Assessment of the Greenhouse Gas Emission Benefits of Heavy Duty Natural Gas Vehicles in the United States

Final Report

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EXECUTIVE SUMMARY

Research Objective

The objective of this research effort is to reduce the uncertainty associated with the greenhouse gas (GHG) benefits of heavy duty natural gas vehicles by producing new exhaust emission factors for carbon dioxide (CO_2) and methane (CH_4) from different heavy duty compressed natural gas (CNG) and liquefied natural gas (LNG) vehicle applications through a comprehensive analysis of existing vehicle emissions test data.

Research Context

GHG emissions data and inventories associated with transportation systems are important because of the increasingly large share of overall anthropogenic GHG emissions from mobile source combustion and its relative contribution to global climate change. At 1,770.4 million metric tons of CO_2 equivalent in 2003, mobile sources account for approximately one third of overall U.S. GHG emissions, and heavy duty vehicles emit roughly 20 percent of mobile source emissions.[1] GHG inventories and reduction strategies for the transportation sector are limited by the availability of emission factors, which are unavailable or uncertain for subclasses of natural gas-fueled heavy-duty vehicles. Vehicle emission factors provide estimates of GHGs emitted per unit of fuel consumed or distance traveled.[2] Accurate emission factors are important for entities seeking strategies to reduce emissions and as inputs to air quality models and forecasts.

Research Importance

Additional research on the GHG emissions from heavy-duty vehicles is necessary so that project developers, fleet decision makers, government policy makers, and industry researchers can consider the GHG consequences and risks along with the known benefits of natural gas fuel switching and advanced technology programs. More accurate emission factors for heavy duty diesel and natural gas vehicle exhaust are important because organizations are proactively implementing fuel switching projects and purchasing natural gas vehicle fleets, and claiming GHG benefits. For example, the Governor's Office of the State of Washington specifically mentions the conversion of buses from diesel power to natural gas as an option to comply with a

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[1] U.S. Environmental Protection Agency. *Inventory of U.S. Greenhouse Gas Emissions and Sinks*. (EPA 430-R-05-003), Washington, DC., 2005. Note: Alternative fuels account for less than one percent of total heavy duty vehicle emissions.

[2] The Intergovernmental Panel on Climate Change inventory guidance states that CO_2 emissions are most accurately estimated based on the carbon content of the fuel consumed, whereas CH_4 emissions should be estimated based on mileage-based emission factors.

2004 law requiring power plants to offset their CO_2 emissions.[3] Approximately 22 percent of all new transit bus purchases are for natural gas-fueled vehicles.[4] While the assumptions of GHG benefits of natural gas-fueled vehicles may be based on the best information publicly available today, they are highly uncertain because of a general lack of published GHG emission coefficients for heavy duty vehicles. GHG reduction estimates for fuel switching projects are often based on estimates of CO_2 only, without considering increases in CH_4 emissions from natural gas vehicles. In the case of heavy duty natural gas vehicles, this may present a problem for the crediting of GHG benefits because these vehicles may not always reduce overall GHG emissions when compared with their conventional diesel-fueled counterparts. Natural gas vehicles generally produce more CH_4, which has a much higher global warming potential than CO_2. Further, under certain driving conditions, a reduction in the fuel economy of natural gas vehicles relative to diesel may counteract the expected CO_2 benefits.

Research Overview

To improve the state of knowledge about the environmental effects of different natural gas vehicle applications, Science Applications International Corporation (SAIC) and West Virginia University (WVU) examined past emission tests undertaken at WVU's mobile testing facility, extracted previously unpublished data on CO_2 and CH_4 emissions from heavy duty vehicles, analyzed emissions from different fuels, vehicle types, engine technologies, and drive cycles, and summarized the results in this Final Report. The results of SAIC's research reduce some of the uncertainty about the CO_2 and CH_4 emission benefits of diesel and natural gas-fueled vehicles by providing emission factors.

Report Overview

This paper presents a review of existing literature on emission factors, emission data collection techniques and analytic approaches; presents the results of SAIC's analysis of available CO_2 and CH_4 GHG emission data from chassis dynamometer tests of heavy-duty vehicle exhaust; identifies sources of emission factor uncertainty; and provides suggestions for further reducing this uncertainty. The summary includes the background, methodology, results, and conclusions. The research focused on emissions data from diesel-, LNG- and CNG-fueled heavy-duty vehicles, but the some of the paper's findings about statistical issues may be extrapolated to emission factors for different vehicle types and technologies.

