is not statistically significant. NH_3 originates from the three-way catalyst, not the engine; thus, a catalyst malfunction would lower rather than raise NH_3 emissions. Instead, the fleet 99th percentiles reflect the tail distribution of a functional catalyst at operating points that reduce NO to NH_3 instead of N_2.

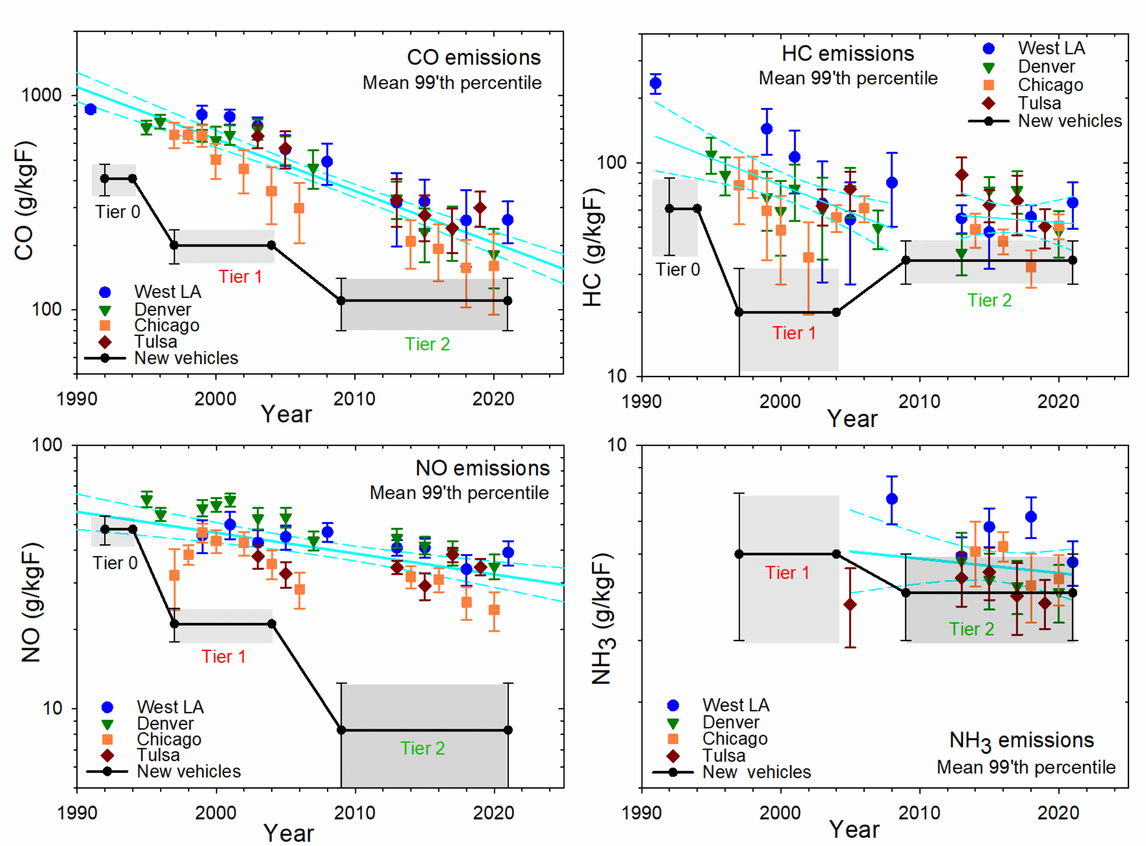

Figure 28. Comparison of new vehicle to fleet mean 99th percentile emissions. Top left: CO. Top right: HC. Bottom left: NO. Bottom right: NH_3. Transitions between Tiers occur at the ends of the phase-ins. Shaded regions show 95% confidence intervals. Light blue solid and dashed lines show fleet emissions regressions and 95% confidence intervals.

The major observation from the EVT analysis is that improvements in high emitter emissions have lagged those in the fleet average. The ratio of mean 99th to fleet average CO emissions has increased from 10 to nearly 30 between 1991 and 2021 (Figure 10). The ratio for HC emissions has risen from 7 to 25, and the ratio for NO has seen the largest increase, from about 6 to 35 (Figures 11 and 12). As a result, the top 1% of emitters currently represent approximately 30 % of fleet CO emissions, 25% of HC and 35% of NO emissions. Figure 28 indicates that these derive largely from vehicles not meeting current or earlier standards. Clearly, these high emitters are becoming the low hanging fruit for future motor vehicle emissions improvements.

Future prospects

As fleet emissions continue to decrease, the question of RSD sensitivity arises. In fact, most of the individual vehicle measurements in the most recent campaigns are zero. Examination of the 2021 West LA and 2022 Oakland campaigns, with widely disparate VSP distributions, reveals that 24% and 21% of the vehicles, respectively, had CO emissions statistically distinct from zero at the 95% confidence level. The fractions for NO were similar, at 17% and 25%; but for HC, only 10% and 7% had values statistically above zero.

The question of sensitivity depends on the intended RSD application. Fleet wide statistics, such as fleet average and mean 99th percentile benefit from measurement error cancellation. Relative to the fleet average noise uncertainty, roughly 75%, 60% and 64% of vehicles, respectively for CO, HC and NO contribute and, thus, current RSD efficiency is sufficient. However, this may not be the case for applications to smaller vehicle subsets, select model years for example, or for use in screening specific vehicles for high emissions.

Other areas for improvement include refinement of the HC measurement and development of PM capability. The current RSD HC measurement is an infrared absorption weighted average as compared to the flame ionization weighted average used for laboratory and regulatory measurement. It needs a factor of two adjustment to match flame ionization for propane, and it is subject to an unexplained offset. It would also be helpful to distinguish total and non-methane HCs. These objectives might be achieved via Fourier transform infrared absorption (Gierczak et al. 2017), if this technique can be extended to the roadside environment, or by other means of HC detection.

The ability of RSD to interrogate a very large number of vehicles remains hard to beat. With these and other ideas, RSD appears to remain a useful real world emissions measurement tool for the future, one that can inform us on the real-world impacts of changes in emissions standards and technologies.

Acknowledgments

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Appendix A

CRC RSD reports and publications

This appendix lists RSD reports found on the CRC website. Contact CRC staff to see if reports exist for campaigns included in the present review but not listed here.