Research Results

The WVU data are insufficient to draw universal conclusions about natural gas relative to diesel use in heavy duty vehicles. The analysis indicates that most emission factors that could be extracted from the WVU data set are not robust enough to be representative of any population. This is attributed to the limited number of emission tests taken from a high number of different

[3] Office of Governor Gary Locke. "Gov. Gary Locke Signs Bills Strengthening Environmental Protection Policies," State of Washington, For Immediate Release – March 31, 2004. http://www.governor.wa.gov/press/press-view.asp?pressRelease=1573&newsType=1. Accessed 2 April 2004.
[4] The Natural Gas Vehicle Coalition. NGVC.org - About Natural Gas Vehicles – Fast Facts. http://www.ngvc.org/ngv/ngvc.nsf/bytitle/fastfacts.htm. Accessed 19 March 2004.

vehicle types and driving cycles. The mean emission values reported in the tables reflect emissions from vehicles that span a wide range in model year and weight categories, which contributes to the lack of statistical certainty, but may be useful for estimating aggregate emissions from a large, heterogeneous population of heavy duty vehicles. Owing to the few tests relative to the high number of variables, the emission factors could not be developed for certain useful subcategories of data, such as vehicle weight, number of axles, number of cylinders, or model year. The results are identified by the variables of fuel type, vehicle type, and drive cycle, but could not be subdivided further. To address this limitation, further research is needed to identify additional unpublished heavy duty vehicle emissions data sets and additional emissions testing based on statistical samples. Despite the limitations of the data, some useful results were observed.

Major findings are illustrated in Tables ES1 through ES5. Although the resulting emission factors were not found to be statistically significant, the available data shown in Tables ES1 and ES2 suggest that for refuse trucks and school buses operating in conditions similar to the central business district driving cycle, total GHG emissions from natural gas-fueled vehicles may be equivalent or greater than diesel-fueled vehicles. Another important result was that the CO_2 and CH_4 data results for CNG buses tested by WVU are generally consistent with the results of recent emission tests on some of the same vehicle types, fuel types, and drive cycles, as shown in Table ES3. Table ES3 also emphasizes the strong impact of the operating conditions, as indicated by the drive cycle, on both CO_2 and CH_4 emissions from heavy duty vehicles. Table ES4 presents selected results of the analysis of WVU's heavy duty vehicle emission test data. Table ES5 compares selected results of the analysis of heavy duty vehicle emission test data to other published emission factors.

Table ES1. Comparison of Refuse Truck Emissions on CBD Cycle

Fuel	Number of Samples	CO_2 Mean (g/mi)	CH_4 Mean (g/mi)	GWP -Weighted Emissions CO_2E (g/mi)
CNG	165	2,844	14.6	3,180
Diesel	153	3,223	*Not tested*	3,223
LNG	5	2,919	*Not tested*	*Not available*

Table ES2. Comparison of School Bus Emissions on CBD Cycle

Fuel	Number of Samples	CO_2 Mean (g/mi)	CH_4 Mean (g/mi)	GWP -Weighted Emissions CO_2E (g/mi)
CNG	68	2,008	18.5	2,434
Diesel	18	2,001	*Not tested*	2,001

Table ES3. Impact of Drive Cycle: Consistent Results for CNG Bus on CBD and NYBUS Cycles

<table>
<tr><th>Fuel Type</th><th>Vehicle Type/Control Technology</th><th>Drive Cycle</th><th>Source</th><th>Mean CH_4 Emissions (g/mi)</th><th>Mean CO_2 Emissions (g/mi)</th></tr>
<tr><td rowspan="4">CNG</td><td rowspan="4">Transit Bus</td><td rowspan="2">CBD</td><td>This study</td><td>16.8</td><td>2,502</td></tr>
<tr><td>ERMD (2001)</td><td>16.4</td><td>2,287</td></tr>
<tr><td rowspan="2">NY BUS</td><td>This study</td><td>53.6</td><td>6,077</td></tr>
<tr><td>ERMD (2001)</td><td>54.5</td><td>5,609</td></tr>
</table>

Table ES4. Mean CO_2 Emissions from Heavy-Duty, CNG-, LNG-, and Diesel-Fueled Vehicles, and Corresponding CH_4 Emission Rates from Same Vehicle Samples

Fuel Type	Vehicle Type/Control Technology	Drive Cycle	Mean CO_2 Emissions (g/mi)	Mean CH_4 Emissions from Same Sample (g/mi)	GWP -Weighted Emissions CO_2E (g/mi)
LNG	Transit Bus	CBD Cycle	2,374	11.3	2,634
CNG	Chassis Bus	Arterial Cycle	1,937	10.4	2,177
	Refuse Truck	CBD Cycle	2,844	14.6	3,179
	Refuse Truck	New York Garbage Truck Cycle	6,810	48.3	7,922
	School Bus	CBD Cycle	2,008	18.5	2,434
	Street Sweeper	NYC Street Sweeper Cycle	4,079	26.2	4,681
	Tractor Truck	City Suburban Route	2,018	41.7	2,977
	Transit Bus	Triple Length CBD	2,495	9.5	2,713
Diesel	Refuse Truck	WHM Cycle	3,314	Not tested	3,314