1. On-Road Remote Sensing of Automobile Emissions in the Denver Area: Year 2, February 2001, E-23-4, Jan. 2000, (test Dec. 1999-Jan. 2000, report Feb. 2001)
2. On-Road Remote Sensing of Automobile Emissions in the Phoenix Area: Year 2, January 2001, E-23-4, Jan. 2001, (test Nov. 1999, report Jan. 2001)
3. On-Road Remote Sensing of Automobile Emissions in the Los Angeles Area: Year 2, March 2001, E-23-4, Mar. 2001, (test May-Jun. 2000, report Mar. 2001)
4. On-Road Remote Sensing of Automobile Emissions in the Chicago Area: Year 4, August 2001, E-23-4, Aug. 2001, (test Sep. 2000, report Aug. 2001)
5. On-Road Remote Sensing of Automobile Emissions in the Denver Area: Year 3, January 2002, E-23-4, Jan. 2002, (test Jan. 2001, report Jan. 2002)
6. Remote Sensing Measurement of Real World Vehicle High-Exhaust Emitters, Interim Report, CRC Project E-23, Apr. 2002
7. On-Road Remote Sensing of Automobile Emissions in the Phoenix Area: Year 3, May 2002, E-23-4, May 2002, (test Nov. 2000, report May 2002)
8. On-Road Remote Sensing of Automobile Emissions in the Los Angeles Riverside Area: Year 3, June 2002, E-23-4, Jun. 2002, (test Jun. 2001, report Jun. 2002)
9. On-Road Remote Sensing of Automobile Emissions in the La Brea Area: Year 2, February 2003, E-23-4, Feb. 2003, (test Oct. 2001, report Feb. 2003)
10. On-Road Remote Sensing of Automobile Emissions in the Denver Area: Year 4, January 2003, E-23-4, Jul. 2003, (test Dec. 2002-Jan. 2003, report Jul. 2003)
11. On-Road Remote Sensing of Automobile Emissions in the Phoenix Area: Year 4, November 2002, E-23-4, Nov. 2003, (test Nov. 2002, report Nov. 2003)
12. On-Road Remote Sensing of Automobile Emissions in the La Brea Area: Year 3, October 2003, E-23-4, May 2004, (test Oct. 2003, report May 2004)
13. On-Road Remote Sensing of Automobile Emissions in the Tulsa Area: Year 1, September 2003, CRC Report E-23-8a, Jul. 2004, (test Sep. 2003, report Jul. 2004)
14. On-Road Remote Sensing of Automobile Emissions in West Los Angeles: Year 4, October 2005, E-23-9, Apr. 2006, (test Oct. 2005, report Apr. 2006)
15. Analysis of Remote Sensing Data to Determine Deterioration Rates for OBDII Equipped Vehicles, CRC Report No. E-23-8, Sep. 2006

16. On-Road Remote Sensing of Automobile Emissions in the Chicago Area: Year 7, September 2006, E-23-9, Feb. 2007, (test Sep. 2006, report Feb. 2007)
17. On-Road Remote Sensing of Automobile Emissions in the Phoenix Area: Year 6, November 2006, E-23-9, Jul. 2007, (test Nov. 2006, report Jul. 2007)
18. Remote Sensing in Four Cities to Determine the Change in On-Road Vehicle Fleet Emissions Over Time, CRC Report E-23, Nov. 2007
19. Remote Sensing Measurements for the E-100a Longitudinal Emission Pilot Study, E-100a, Aug. 2011
20. On-Road Remote Sensing of Automobile Emissions in the Tulsa Area: Fall 2013, CRC Report E-106, Jul. 2014, (test Sep.-Oct. 2013, report Jul. 2014)
21. On-Road Remote Sensing of Automobile Emissions in the Chicago Area: Fall 2014, CRC Report E-106, Jun. 2015, (test Sep. 2014, report Jun. 2015)
22. On-Road Remote Sensing of Automobile Emissions in the Tulsa Area: Fall 2015, CRC Report E-106, Jun. 2016, (test Sep. 2015, report Jun. 2016)
23. On-Road Remote Sensing of Automobile Emissions in the Chicago Area: Fall 2016, CRC Report E-106, Jun. 2017, (test Sep. 2016, report Jun. 2017)
24. On-Road Remote Sensing of Automobile Emissions in the Rolling Meadows Area: Fall 2016, CRC Report E-119, Jan. 2018, (test Sep. 2016, report Jan. 2018)
25. On-Road Emission Measurements in the Chicago Area: Comparison of Two University of Denver Remote Sensing Datasets, CRC Report E-119a, Feb. 2018, (test Sep. 2016, report Feb. 2018)
26. G. Bishop, M. Haugen, The Story of Ever Diminishing Vehicle Tailpipe Emissions as Observed in the Chicago, Illinois Area, Environ. Sci. Technol. 2018, 52, 13, 7587-7593
27. On-Road Remote Sensing of Automobile Emissions in the Tulsa Area: Fall 2017, CRC Report E-123, Mar. 2018, (test Sep. 2017, report Mar. 2018)
28. Hager Environmental and Atmospheric Technologies (HEAT) and Denver University (DU) Remote Sensing Device (RSD) Data Mining, E-119-2, Aug. 2018
29. On-Road Remote Sensing of Automobile Emissions in the Denver Area: Winter 2017, CRC Report E-123, Aug. 2018, (test Dec. 2017-Jan. 2018, report Aug. 2018)
30. 17) On-Road Remote Sensing of Automobile Emissions in the Lynwood, CA Area, E-124, Jan. 2019, (test May 2018, report Jan. 2019)
31. On-Road Remote Sensing of Automobile Emissions in the Chicago Area: Fall 2018, CRC Report E-123, Jun. 2019, (test Sep. 2018, report Jun. 2019)
32. Analyze Existing West Los Angeles Data Set for On-Road Evaporative Emissions, CRC Report No. E-123-3, Jul. 2019

33. On-Road Remote Sensing of Automobile Emissions in the Tulsa Area: Fall 2019, CRC Report E-123, Apr. 2020, (test Sep. 2019, report Apr. 2020)
34. Inspection and Maintenance Evaluation using Historical U.S. Remote Sensing Measurements, E-123-4, Aug. 2020
35. On-Road Remote Sensing of Automobile Emissions in the Denver Area: Winter 2020, CRC Report E-123, Jul. 2020, (test Jan.-Feb. 2020, report Jul. 2020)
36. G. Bishop, T. DeFries, J. Sidebottom, J. Kemper, Vehicle Exhaust Remote Sensing Device Method to Screen Vehicles for Evaporative Running Loss Emissions, Environ. Sci. Technol. 2020, 54, 22, 14627-14634
37. On-Road Remote Sensing of Automobile Emissions in the Chicago Area: Fall 2020, CRC Report E-123, Jun. 2021, (test Sep. 2020, report Jun. 2021)
38. On-Road Remote Sensing of Automobile Emissions in the Fresno, CA Area: Spring 2021, RW-117, Oct. 2021, (test Jun. 2021, report Oct. 2021)
39. Re-locating the FEAT Data Repository to the University of Denver Library, RW-118, Nov. 2021
40. On-Road Remote Sensing of Automobile Emissions in the Phoenix Area: Spring 2021, E-119-3 (DU), Mar. 2022, (test Apr. 2021, report Mar. 2022)
41. On-Road Remote Sensing of Automobile Emissions in the Phoenix Area: Spring 2021, E-119-3 (HEAT), Mar. 2022, (test Apr. 2021, report Mar. 2022)
42. On-Road Remote Sensing of Automobile Emissions in the Phoenix Area: Spring 2021, E-119-3 (Opus), Aug. 2022, (test Apr. 2021, report Aug. 2022)
43. Remote Sensing Device (RSD) Statistical Analysis, CRC Report E-119-3a, Apr. 2023 (testing Phoenix Apr. 2021, report Apr. 2023)
44. Roadside Measurement of Evaporative and PM Emissions, CRC Report RW-105, Apr. 2023 (test Phoenix Apr. 2021, report Apr. 2023)

Appendix B

FEAT criteria to render a reading "invalid" or not measured.

Not measured:

1) Beam block and unblock and then block again with less than 0.5 seconds clear to the rear. Often caused by elevated pickups and trailers causing a "restart" and renewed attempt to measure exhaust. The restart number appears in the database.

2) Vehicle which drives completely through during the 0.4 seconds "thinking" time (relatively rare).

Invalid:

1) Insufficient plume to rear of vehicle relative to cleanest air observed in front or in the rear; at least five, 10ms averages >0.25% CO2 in 8 cm path length. Often heavy-duty diesel trucks, bicycles.