Table ES5. Comparison of Reported Emission Rates for CH_4 from Heavy-Duty, CNG-, LNG-, and Diesel-Fueled Vehicles, and Corresponding CO_2 Emission Rates from Same Vehicle Samples

Fuel Type	Vehicle Type/Control Technology	Drive Cycle	Source	Mean CH_4 Emissions (g/mi)	Mean CO_2 Emissions from Same Sample (g/mi)	GWP-Weighted Emissions CO_2E (g/mi)
LNG	Heavy-duty (HD) vehicles	Not specified	EPA (2004)	6.9	Not reported	Not available
	Transit Bus	Arterial cycle	***This study***	11.8	1,717	1,988
CNG	Garbage Truck	AQMD Compactor cycle	***This study***	9.9	1,689	1,917
	Transit Bus	Triple Length CBD	***This study***	9.5	2,495	2,714
	Buses (1999 DDC Series 50G)	CBD cycle	ERMD (2001)	16.4	2,287	2,664
	Buses (1999 DDC Series 50G)	NY BUS cycle	ERMD (2001)	54.5	5,609	6,863
	Buses	Not specified	EPA (2004)	12.4	Not reported	Not available
	HD vehicles	Not specified	EPA (2004)	9.6	Not reported	Not available
Diesel	Advanced HD vehicles	FTP cycle	Browning (2004)	0.004	1,588	1,588
	Moderate HD vehicles	FTP cycle	Browning (2004)	0.004	1,627	1,627
	Uncontrolled HD vehicles	FTP cycle	Browning (2004)	0.004	1,765	1,765

The conclusions, based on the review of literature and detailed data analysis, describes sources of uncertainty in emission factors and suggests the use of more detailed survey work and data collection. In particular, additional emissions data testing is recommended. This testing would be most effective if it is based on surveys of vehicle use and conditions across the country. These surveys can be used to clearly define emission tests that represent not only a vehicle's type and fuel but also regional driving patterns.

1. BACKGROUND

Extensive research on the comparative greenhouse gas (GHG) emissions from different *light-duty vehicles* has been conducted in the past and has resulted in a large body of emissions test data and models demonstrating the GHG emission benefits of switching from certain conventional fuels to natural gas. However, only few studies have been undertaken to examine the GHG benefits of various fuel options in different classes of *heavy duty vehicles.* Among these studies, not all emission tests have shown a uniform reduction in GHG emissions from natural gas vehicles, particularly when compared to similar diesel-fueled vehicles. This is because the high methane content of natural gas and the reduction in vehicle fuel economy of some heavy duty natural gas vehicles sometimes leads to higher *overall* GHG emissions than similar heavy duty diesel vehicles. This study attempts to improve the state of knowledge about the GHG emissions from heavy duty natural gas and diesel vehicles by examining previously unpublished carbon dioxide (CO_2) and methane (CH_4) emissions test data recorded by West Virginia University (WVU). WVU operates a mobile emissions testing laboratory which has been used for testing criteria pollutants from hundreds of heavy duty vehicles. During many of these tests, data on CO_2 and CH_4 emissions were also recorded by WVU, but were never analyzed or published, owing to the absence of regulatory control of GHGs. The DOT Center for Climate Change and Environmental Forecasting funded this study to determine whether the unpublished test results recorded by WVU could be used to develop representative or statistically meaningful CO_2 and CH_4 emission factors for different classes of heavy duty diesel and natural gas vehicles.

Improved data on GHG emissions from heavy duty natural gas vehicles would be useful for project developers, fleet decision makers, government policy makers, and industry researchers as they consider the GHG consequences along with other environmental benefits of natural gas fuel switching. Currently, GHG inventories and reduction strategies for the transportation sector are limited by the availability of emission factors, which at present are unavailable or uncertain for subclasses of natural gas heavy duty vehicles. Updated emission factors will allow for increased accuracy of emission inventories, GHG offset project benefits, and may improve current assumptions about the benefits of some heavy duty natural gas vehicle applications. More accurate emission factors are important because organizations already are implementing fuel switching projects and purchasing natural gas vehicle fleets, and claiming GHG benefits. For example, the Governor's Office of the State of Washington specifically mentioned the conversion of buses from diesel power to natural gas as an option to comply with the 2004 law requiring power plants to offset their CO_2 emissions.[5] Approximately 22 percent of all new transit bus purchases are for natural gas-fueled vehicles.[6] While the assumptions of GHG benefits of natural gas-fueled vehicles may be based on the best information publicly available today, they are highly uncertain because of a general lack of published GHG emission coefficients for heavy duty vehicles.