2) Too much error on CO/CO2 slope, equivalent to +20% for %CO. >1.0, 0.2%CO for %CO<1.0.

3) Reported %CO , <-1% or >21%. All gases invalid in these cases.

4) Too much error on HC/CO2 slope, equivalent to +20% for HC >2500ppm propane, 500ppm propane for HC <2500ppm.

5) Reported HC <-1000ppm propane or >40,000ppm. HC "invalid".

6) Too much error on NO/CO2 slope, equivalent to +20% for NO>1500ppm, 300ppm for NO<1500ppm.

7) Reported NO<-700ppm or >7000ppm. NO "invalid".

8) Excessive error on NH3/CO2 slope, equivalent to +50ppm.

9) Reported NH3 < -80ppm or > 7000ppm. NH3 "invalid".

10) Excessive error on NO2/CO2 slope, equivalent to +20% for NO2 > 200ppm, 40ppm for NO2 < 200ppm

11) Reported NO2 < -500ppm or > 7000ppm. NO2 "invalid".

12) Speed/Acceleration valid only if at least two blocks and two unblocks in the time buffer and all blocks occur before all unblocks on each sensor and the number of blocks and unblocks is equal on each sensor and 100mph>speed>5mph and 14mph/s>accel>-13mph/s and there are no restarts, or there is one restart and exactly two blocks and unblocks in the time buffer.

Appendix C

Fleet average, mean 99th percentiles, and EVT parameters for RSD campaigns

This appendix tabulates the statistical parameters for the 1991 – 2021 campaigns in Chicago, Denver, Tulsa, and West LA and the 2021/22 campaigns in Fresno, Oakland, Phoenix and Stockton. The error bars represent 95% confidence intervals, i.e., ±2σ uncertainties. The location parameter for the Fréchet distribution is fixed at a = 0, representing a lower bound on emissions of 0 g/kgF. The Weibull distribution location parameter is fixed at a physical upper limit of a = 1600 gCO/kgF for CO, and 700 gHC/kgF for HC emissions. For nitrogen compound emissions it is set to a = 200 gNO/kgF for NO and 20 g/kgF for NO_2 and NH_3. This leaves two parameters that were fit for each of the EVT distributions, shape and scale for Fréchet and Weibull distributions and location and scale for the Gumbel distribution.

The maximum likelihood statistics for the two parameters obey a distribution that is approximately bivariate normal. The means are the maximum likelihood estimates and the covariance matrix is N/N_{veh} I^{-1}, where N is the block size (500 for the results in this appendix), N_{veh} is the number of vehicles in the campaign, and I is the Fisher information for the bivariate normal distribution. The off-diagonal covariance matrix element, $\sigma_{ij}^2 = \sigma_{ji}^2$, is listed directly in last column of the tables. The diagonal elements can be recovered from the shape, location, and scale parameter uncertainties, which equal $\pm 2\sigma_{ii}$.

Tables 1 – 4 list the statistics for the Chicago, Denver, Tulsa and West LA campaigns. Table 5 lists the results from the 2021/22 Fresno, Oakland, Phoenix, Stockton and West LA campaigns.

Table 1
Chicago Fleet emissions statistics

Year	# vehicles	Average (g/kgF)	Mean 99th (g/kgF)	EVT domain	Shape	Scale	Location	Covariance
CO								
1997	19462	56±1.6	658±90	weibull	4.2±1.1	3070±1090	1600	-285
1998	23315	49±1.3	656±54	weibull	6.2±1.4	2140±470	1600	-164
1999	22800	44.6±1.3	652±77	weibull	4.5±1.1	2880±880	1600	-225
2000	21785	33±1.2	503±93	weibull	4.4±1.1	3410±1090	1600	-279
2002	22054	29.2±1.1	454±103	weibull	4.2±1	3820±1280	1600	-306
2004	21531	21.6±0.8	358±106	weibull	4.4±1	3880±1240	1600	-318
2006	21900	16.2±0.7	298±93	weibull	5.1±1.2	3480±950	1600	-279
2014	20041	9.5±0.6	209±54	gumbel	-	150±40	-590±220	-2070
2016	29471	11.1±0.5	193±57	gumbel	-	200±40	-830±240	-2339
2018	21258	7.2±0.5	157±54	gumbel	-	160±40	-670±230	-2109
2020	18632	11±0.6	160±65	gumbel	-	180±50	-770±270	-3067
HC								
1997	19462	4.9±0.2	79±27	gumbel	-	75±19	-310±110	-527
1998	23315	4.4±0.3	88±19	gumbel	-	59±14	-220±80	-267
1999	22800	4.2±0.2	60±25	gumbel	-	75±17	-330±100	-438
2000	21785	3.7±0.2	48±22	gumbel	-	64±15	-290±90	-333
2002	22054	3.2±0.1	36±17	gumbel	-	50±12	-220±70	-198
2004	21531	2.8±0.2	55±8	frechet	2.2±0.5	4.4±2.8	0	0.36
2006	21900	2.2±0.2	61±9	frechet	2.3±0.5	5.1±3.1	0	0.41
2014	20041	1.3±0.1	49±9	frechet	2±0.5	2.7±2	0	0.24
2016	29471	1.9±0.1	43±6	frechet	2.2±0.4	3±1.7	0	0.18
2018	21264	1.6±0.1	33±6	frechet	1.9±0.4	1.4±1.1	0	0.12
2020	18632	2.3±0.2	51±7	frechet	2.5±0.6	5.5±3.3	0	0.52
NO								
1997	19462	5.3±0.1	32±8	weibull	7.7±1.9	325±63	200	-30
1998	23315	5.5±0.1	38±3	weibull	16.2±3.7	222±19	200	-17
1999	22800	5.2±0.1	47±4	weibull	13.6±3.2	223±23	200	-17
2000	21785	4.3±0.1	43±4	weibull	12.6±3	236±26	200	-19
2002	22054	3.6±0.1	43±4	weibull	12.4±2.9	238±27	200	-19
2004	21531	3.2±0.1	35±4	weibull	12.9±3.1	245±27	200	-20
2006	21900	1.6±0.1	28±4	weibull	13.5±3.2	251±26	200	-20
2014	20041	1.3±0.1	32±3	gumbel	-	8.7±2.1	-13±13	-6.6
2016	29471	1±0.1	31±3	gumbel	-	11.3±2.3	-27±14	-7.6
2018	21273	0.76±0.05	25±4	gumbel	-	10.7±2.5	-30±15	-9.3
2020	18632	0.76±0.05	24±4	gumbel	-	11±2.8	-33±17	-11.5

Table 1, cont.
Chicago Fleet emissions statistics continued

Year	# vehicles	Average (g/kgF)	Mean 99th (g/kgF)	EVT domain	Shape	Scale	Location	Covariance
NO2								
2014	18036	-0.1±0.02	4.5±1	gumbel	-	2.8±0.7	-10±4.3	-0.77
2016	29472	0.07±0.004	1.9±0.2	frechet	2.4±0.5	0.2±0.1	0	0.01
2018	21273	0.06±0.01	1.9±0.4	gumbel	-	1.1±0.3	-4±1.6	-0.11
2020	17874	0.1±0.01	2.5±0.3	frechet	2.9±0.8	0.4±0.2	0	0.04
NH3								
2014	20041	0.72±0.02	6.1±0.9	weibull	5.7±1.4	33.5±8.5	20	-2.95
2016	29472	0.65±0.01	6.2±0.4	gumbel	-	1.5±0.3	-1.4±1.8	-0.13
2018	21273	0.61±0.01	5.2±0.8	weibull	6.5±1.5	32.3±7	20	-2.65
2020	18632	0.57±0.01	5.3±0.6	gumbel	-	1.7±0.4	-3.6±2.6	-0.28

Table 2
Denver Fleet emissions statistics

Year	# vehicles	Average (g/kgF)	Mean 99th (g/kgF)	EVT domain	Shape	Scale	Location	Covariance
CO								
1995	30394	66.4±1.5	712±54	weibull	5.1±1	2380±550	1600	-137
1996	45527	63.5±1.3	758±58	weibull	3.8±0.6	3120±790	1600	-121
1999	26163	57.2±1.5	671±62	weibull	5.1±1.1	2500±630	1600	-169
2000	22550	54.2±1.6	621±94	weibull	3.9±0.9	3540±1260	1600	-277
2001	20644	42.3±1.5	657±69	weibull	5.2±1.3	2500±700	1600	-214
2003	20787	44.6±1.5	699±76	weibull	4.5±1.1	2750±870	1600	-230
2005	19487	29.7±1.2	560±86	weibull	4.8±1.2	2990±930	1600	-270
2007	20776	24.7±1	461±94	weibull	4.6±1.1	3390±1050	1600	-284
2013	18601	12.7±0.7	332±66	gumbel	-	180±50	-610±280	-3133
2015	22498	12.7±0.7	232±65	gumbel	-	200±50	-800±270	-3075
2017	21510	8.1±0.7	237±67	gumbel	-	200±50	-790±280	-3240
2020	19275	4.8±0.6	182±56	gumbel	-	160±40	-640±230	-2261
HC								
1995	30394	9.5±0.3	110±21	gumbel	-	73±15	-271±87	-311
1996	42506	10.1±0.2	88±18	gumbel	-	77±13	-312±75	-231
1999	26163	5±0.2	69±21	gumbel	-	69±15	-289±89	-324
2000	22550	4.4±0.2	60±23	gumbel	-	69±16	-298±95	-372
2001	20644	4.1±0.2	76±22	gumbel	-	65±16	-259±93	-359
2003	20787	3.4±0.2	60±25	gumbel	-	73±18	-320±105	-451
2005	19487	1.9±0.2	75±20	frechet	1.7±0.4	2.1±1.9	0	0.19
2007	20776	1.9±0.1	50±10	frechet	1.8±0.4	2.1±1.6	0	0.18
2013	18601	1.8±0.1	38±8	frechet	1.8±0.5	1.6±1.3	0	0.15
2015	22498	2.6±0.2	74±11	frechet	2.2±0.5	5.4±3.4	0	0.42
2017	21510	2.6±0.1	74±17	frechet	1.7±0.4	2.6±2.1	0	0.21
2020	19275	2.2±0.1	48±12	frechet	1.7±0.4	1.5±1.3	0	0.14
NO								
1995	30394	11.9±0.2	62±4	weibull	9.7±1.9	232±28	200	-13
1996	45527	8.5±0.1	55±3	weibull	11.3±1.8	229±20	200	-9
1999	26163	8±0.1	58±4	weibull	10.9±2.4	227±27	200	-15
2000	22550	7±0.1	59±4	weibull	13.6±3.2	205±21	200	-16
2001	20644	6.6±0.2	62±4	weibull	14±3.4	199±21	200	-17
2003	20787	6±0.2	53±5	weibull	10.7±2.6	237±32	200	-20
2005	19487	4.8±0.1	53±5	weibull	11.7±2.9	227±29	200	-20
2007	20776	3.5±0.1	44±4	weibull	15.1±3.6	220±21	200	-18
2013	18601	2.3±0.1	45±4	gumbel	-	10±3	-8±15	-10
2015	22498	1.5±0.1	42±3	gumbel	-	10±2	-9±13	-7
2017	21510	1.4±0.1	39±4	gumbel	-	12±3	-24±17	-12
2020	19275	1.2±0.1	35±4	gumbel	-	11±3	-20±16	-10

Table 2, cont.
Denver Fleet emissions statistics continued

Year	# vehicles	Average (g/kgF)	Mean 99th (g/kgF)	EVT domain	Shape	Scale	Location	Covariance
NO2								
2013	17653	0.11±0.01	3.15±0.67	frechet	1.9±0.5	0.1±0.1	0	0.01
2015	22498	0.07±0.01	1.6±0.6	gumbel	-	1.9±0.5	-8.5±2.7	-0.3
2017	21510	0.06±0.01	1.9±0.2	frechet	2.8±0.7	0.3±0.1	20	0.02
2020	19275	0.06±0.01	1.9±0.2	frechet	2.8±0.7	0.3±0.1	0	0.02
NH3								
2013	18601	0.45±0.01	5.8±0.8	weibull	6.8±1.8	29.8±6.6	20	-2.83
2015	22498	0.43±0.01	5.3±0.7	gumbel	-	2.1±0.5	-5.6±2.9	-0.35
2017	21510	0.38±0.01	5.2±0.6	gumbel	-	1.9±0.5	-4.7±2.7	-0.3
2020	19275	0.35±0.01	5±0.7	gumbel	-	1.9±0.5	-4.9±2.8	-0.33

Table 3
Tulsa Fleet emissions statistics

Year	# vehicles	Average (g/kgF)	Mean 99th (g/kgF)	EVT domain	Shape	Scale	Location	Covariance
CO								
2003	19817	34.3±1.3	649±82	weibull	4.6±1.1	2830±910	1600	-256
2005	18408	34±1.3	570±112	weibull	3.8±1	3840±1540	1600	-366
2013	20516	13.6±0.8	326±81	gumbel	-	240±60	-890±340	-4763
2015	19065	14.6±0.7	276±67	gumbel	-	190±50	-680±280	-3176
2017	21888	11.3±0.6	240±56	gumbel	-	170±40	-630±230	-2254
2019	22683	11.9±0.6	300±56	gumbel	-	170±40	-600±240	-2284
HC								
2003	19817	3.1±0.2	63±12	frechet	1.9±0.5	3.2±2.5	0	0.29
2005	18408	2.2±0.2	75±16	frechet	1.9±0.5	3.5±2.8	0	0.33
2013	20516	2±0.2	88±18	frechet	1.9±0.5	3.9±3	0	0.34
2015	19065	2.4±0.2	63±11	frechet	2.1±0.5	4.2±3	0	0.38
2017	21888	1.7±0.1	66±21	frechet	1.5±0.4	1.1±1	0	0.09
2019	22683	1.9±0.1	50±11	frechet	1.8±0.4	1.9±1.4	0	0.14
NO								
2003	19826	3.4±0.1	38±4	weibull	15.5±3.9	226±22	200	-20
2005	18408	2.5±0.1	32±4	weibull	17.3±4.4	225±20	200	-21
2013	20516	1.3±0.1	34±2	gumbel	-	6±1.5	3.6±8.6	-3.1
2015	19065	1.1±0.1	29±3	gumbel	-	9.5±2.4	-20±14	-8.4
2017	21888	1.2±0.1	38±2	gumbel	-	7.4±1.7	0.3±10	-4.3
2019	22683	0.9±0.1	35±2	gumbel	-	7.5±1.7	-4.5±10	-4.3
NO2								
2013	17915	0.06±0.01	2.3±0.2	frechet	3.7±0.9	0.53±0.22	0	0.052
2015	19065	0.09±0.01	1.6±0.2	frechet	2.6±0.7	0.2±0.11	0	0.018
2017	21888	-0.01±0.01	1.9±0.3	gumbel	-	0.82±0.19	-2.4±1.1	-0.054
2019	22683	-0.01±0.01	1.5±0.1	frechet	3.1±0.7	0.25±0.11	0	0.019
NH3								
2005	18408	0.51±0.01	4.7±0.9	weibull	6.9±1.8	32±7.1	20	-3.04
2013	20516	0.44±0.01	5.4±0.7	gumbel	-	1.9±0.5	-4.7±2.8	-0.32
2015	19065	0.38±0.01	5.5±0.7	gumbel	-	1.9±0.5	-4.2±2.8	-0.33
2017	21888	0.38±0.01	4.9±0.8	weibull	6.6±1.5	32.5±6.9	20	-2.6
2019	22683	0.35±0.01	4.8±0.5	gumbel	-	1.6±0.4	-3.8±2.3	-0.21