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[5] Office of Governor Gary Locke. "Gov. Gary Locke Signs Bills Strengthening Environmental Protection Policies," State of Washington, For Immediate Release – March 31, 2004. http://www.governor.wa.gov/press/press-view.asp?pressRelease=1573&newsType=1. Accessed 2 April 2004.

[6] The Natural Gas Vehicle Coalition. NGVC.org - About Natural Gas Vehicles – Fast Facts. http://www.ngvc.org/ngv/ngvc.nsf/bytitle/fastfacts.htm. Accessed 19 March 2004.

Natural gas vehicles have often been highlighted for their potential to reduce GHG emissions from transportation. This is primarily based on studies indicating that natural gas, including liquefied natural gas (LNG) and compressed natural gas (CNG), in light duty spark ignition engines may reduce GHG emissions by up to 20 percent when compared with similar gasoline engines.[7] However, the estimated GHG benefits of replacing diesel with natural gas in heavy duty vehicles are much more uncertain and available test data do not always show an improvement in total GHG emissions from natural gas vehicles when compared with similar conventional diesel vehicles.

Most published results of heavy duty vehicle emission tests have focused on local air pollutants, such as particulate matter (PM), nitrogen oxides (NOx), and carbon monoxide (CO), and rarely include a discussion of the GHG emissions of the vehicles examined. The few studies that addressed GHG emissions from heavy duty vehicles have focused on CO_2 emissions and excluded other potential GHGs, such as CH_4 and nitrous oxide (N_2O).[8] In the few cases where all potential GHG emissions have been discussed the conclusions are conflicting or limited.[9] As a result, GHG inventory and reporting programs have little information to use as they develop emission estimates and accounting guidance for entities reporting on the emission impacts of fuel switching in their heavy duty vehicle fleets. In 2004, EPA attempted to identify emissions factors for alternative fuel heavy duty vehicles, and concluded that "limited data exists on N_2O and CH_4 emission factors for alternative fuel vehicles, and most of this data is for older emission control technologies."[10] Similarly, the General Reporting Protocol for the California Climate Change Registry (CCAR) provides CH_4 and N_20 emission factors for different weight classes of gasoline- and diesel-fueled heavy duty vehicles, but does not provide emission factors for heavy duty natural gas and other alternative fuel vehicles.[11]

Partly owing to the limited data availability regarding the potential GHG emissions benefits from heavy-duty natural gas vehicles, some of the widely used accounting protocols for estimating and reporting GHG emissions at the corporate and/or project level assume that heavy duty natural gas vehicles lead to lower emissions. This is because some protocols focus on reporting of CO_2 only and do not require an examination of other GHGs. For example, the World Resources Institute/World Business Council for Sustainable Development (WRI/WBCSD) GHG Reporting Protocol, which has become a worldwide standard for the reporting of GHG emissions at the entity level, includes procedures for estimating CO_2 emissions from vehicle fuel switching

[7] Wang, M., *Regulated Emissions and Energy Use in Transportation (GREET)*, Argonne National Laboratory, <http://www.transportation.anl.gov/ttrdc/greet>

[8] Northeast Advanced Vehicle Consortium. Hybrid-Electric Drive Heavy-Duty Vehicle Testing Project—Final Emissions Report. February 15, 2000; and Environmental Technology Centre Emissions Research and Measurement Division, Environment Canada. Diesel and Natural Gas Urban Transit Bus Evaluation—Regulated and Speciated Emissions. ERMD Report #01-34.

[9] Gaines, Linda et. al.. Life-Cycle Analysis for Heavy Vehicles. June 1998; Verstegen, Peter. Natural Gas Vehicles and their Impact on Global Warming. European Natural Gas Vehicle Association – Issue Paper. March 1996; and Beer, Tom et. al. Fuel-Cycle Greenhouse Gas Emissions from Alternative Fuels in Australian Heavy Vehicles. *Atmospheric Environment* 36 (2000) 753-763.

[10] U.S. Environmental Protection Agency. *2003 Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2001*, EPA430-R-03-004. 2003.

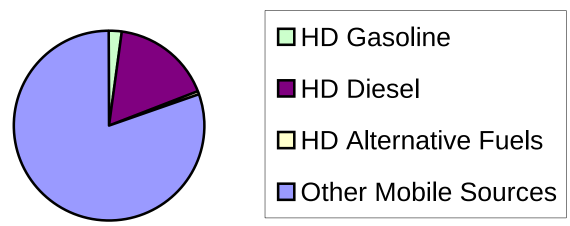
[11] California Climate Action Registry, General Reporting Protocol, Version 2.0, October 2003

projects, but does not address CH_4.[12] As a result, reporters using the WRI/WBCSD GHG Protocol for estimating the emission benefits of switching from diesel to natural gas heavy-duty vehicles may end up reporting higher estimated GHG emission reductions than actually achieved. Increased availability of test results and emission factors could help guide policy makers as they consider relevant options for reducing GHG emissions from the transportation sector and could serve as useful background information for improving the accuracy of existing GHG reporting and accounting tools.

1.1 Transportation GHG Emissions

GHG emissions data and inventories associated with transportation systems are important because of the increasingly large share of overall anthropogenic GHG emissions from mobile source combustion and its relative contribution to global climate change. At 1,770.4 million metric tons of CO_2 equivalent in 2003, mobile sources account for approximately one third of overall U.S. GHG emissions, and heavy duty vehicles emit roughly 20 percent of mobile source emissions (Figure 1).[13]

Figure 1. Heavy Duty Vehicles Share of Total GHG Emissions from Mobile Sources (Tg CO_2 E)



The GHGs most closely identified with the transportation sector include CO_2, N_2O and CH_4.[14] CO_2 contributes the largest share of these GHG emissions, typically resulting in 85 percent of lifecycle emissions from conventional gasoline light-duty vehicles and about two thirds of total lifecycle emissions of light-duty natural gas vehicles.[15] CO_2 emissions are easy to estimate, because CO_2 is directly related to the carbon content of each fuel and thus the quantity of fuel consumed. Most fleet operators already track fuel consumption as part of their financial operations and can therefore quickly apply this data to existing fuel-specific emission factors to estimate CO_2 emissions.

Combustion emissions of CH_4 and N_2O are less directly related to fuel composition as they also depend on the combustion dynamics and emission control technologies of the vehicle. CH_4 and N_2O emissions can therefore not be easily derived and instead must be determined through use of published emission factors for each combination of fuel, end-use technology, combustion

[12] World Resources Institute (WRI)/World Business Council for Sustainable Development (WBCSD). “Calculating CO2 Emissions from Mobile Sources—Guidance to Calculation Worksheets” from the GHG Protocol – Mobile Guide. July 15, 2002.
[13] U.S. Environmental Protection Agency. *Inventory of U.S. Greenhouse Gas Emissions and Sinks*. (EPA 430-R-05-003), Washington, DC., 2005. Note: Alternative fuels account for less than one percent of total heavy duty vehicle emissions.
[14] Mobile emission sources include not only GHGs, but also significant quantities of other local, regulated air pollutants, such as PM, NOx, and CO. Most published results of heavy duty vehicle emission tests have focused on these local air pollutants. This study addresses this gap in published literature by focusing on GHG emissions, which are less well understood than the local air pollutants.
[15] Timothy Lipman and Mark A. Delucchi, “Emissions of Nitrous Oxide and Methane form Conventional and Alternative Fuel Motor Vehicles,” *Climatic Change*, 53: 477-516, 2002

conditions, and emissions control system. For this reason, CH_4 and N_2O emission factors are typically expressed in terms of mass of compound emitted per distance traveled, and the preferred method of calculating these emissions is based on mileage.

Per unit of energy, natural gas contains less carbon than either motor gasoline or diesel fuel,[16] and therefore is often assumed to produce fewer CO_2 emissions per vehicle distance traveled. Although this is generally the case when natural gas vehicles are compared with gasoline vehicles, this is not always true when compared with diesel, which is the most widely used fuel for heavy duty vehicles. While natural gas-fueled engines offer significant reductions in regulated emissions (i.e., SO_2, PM), they tend to show reduced efficiency and greater equivalent fuel consumption when compared to diesel engines. Due to engine throttling losses under part load operation and greater vehicle weight, heavy duty natural gas vehicles often have a poorer fuel economy on urban driving cycles, canceling out some of the CO_2 benefits gained from using a low carbon content fuel.[17] As a result, depending on the drive cycle, using natural gas instead of diesel in heavy duty vehicles may not provide substantial GHG emission benefits and may even increase emissions in some instances. CH_4 is a potent GHG, with a global warming potential 23 times[18] higher than that of CO_2, and should be addressed in any study comparing the GHG emission impacts of different vehicle fuel types. This is particularly important for vehicles operating on natural gas because of the high methane content of this fuel. N_2O emissions have a higher global warming potential[19] relative to CO_2 and CH_4 but are less important for comparing diesel and natural gas-fueled heavy duty vehicles. N_2O emissions are understood to be largely a function of the catalytic converter used for emission control, and it is expected that comparable diesel and natural gas heavy duty vehicles would have similar emissions control technologies installed.[20]

1.2 GHG Emission Factors

A GHG emission factor is a factor that relates activity data and absolute GHG emissions to estimate emissions from specific activities. CO_2 emission factors for mobile sources are typically presented in terms of grams per unit of energy consumed because this "mass-balance" method is the most accurate approach available for estimating CO_2 emissions. As mentioned in Section 1.1, CH_4 and N_2O emission factors are presented in terms of distance traveled to capture differences caused by combustion dynamics and emission control technologies. Because CH_4 and N_2O have not been regulated in the past, emission test data are limited and representative emission factors are not available for all vehicle types and fuels.