Table 4
West LA Fleet emissions statistics

Year	# vehicles	Average (g/kgF)	Mean 99th (g/kgF)	EVT domain	Shape	Scale	Location	Covariance
CO								
1991	90064	96.6±1.2	863±25	weibull	5.3±0.6	1900±240	1600	-37
1999	18579	72±2.3	815±81	weibull	4±1	2760±1060	1600	-263
2001	19697	55.1±1.9	797±66	weibull	4.8±1.2	2290±710	1600	-207
2003	19665	43.4±1.6	722±71	weibull	4.9±1.2	2470±750	1600	-223
2005	21531	21.6±0.8	562±92	weibull	4.5±1.1	3140±1040	1600	-291
2008	17634	21.7±1.2	491±107	weibull	4.3±1.1	3530±1280	1600	-355
2013	26632	16.6±0.8	317±119	weibull	3.7±0.8	4890±1670	1600	-325
2015	21767	13.2±0.8	320±86	weibull	5.4±1.3	3240±830	1600	-259
2018	18931	11.2±0.7	261±102	weibull	5.2±1.3	3530±1020	1600	-328
2021	18498	12.1±0.6	263±58	gumbel	-	160±40	-560±240	-2374
HC								
1991	90064	27.3±0.3	235±25	weibull	3.5±0.4	1912±374	700	-37
1999	18579	7.1±0.4	144±35	gumbel	-	95±24	-350±145	-865
2001	19697	4.6±0.3	106±35	gumbel	-	98±24	-400±145	-861
2003	19665	4.5±0.2	65±37	gumbel	-	104±26	-475±154	-977
2005	19118	3.1±0.2	54±27	gumbel	-	75±19	-336±113	-525
2008	17634	1.8±0.2	81±30	frechet	1.4±0.4	1.1±1.2	0	0.11
2013	26632	2.2±0.1	55±8	frechet	2.1±0.4	3.4±2.1	0	0.22
2015	21767	1.2±0.1	47±16	frechet	1.4±0.3	0.7±0.7	0	0.05
2018	18931	1.5±0.1	56±8	frechet	2.5±0.6	5.7±3.5	0	0.53
2021	18498	2.1±0.2	65±16	frechet	1.7±0.4	2.2±1.9	0	0.21
NO								
1999	18579	6.5±0.2	45±7	weibull	9.1±2.3	270±45	200	-26
2001	19697	5.5±0.1	50±6	weibull	9.5±2.4	257±40	200	-23
2003	19665	4.3±0.1	43±5	weibull	12±3	241±30	200	-22
2005	21531	3.1±0.1	44±5	weibull	12.4±3.1	236±29	200	-22
2008	17634	3.5±0.1	47±4	gumbel	-	10±3	-6±16	-10
2013	26632	1.9±0.1	41±3	gumbel	-	9±2	-7±12	-5.7
2015	21767	1.8±0.1	41±3	gumbel	-	10±2	-13±15	-8.7
2018	18931	1.5±0.1	34±5	gumbel	-	13±3	-31±19	-15
2021	18498	1.2±0.1	39±4	gumbel	-	11±3	-20±17	-12

Table 4, cont.
West LA Fleet emissions statistics continued

Year	# vehicles	Average (g/kgF)	Mean 99th (g/kgF)	EVT domain	Shape	Scale	Location	Covariance
NO2								
2008	17634	0.05±0.01	1.1±0.7	weibull	10.7±2.8	30.5±4.5	20	-3.07
2013	25709	0.11±0.01	1.8±0.4	gumbel	-	1.39±0.3	-5.4±1.8	-0.13
2015	19781	-0.06±0.01	2.7±0.9	gumbel	-	2.46±0.61	-10±3.6	-0.531
2018	18931	0.04±0.005	1.1±0.4	gumbel	-	1.09±0.27	-4.5±1.6	-0.11
2021	14981	-0.15±0.01	2.9±0.5	frechet	2.3±0.6	0.24±0.18	0	0.028
NH3								
2008	17634	0.8±0.02	7.4±1.1	weibull	4.8±1.3	36±12	20	-3.63
2013	26632	0.59±0.01	5.9±0.6	gumbel	-	1.8±0.4	-3.6±2.3	-0.22
2015	21767	0.71±0.02	6.7±0.7	weibull	7.0±1.6	28±6	20	-2.2
2018	18931	0.68±0.02	7.1±0.7	gumbel	-	1.9±0.5	-2.7±2.9	-0.34
2021	18498	0.49±0.01	5.8±0.6	gumbel	-	1.7±0.4	-2.8±2.5	-0.26

Table 5
2021 - 2022 Feet emissions statistics

Species	# vehicles	Average (g/kgF)	Mean 99th (g/kgF)	EVT domain	Shape	Scale	Location	Covariance
Fresno 2021								
CO	8423	10.4±0.9	291±94	gumbel	-	180±70	-620±390	-6391
HC	8423	1.8±0.3	51±11	frechet	2.4±0.9	5±4.6	0	1.03
NO	8423	1±0.1	38±5	gumbel	-	9±4	-11±21	-19
NO2	6622	0.05±0.01	1.5±0.3	gumbel	-	0.5±0.21	-1.1±1.2	-0.063
NH3	8423	0.3±0.01	3.8±0.7	gumbel	-	1.2±0.5	-2.7±2.8	-0.32
Stockton 2021								
CO	27023	26.3±1.1	635±51	weibull	6.2±1.3	2180±440	1600	-142
HC	26794	2.5±0.2	58±8	frechet	2.2±0.5	4.3±2.5	0	0.28
NO	27015	1.9±0.1	45±3	gumbel	-	11±2	-15±14	-8
NO2	22671	0.04±0.01	1.7±0.2	frechet	3.1±0.7	0.3±0.13	0	0.023
NH3	26974	0.73±0.01	7.7±0.6	weibull	6.9±1.5	25.7±4.7	20	-1.68
West LA 2021								
CO	18498	12.1±0.6	263±58	gumbel	-	160±40	-560±240	-2374
HC	18498	2.1±0.2	65±16	frechet	1.7±0.4	2.2±1.9	0	0.21
NO	18498	1.2±0.1	39±4	gumbel	-	11±3	-20±17	-12
NO2	14981	-0.15±0.01	2.9±0.5	frechet	2.3±0.6	0.24±0.18	0	0.028
NH3	18498	0.49±0.01	5.8±0.6	gumbel	-	1.7±0.4	-2.8±2.5	-0.26
Oakland 2022								
CO	25696	23.7±1	547±58	weibull	6.1±1.3	2420±510	1600	-167
HC	25696	2.1±0.1	43±6	frechet	2.3±0.5	3.6±2	0	0.25
NO	25696	1.6±0.1	49±3	gumbel	-	10±2	-5±14	-8
NO2	21560	-0.02±0.01	2±0.2	frechet	2.8±0.7	0.27±0.14	0	0.022
NH3	25696	0.79±0.02	8.9±0.5	gumbel	-	1.6±0.4	0.5±2.1	-0.18
Phoenix 2021								
CO	17734	11.7±0.6	212±81	gumbel	-	220±57	-930±340	-4730
HC	17734	2.1±0.1	37±5	frechet	2.5±0.7	3.9±2.4	0	0.39
NO	17734	1.2±0.1	36±5	weibull	13±3	240±28	200	-23
NO2	17734	0.03±0.01	1.4±0.2	frechet	2.8±0.7	0.19±0.1	0	0.018
NH3	17734	0.32±0.01	5.2±0.6	gumbel	-	1.7±0.4	-3.7±2.7	-0.29