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[16] U.S. Department of Energy, Energy Information Administration, *Documentation for Emissions of Greenhouse Gases in the United States 2002*, Table 6-1. DOE/EIA-0638(2002). Washington D.C., January 2004.

[17] The reductions in efficiency for natural gas engines are greatest under part load conditions, primarily due to throttling losses. Throttling at light loads with engines burning homogeneous fuel-air mixtures requires reducing the fuel flow rate. However, the 'leaning out' of the mixture results in the engine approaching its lean limit; hence, the engine misfires.

[18] The IPCC's Third Assessment Report (TAR) identifies the GWP of CH_4 as 23 rather than the 21 found in the Second Assessment Report. In this study, we use 23, as reported in the TAR.

[19] The Global Warming Potential (GWP) of a GHG is the ratio of global warming, or radiative forcing (both direct and indirect), from one unit mass of a GHG to one unit mass of CO_2 over a period of time.

[20] U.S. Environmental Protection Agency. *2003 Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2001*, EPA430-R-03-004. 2003.

For the development of national or regional GHG inventories, the Intergovernmental Panel on Climate Change (2005) recommends that emission factors per distance traveled be developed based on estimates of cold start emissions and running emissions and data on the average number of vehicle starts and distance traveled per day for a specific demographic (e.g., national average). Because emission test laboratories undertake vehicle testing in response to a variety of research objectives, which may not include the development of emission factors, they do not always perform cold start emission testing. The resulting inconsistencies in emission factor development may impede comparison of emission factors across vehicle fuels and technology type.

1.3 WVU Emissions Test Data

To improve the understanding of the potential emissions impact of heavy duty natural gas and diesel vehicles, SAIC and WVU extracted, organized, and evaluated emissions data recorded by WVU over the past 14 years during the testing of hundreds of heavy duty vehicles over thousands of test runs at the university's mobile emissions testing laboratories. The existing WVU tests were undertaken mainly to examine mass emission rates of local air pollutants, such as PM, NOx, CO, and total hydrocarbons (THC), and to make the results of these tests publicly available. Although typically not analyzed or published, many of WVU's heavy duty vehicle emission tests also measured emissions of CO_2 and CH_4.

Some records in the database contain data on both CO_2 and CH_4; other records contain only CO_2 data. Although the test dates go back as far as March 1992, CH_4 data were not collected until July 1996 for natural gas-fueled vehicles. WVU did not measure or record data on CH_4 emissions from any heavy duty diesel vehicles because such vehicles emit CH_4 in minimal quantities.[21] N_2O data were not collected by the WVU mobile emissions lab, so no N_2O emissions data are available for this analysis.

The WVU emissions database contained CO_2 and CH_4 emissions data in units of grams per mile and grams per cycle. The tests were based on laboratory test values for heavy duty vehicle running emissions over specific transient drive cycles that include accelerations and decelerations, but not cold starts. For light duty vehicles, chassis dynamometer tests are normally conducted for regulatory purposes (i.e., certification) and therefore include both hot and cold start testing. However, in the case of heavy duty vehicles, chassis dynamometer testing is not done for regulatory purposes, and therefore typically does not include cold start testing unless specifically requested by the user.

WVU recorded 4,351 emissions tests performed on 1,095 heavy duty vehicles, using the following variables to describe each emission value:

1. Identification Variables
    a. Test identification number
    b. Test run identification number

[21] Studies of heavy-duty vehicles have shown CH_4 emissions to generally be below 10 mg/mi, and near background levels compared with total hydrocarbons (THC). Source: Durbin (2004).

2. Classification Variables
    a. Cycle full name
    b. Vehicle Type
    c. Primary Fuel
    d. Catalytic Converter Model
    e. Engine Displacement
    f. Engine Model Year
    g. Odometer Reading (mi)
    h. Gross Vehicle Weight (lb)
    i. Number Of Axles
    j. Number Of Cylinders
    k. Vehicle Model Year
    l. Vehicle Transmission Configuration
    m. Vehicle Transmission Type
    n. Turbo
3. Data Values
    a. CO_2 (g/cycle)
    b. CO_2 (g/mi)
    c. CH_4 (g/cycle)
    d. CH_4 (g/mi)

The data analyzed cover a broad selection of heavy duty vehicle types and engine technologies, ranging from urban trucks, school buses, and tractor trailers. The fuel types tested include two grades of on- and off-road diesel fuel (D1 and D2), CNG, and LNG. No other transportation fuel types, such as LPG, were tested for heavy duty vehicles.

2. DATA AND ANALYSIS

SAIC reviewed a broad scope of literature to develop the analytic approach to the research. The review included past studies of emissions from road vehicles and sources of emission factor uncertainty, such as differences in data collection procedures, tested vehicles, and engine technologies. The review included the following studies:

- Austin, et al (1997)
- Bishop, Stedman, and Ashbaugh (1996)
- Browning (2004)
- Durbin (2004)
- EPA (1997)
- EPA (2004)
- ERMD (2001)
- Frey, Zheng, and Unal (1999)
- Gillenwater (2004)
- Holmén and Niemeier (1998)
- IPCC/UNEP/OECD/IEA (1997)
- Knepper, et al (1993)

- Lawson, et al (1990)
- Lipman and Delucchi (2002)
- McClintock (1999)
- Singer and Harley (1996)
- Stedman, et al (1997
- Wenzel, Singer, and Slott (2000)
- Zhang, Bishop, and Stedman (1994)

The literature review focused on two aspects:

(1) The specific data categories that would be useful for grouping and analyzing the heavy-duty vehicles emissions data, and
(2) Statistical issues and analytic methods associated with vehicle emissions data.

After completing the literature review, a research strategy was developed to analyze the emission test data collected at WVU's mobile testing facility. The results of the literature review are summarized below.

2.1 Data Categories

This research required us to determine for which data categories there would be enough data to develop statistically robust results and meaningful emission factors. The development of data classes began by identifying the broadest subsets of heavy-duty vehicles, starting with fuel type. We then evaluated each fuel type subset, vehicle type, and drive cycle. The following paragraphs review past findings regarding each of these data groupings and summarize how WVU's database reflects each category.

Fuel type

CO_2 emissions from vehicles are primarily dependent on the carbon content of the fuel consumed,[22] and CO_2 emissions per mile are a function of the same factors that influence fuel economy (e.g., fuel type, engine design, condition, and load, vehicle weight, drive cycle). For CH_4, some of the factors that influence emission rates are different from those that affect CO_2. CH_4 emissions from motor vehicles are a function of the type of fuel used; the type, condition, and age of the engine; the type, condition, and age of emissions control technology; and the drive cycle.[23]

Because of these differences across fuels, the IPCC recommends that national inventories of emissions from mobile sources be developed, at a minimum, based on fuel consumption estimates sorted according to fuel type. If additional data are available, emissions should also be estimated based on vehicle and control technology type.[24]

[22] IPCC/UNEP/OECD/IEA (1997).
[23] Lipman and Delucchi (2002); Gillenwater (2004).
[24] IPCC/UNEP/OECD/IEA (1997).

Following this guidance, the WVU data was grouped as follows:[25]

- CNG
- LNG
- Diesel (D1 and D2)

Of the 1,095 vehicles tested, 601 used CNG or LNG as primary fuel, and 494 used diesel fuel. Of the emissions tests, WVU conducted 2,283 on natural gas-fueled (CNG or LNG) vehicles and 2,068 on diesel-fueled (D1 or D2) vehicles. Of the 2,283 emissions data records for heavy duty vehicles using natural gas, 646 represent tests on LNG-fueled vehicles and 1,636 on CNG-fueled vehicles. Table 1 presents the range and average number of tests conducted on vehicles of each fuel type. Table 2 summarizes the emissions data that WVU collected by GHG and vehicle fuel type.

Table 1. Range and Average Number of Tests per Vehicle

Fuel Type	Maximum Tests for a Given Vehicle	Mean Tests per Vehicle
CNG	13	4.01
LNG	12	3.34
Diesel (D1 and D2)	14	4.18

Table 2. Emissions Data Type per Vehicle Fuel Type

Data Collected per Emissions Test	LNG	CNG	Diesel
Contains CO_2 and CH_4 data	475	727	--
Contains CO_2 data only	168	826	2,283
Contains CO_2 data and some CH_4 data	3	83	--

Drive cycle

The drive cycle is a testing procedure developed to compare engines and their emissions under identical preparation and operating conditions. A drive cycle (also called driving cycle) is a standardized driving pattern that specifies ambient temperature, vehicle load, and the time and distance of operation at various speeds.[26] The Federal Test Procedure (FTP),[27] for example, is a common drive cycle defined in the Code of Federal Regulations pursuant to the Clean Air Act Amendments of 1970 to represent combined highway and city driving in urban Los Angeles.[28] Browning (2004) recently developed vehicle emission factors based on the FTP.

The drive cycle is expected to affect emissions per mile of CO_2 and CH_4, although the effects may be quite different for each gas. Wenzel, Singer, and Slott state that "emissions of most vehicles will vary substantially with environmental and driving conditions."[29] Lipman and

[25] The WVU data set, which is the basis of this research, includes CNG-, LNG-, and diesel-fueled vehicles. Diesel is the most common fuel type in heavy duty vehicles. Although not evaluated in this analysis, other conventional and alternative fuel types, including gasoline and liquefied petroleum gas (LPG), are used in heavy duty vehicles.
[26] Wenzel, Singer, and Slott (2000).
[27] Browning (2004).
[28] Wenzel, Singer, and Slott (2000).
[29] Wenzel, Singer, and Slott (2000).