Appendix D

Model year specific average and mean 99th percentile emissions

This appendix tabulates model year specific emissions as a function of vehicle age. Model years were selected to fall between emission standard phase-in periods. They include 1992 and 1993 to represent Tier 0 vehicles, 2000-2003 for Tier 1 and 2010-2013 for Tier 2. Except for Denver Tier 0 and Tier 1 vehicles, two successive model years were combined to increase statistical confidence: thus, 1992/93 for Tier 0, 2000/01 and 2002/03 for Tier 1 and 2010/11 and 2012/13 for Tier 2. In the case of Denver, 1992 and 1993 are analyzed individually, as well as 2000 and 2002. In the first case it adds an additional trend line to the more limited Tier 0 data. In the second case it serves as a check that combining successive years does not distort the statistical behavior. The error bars represent 95% confidence intervals, i.e., ±2σ uncertainties. The vehicle age range extends from 2 to 15 years for Tier 0 vehicles, from 0 to 19.5 years for Tier 1 and from 0.5 to 10.5 years for Tier 2. The vehicle age dependent emissions are listed below in Tables 6, 7 and 8, respectively for Tier 0, 1 and 2.

For Tier 0, 1 and 2, the vehicle emissions are fit to a linear dependence on age. Table 9 lists the best fit slopes (deterioration rate) and intercepts (new vehicle emissions), along with the R^2 coefficients.

The last University of Denver RSD campaigns were completed in 2021 and 2022, before completion of the Tier 3 phase-in. Model year 2020/21 vehicles are analyzed for Fresno, Oakland, Phoenix, Stockton and West LA to provide a view of emissions about halfway through the Tier 3 phase-in. At this point, the light duty fleet average NMOG+NOx FTP standard is about 61 mg/mi as compared to a Tier 2 bin 5 value of 160 mg/mi and a final Tier 3 level of 30 mg/mi. Table 10, with the title Tier 3* to denote that the phase-in is incomplete, lists the 2020/21 MY emissions. Table 11 lists average and mean 99th percentile emissions for two Tier 2 and two Tier 3 vehicles run over the hot start + city phases of the FTP and the US06 phase of the SFTP cycles.

Table 6
Tier 0 – Emissions deterioration with vehicle age

Year	Vehicle Age (years)	Model year average emissions CO (g/kgF)	HC (g/kgF)	NO (g/kgF)	Mean 99th percentile emissions CO (g/kgF)	HC (g/kgF)	NO (g/kgF)
Chicago 1992/93 MY							
1997	4.5	59.5±3.7	4.4±0.4	6.1±0.3	592±63	60±15	37±3
1998	5.5	58.7±3.6	4.9±0.7	7.3±0.3	630±68	99±23	44±3
1999	6.5	63.5±4.2	5.6±0.5	7.7±0.4	684±71	92±40	50±5
2000	7.5	53.9±3.9	5.6±0.5	7.8±0.4	557±63	64±20	54±4
2002	9.5	66.5±6	6.9±0.6	8±0.6	703±110	68±21	54±7
2004	11.5	55±6.2	8±1.5	9.5±0.7	607±138	163±123	53±6
2006	13.5	72.3±12	8.5±1.6	6.1±0.7	933±87	124±50	47±11
Denver 1992 MY							
1995	3	31.8±3	6.1±0.7	9.2±0.6	479±69	81±10	54±4
1996	4	36.4±2.9	8.1±0.6	7.3±0.5	500±61	71±15	52±5
1999	7	49.7±5.2	4.5±0.6	9.4±0.6	581±108	80±43	59±6
2000	8	52.6±5.6	3.7±0.8	8.7±0.7	529±99	69±38	54±6
2001	9	53.1±6.6	4.7±0.9	9.2±0.8	586±100	78±21	62±12
2003	11	68.4±8.8	5.9±1	11.4±1.1	669±86	117±86	67±5
2005	13	61±9.6	6.1±1.9	11.5±1.2	751±218	120±70	64±11
2007	15	79.8±13.9	5.7±1.1	10.4±1.3	781±246	67±52	61±8
Denver 1993 MY							
1995	2	27±2.4	5.4±0.6	8.3±0.6	436±71	74±10	57±6
1996	3	29±2.1	7.7±0.5	6.6±0.4	442±48	65±11	46±4
1999	6	39.8±3.6	3.6±0.5	8.6±0.5	499±81	49±10	56±5
2000	7	44.1±3.9	3.4±0.6	8.3±0.6	416±56	58±19	59±7
2001	8	46.1±6	3.8±0.7	9.2±0.7	615±103	61±15	60±6
2003	10	64.8±8	5.1±0.9	10.4±0.9	673±99	115±84	69±10
2005	12	60.7±9	4±0.9	11.3±1.1	732±235	77±49	67±4
2007	14	62.1±10.7	5.6±1.1	10±1.1	673±209	77±44	60±6
West LA 1992/93 MY							
1999	6.5	53±4.6	5±0.7	6.8±0.5	621±92	93±44	52±5
2000	7.5	53.9±3.9	5.2±0.6	8±0.6	698±104	78±26	60±6
2002	9.5	58.6±5.6	6.1±0.7	8±0.6	676±93	77±19	57±8
2004	11.5	61±7.5	7.6±1.2	8.4±0.7	682±160	130±47	56±7
2006	13.5	66.7±9.4	5.4±0.9	12.7±1.1	631±147	60±35	58±7

Table 7
Tier 1 – Emissions deterioration with vehicle age

Year	Vehicle Age (years)	Model year average emissions CO (g/kgF)	HC (g/kgF)	NO (g/kgF)	Mean 99th percentile emissions CO (g/kgF)	HC (g/kgF)	NO (g/kgF)
Chicago 2000/01 MY							
2002	1.5	9.2±0.9	1.3±0.2	1.3±0.1	190±24	33±5	24±3
2004	3.5	12.1±1.1	1.5±0.3	1.7±0.2	248±37	42±6	33±4
2006	5.5	12.4±1.3	1.5±0.3	1.2±0.1	258±42	43±6	21±3
2014	13.5	20.4±3.3	2.3±0.8	3.6±0.4	314±91	54±32	39±6
2016	15.5	25.6±3.3	3.3±0.7	4±0.5	335±114	65±45	50±10
2018	17.5	24.1±4.6	3.8±0.9	4.7±0.8	267±108	62±58	47±7
2020	19.5	26±7.2	7.7±3.6	4.7±1			
Chicago 2002/03 MY							
2004	1.5	5.8±0.6	1.5±0.3	1±0.1	128±21	46±8	22±4
2006	3.5	6.7±0.8	0.8±0.3	0.7±0.1	170±31	42±8	16±3
2014	11.5	15.1±2.2	1.3±0.5	2.2±0.3	248±43	45±18	35±7
2016	13.5	21.7±3.1	2.4±0.5	3.1±0.4	418±128	42±20	39±6
2018	15.5	16.6±3.7	2.3±0.8	2.7±0.5	316±73	44±34	36±11
2020	17.5	26.8±5	3.2±1	3.6±0.7	406±100	61±25	40±7
Denver 2000 MY							
2000	0	12.2±3	1.2±0.7	2.3±0.5	290±135	35±8	33±6
2001	1	10.3±1.7	1.9±0.5	1.9±0.2	280±66	48±12	32±5
2003	3	18.2±2.4	1.1±0.3	2.7±0.3	369±90	33±15	38±5
2005	5	15.3±1.8	0.4±0.2	2.5±0.3	242±66	46±9	33±6
2007	7	17.4±2.5	1.1±0.3	2.5±0.3	302±65	21±4	33±6
2013	13	19.5±3.6	1.8±0.5	3.9±0.5	353±113	42±18	44±5
2015	15	27.3±5.1	3.3±0.9	3.4±0.6	525±135	59±21	48±9
2017	17	23.7±5.8	4.2±1.1	3.7±0.7	394±107	82±32	51±13
Denver 2002 MY							
2003	1	12.9±1.7	0.8±0.2	1.7±0.2	270±64	21±5	29±4
2005	3	9.2±1.4	0.3±0.2	1.7±0.2	213±50	18±7	32±6
2007	5	10.1±1.5	0.7±0.3	1.7±0.2	206±51	25±11	32±6
2013	11	13.6±2.7	1.3±0.4	2.4±0.4	228±84	28±9	35±8
2015	13	19.8±4.2	3.5±1	2.5±0.4	433±112	78±32	46±9
2017	15	15.5±3.6	2.8±1	3±0.5	332±116	101±149	45±11
2020	18	17.4±5.3	2.1±0.7	3.1±0.7			

Table 7 cont.
Tier 1 – Emissions deterioration with vehicle age

Year	Vehicle Age (years)	Model year average emissions CO (g/kgF)	HC (g/kgF)	NO (g/kgF)	NH_3 (g/kgF)	Mean 99th percentile emissions CO (g/kgF)	HC (g/kgF)	NO (g/kgF)	NH_3 (g/kgF)
Tulsa 2000/01 MY									
2003	2.5	11.5±1	1.5±0.2	1.2±0.1		213±34	33±9	24±3	
2005	4.5	17.9±1.2	0.8±0.4	1.1±0.1	0.5±0.1	203±33	37±5	20±4	6±1
2013	12.5	21.3±3.9	2.2±0.9	2.8±0.4	0.6±0.1	448±151	77±31	39±6	6±1
2015	14.5	26.7±4.7	3.9±1.2	3.5±0.5	0.6±0.1	491±278	102±74	40±7	7±2
2017	16.5	33.6±6.1	3.8±1.2	4.8±0.7	0.6±0.1	490±150	122±46	57±11	7±2
2019	18.5	30.1±5.9	3.5±1.1	4.1±0.9	0.6±0.1	403±183	72±37	51±6	5±2
Tulsa 2002/03 MY									
2003	0.5	7.2±0.9	1.6±0.2	0.6±0.1		202±103	30±3	17±3	
2005	2.5	15.4±1.1	1.1±0.3	0.7±0.1	0.4±0.1	178±32	34±3	18±4	6±1
2013	10.5	16.1±2.4	1.5±0.5	1.7±0.2	0.6±0.1	334±87	43±7	30±4	6±1
2015	12.5	20.6±3.1	3.8±1.1	2.7±0.4	0.5±0.1	358±121	111±73	39±5	5±1
2017	14.5	24.7±4	3.7±1.2	3.9±0.6	0.5±0.1	387±93	130±52	49±6	6±2
2019	16.5	24.6±3.8	3.8±1.4	3.7±0.6	0.5±0.1	280±60	180±264	40±6	8±3
West LA 2000/01 MY									
2001	0.5	9.8±1.3	0.4±0.1	0.6±0.1		316±60	12±2	19±4	
2003	2.5	11.1±1.3	1.2±0.2	0.8±0.1		274±54	30±7	21±3	
2005	4.5	10.3±1.3	1.2±0.2	1±0.1		223±47	27±10	24±4	
2008	7.5	12.7±1.7	0.8±0.2	2.2±0.2	1±0.1	293±61	28±9	31±5	8±1
2013	12.5	18.1±2.5	1.9±0.5	2.9±0.3	0.8±0.1	430±97	48±16	47±7	6±1
2015	14.5	25±3.7	2.4±0.7	3.7±0.4	1.2±0.1	502±131	83±77	49±7	8±1
2018	17.5	26.5±4.5	1.7±0.8	4.2±0.5	1.1±0.1	492±143	79±31	43±8	9±2
West LA 2002/03 MY									
2003	0.5	6.7±0.9	0.6±0.2	0.4±0.1		164±37	23±4	13±3	
2005	2.5	7.3±0.9	0.9±0.2	0.7±0.1		182±37	23±6	20±4	
2008	5.5	10.2±1.7	0.3±0.2	1.4±0.2	0.8±0.1	302±72	24±5	30±5	8±1
2013	10.5	13.8±1.6	1.2±0.3	1.6±0.2	0.7±0.1	276±52	39±7	37±6	7±1
2015	12.5	16.8±2.1	1.2±0.5	2.8±0.3	1±0.1	289±63	42±27	39±5	7±1
2018	15.5	24.4±4.1	1.3±0.7	4.2±0.6	1.1±0.1	403±114	87±98	53±10	8±2

Table 8
Tier 2 – Emissions deterioration with vehicle age

Year	Vehicle Age (years)	Model year average emissions CO (g/kgF)	HC (g/kgF)	NO (g/kgF)	NH_3 (g/kgF)	Mean 99th percentile emissions CO (g/kgF)	HC (g/kgF)	NO (g/kgF)	NH_3 (g/kgF)
Chicago 2010/11 MY									
2014	3.5	2.9±1.1	0.8±0.3	0.34±0.08	0.65±0.04	154±55	36±6	13±4	5.9±0.8
2016	5.5	6.7±0.8	1.5±0.2	0.22±0.05	0.67±0.03	138±27	28±4	8±2	5.9±0.7
2018	7.5	5.8±1.3	1.3±0.2	0.31±0.07	0.67±0.04	177±38	22±3	10±3	5.4±0.6
2020	9.5	12.6±1.8	2.2±0.5	0.57±0.15	0.76±0.06	229±42	36±7	18±6	5.9±0.5
Chicago 2012/13 MY									
2014	1.5	1.4±0.8	0.8±0.3	0.22±0.04	0.65±0.04	102±17	36±7	12±8	7.5±1.1
2016	3.5	6.8±0.8	1.6±0.2	0.23±0.06	0.66±0.03	155±29	27±3	18±10	6.4±0.7
2018	5.5	6.7±1	1.3±0.2	0.23±0.04	0.78±0.04	159±25	26±5	9±5	6.7±0.7
2020	7.5	11±1.4	2±0.4	0.28±0.06	0.72±0.04	194±41	43±9	9±2	6.2±0.7
Denver 2010/11 MY									
2013	2.5	1.7±0.8	1.4±0.2	0.32±0.07	0.26±0.03	111±64	22±4	10±3	4.5±0.8
2015	4.5	5.5±1.3	2.1±0.8	0.53±0.13	0.32±0.04	158±26	55±16	20±6	5.6±1.3
2017	6.5	3.5±1.3	1.9±0.2	0.61±0.13	0.34±0.04	163±29	25±3	19±5	5.5±1
2020	9.5	4.5±1.9	2.1±0.3	0.61±0.16	0.38±0.04	228±57	40±18	22±8	5.2±1.2
Denver 2012/13 MY									
2013	0.5	2.9±0.8	1.4±0.2	0.29±0.06	0.25±0.03	100±34	23±4	17±10	4.3±0.8
2015	2.5	5±1.2	1.7±0.5	0.32±0.07	0.29±0.03	150±24	47±5	15±11	4.5±0.7
2017	4.5	3.5±1.2	1.9±0.2	0.54±0.1	0.33±0.03	191±45	25±4	17±5	5±0.9
2020	7.5	4.4±1.4	2.2±0.3	0.47±0.1	0.4±0.04	174±37	26±4	17±4	5.8±1.1

Table 8 cont.
Tier 2 – Emissions deterioration with vehicle age

Year	Vehicle Age (years)	Model year average emissions CO (g/kgF)	HC (g/kgF)	NO (g/kgF)	NH_3 (g/kgF)	Mean 99th percentile emissions CO (g/kgF)	HC (g/kgF)	NO (g/kgF)	NH_3 (g/kgF)
Tulsa 2010/11 MY									
2013	2.5	2.1±1.2	1.5±0.5	0.13±0.04	0.22±0.02	131±49	57±13	5±1	2.9±0.6
2015	4.5	6.3±1.1	2.1±0.5	0.14±0.05	0.26±0.03	151±64	55±7	7±3	4.2±0.8
2017	6.5	7.4±1.5	1.1±0.3	0.31±0.08	0.36±0.03	245±60	28±7	12±4	4.7±0.9
2019	8.5	8.7±1.4	1.4±0.5	0.32±0.13	0.37±0.03	200±44	40±17	19±7	4.6±0.8
Tulsa 2012/13 MY									
2013	0.5	2.4±0.9	1.9±0.5	0.11±0.03	0.24±0.03	95±23	48±6	3±1	4.9±2.5
2015	2.5	8±0.9	2.7±0.5	0.12±0.04	0.3±0.03	121±23	55±6	6±2	5±1.1
2017	4.5	6.7±1	1.4±0.2	0.31±0.06	0.39±0.03	178±37	30±7		5.9±1
2019	6.5	8.1±1	1.3±0.3	0.15±0.06	0.4±0.03	161±50	39±9		5±0.8
West LA 2010/11 MY									
2013	2.5	3.9±0.6	1.5±0.3	0.15±0.05	0.28±0.02	99±51	27±2	14±20	4±0.8
2015	4.5	3±1.2	0.2±0.2	0.11±0.07	0.5±0.05	344±757	20±7	18±32	6.3±1.2
2018	7.5	4.8±1.1	1.5±0.5	0.37±0.17	0.63±0.06	117±39	45±17	61±285	6.5±1.5
2021	10.5	9.2±1.7	1.6±0.6	0.66±0.24	0.59±0.06	209±156	39±7	31±10	6.2±2
West LA 2012/13 MY									
2013	0.5	4.3±0.5	1.7±0.3	0.15±0.06	0.23±0.02	75±27	32±4	21±39	3.7±0.6
2015	2.5	2.6±0.9	0.1±0.2	0.13±0.06	0.49±0.03	164±152	20±3	11±3	5.8±0.8
2018	5.5	5±1	0.9±0.4	0.21±0.08	0.61±0.05	138±33	35±7	12±5	7.3±1.1
2021	8.5	9.5±1.6	1.6±0.6	0.42±0.13	0.65±0.06	184±61	44±21	19±6	5.8±1.1

Table 9
Regression coefficients for emissions trends with vehicle age. Slopes represent deterioration rates and intercepts represent new vehicle emissions rates.

	MY average			MY Mean 99th		
	slope (g/kgF/year)	**intercept** (g/kgF)	**R^2**	**slope** (g/kgF/year)	**intercept** (g/kgF)	R^2
Tier 0						
CO	2.9±0.8	30±7	0.67	24±8	410±70	0.58
HC[a]	0.24±0.16	3.1±1.6	0.28	3±3	61±24	0.14
NO	0.27±0.15	6.5±1.4	0.34	0.9±0.7	48±6	0.22
Tier 1						
CO	0.93±0.16	7.9±1.8	0.73	12±3	200±36	0.52
HC	0.16±0.04	0.5±0.5	0.58	3.7±1.1	20±12	0.46
NO	0.18±0.03	0.8±0.3	0.77	1.5±0.3	21±3	0.73
NH_3	0.01±0.02	0.6±0.3	0.06	0.06±0.12	6±2	0.05
Tier 2						
CO	0.7±0.3	2.2±1.5	0.44	11±6	110±30	0.36
HC	0.04±0.07	1.3±0.4	0.04	0.1±1.5	35±8	0
NO	0.04±0.02	0.12±0.09	0.41	1.2±0.7	8.3±4.2	0.30
NH_3	0.03±0.02	0.3±0.1	0.23	0.12±0.13	5±1	0.12

[a]Omits 1998 & 1996 HC data, which were not corrected for offset. If the 1992/93 MY averages from these years are included, the slope is 0.06±0.15 and the intercept is 5.1±1.4.

Table 10
Tier 3* – 2020/21 MY vehicle emissions

Location	**Vehicle Age** (years)	**Model year average emissions**				**Mean 99th percentile emissions**			
		CO (g/kgF)	**HC** (g/kgF)	**NO** (g/kgF)	**NH_3** (g/kgF)	**CO** (g/kgF)	**HC** (g/kgF)	**NO** (g/kgF)	**NH_3** (g/kgF)
Fresno	0.5	3.8±1.2	2±1	0.17±0.06	0.09±0.02	76±24	42±9	4±3	1.4±0.6
Oakland	1.5	12.8±2.6	1.9±0.4	0.31±0.11	0.39±0.03	430±94	36±5		5.2±0.8
Phoenix	0.5	5.2±0.7	2.2±0.4	0.27±0.07	0.11±0.02	105±131	31±6	19±33	2.6±0.8
Stockton	0.5	15.2±3.4	2.5±0.6	0.28±0.07	0.3±0.04	543±120	49±10	15±22	5.7±1.3
West LA	0.5	4.2±0.6	2.2±0.6	0.14±0.05	0.16±0.02	130±206	52±17	13±42	2.8±0.7

Table 11.
FTP & US06 average and mean 99th percentile instantaneous fuel based emissions

Emissions Standard	Average (g/kgF)				Mean 99th percentile (g/kgF)			
	FTP hot start & city		US06		FTP hot start & city		US06	
	Vehicle 1	Vehicle 2	Vehicle 1	Vehicle 2	Vehicle 1	Vehicle 2	Vehicle 1	Vehicle 2
CO								
Tier 3	2.5	2.7	1.8	15	26	15	10	150
Tier 2	5.2	1.9	11	4.2	70	49	174	173
HC								
Tier 3	0.07	0.04	0.08	0.18	0.7	0.34	0.64	0.85
Tier 2	0.42	0.24	0.5	0.36	3.9	4.5	6.3	6.4
NO								
Tier 3	0.04	0.02	0.7	0.4	0.67	1-8	16	12
Tier 2	0.08	0.16	0.76	0.21	2.6	3.3	9	4.3