Delucchi report that CH_4 emissions from natural gas-fueled, light-duty vehicles depend on drive cycle. Gillenwater states that CH_4 emissions from road transport are a function of many variables including driving practices. Durbin, in a peer review of Browning (2004) suggests that future research should consider the potential effects of other parameters, including driving cycle and vehicle mileage/age, on CH_4 and N_2O[30] emissions.[31] As a result, all drive cycles for which WVU data were available were included in subsequent analysis in attempt to correlate emissions with test parameters.

Each WVU data record reflects emissions from a vehicle tested by a chassis dynamometer on one of 36 different driving cycles, which are listed in Table 3. The name of each driving cycle (e.g., Central Business District Cycle) generally describes the test case it is intended to simulate. The laboratory dynamometer measures emissions as the vehicle is operated over a specified driving cycle, which is intended to represent the on-road driving conditions for a certain test case and allow for repeatable conditions, such as ambient temperature, acceleration, deceleration, steady state for that test case. The WVU data, summarized in Table 3, indicate that for each driving cycle, both the duration and distance were fixed. For some vehicles, emissions were measured at varied vehicle test weights, a parameter intended to simulate load. Other vehicles were tested only once, or the vehicle test weight was held constant.

Table 3. Driving Cycle Test Conditions

Driving Cycle	Duration Time (Seconds)	Driving Distance (Mile)	Vehicle Test Weight (lbs)		
			Minimum	Maximum	Mean
14 Peak Route	568	2.01	33200	33200	33200
AQMD Compactor Cycle	800	6.83	40600	42000	41300
AQMD Refuse Truck Cycle Extended C	2129	6.79	40600	42000	41300
Arterial Cycle	291.5	2	21300	35210	29574
Background Cycle	1800	0	35800	56000	45900
Business Arterial Cycle	855	2.65	38514	42000	40171
CARB HHDDT Transient Mode	688	2.85	42000	42000	42000
Central Business District Cycle	568	2	11300	45750	31715
Central Business District Route	568	2.44	33200	33200	33200
City Suburban Route	1710	6.67	12600	60400	38733
Cold Start Extended CBD Cycle	2930	10.06	18975	18975	18975
Cold Start William H. Martin Cycle	1298.1	3.82	42000	42000	42000
Commute Cycle	329.5	55	31675	31675	31675
Double New York Garbage Truck Cycle	1170	0.784	40600	40600	40600
Double Test D with Warmup	2122.2	15.58	36400	36400	36400
Double WHM Cycle	2596.2	12.49	42000	42000	42000
Idle State Cycle	900.1	0	12600	56000	33933
Lug Down	0	0	60000	60000	60000
Manhattan	1089.1	2.35	32775	34925	34031
Modified WVU Truck Cycle (Route)	900	5	17914	42000	29935

[30] Light- and heavy-duty vehicles emit N_2O in addition to other GHGs (i.e., CH_4 and CO_2) and local air pollutants (e.g., CO, NOx, and PM). N_2O emissions data were not collected by WVU and therefore were not available in the data set for analysis.
[31] Durbin (2004).

Morgantown On-road Cycle	2806.1	20.33	60400	60400	60400
NYC Street Sweeper Cycle	1800	3.38	25320	26886	26103
New York Bus Cycle	600	0.615	22325	37495	31553
New York Composite Cycle	1029	2.52	19500	37495	30275
New York Garbage Truck Cycle	585	0.374	42000	42000	42000
New York Truck Cycle	1016	2.14	13946	19280	16613
Orange County Transit Authority Bu	1950	6.54	32775	34775	33775
Orange County Transit Authority Cy	3859.6	14	26670	26670	26670
Quadruple CBD	0	0	35800	35800	35800
Route22	530	2.05	22325	37495	32885
Route77	860	4	35820	35899	35860
Steady State Cycle – 20MPH	900.1	5	17914	33200	25557
Steady State Cycle – 30MPH	900.1	7.5	17914	17914	17914
Steady State Cycle – 40MPH	900.1	10	37495	42000	39748
Triple Length CBD	1136	6.03	18975	42000	33413
UDDS	1060	5.54	28531	56000	37689
Unknown			25000	60000	40462
Viking Freight Adhoc Cycle	1888.6	19.09	36400	36400	36400
WHM Cycle	1298.1	6.17	42000	42000	42000
WVU Truck Cycle (5 Peak)	900.2	5	18000	42000	32347
Washington DC Metro Transit Bus Cy	1839	4.25	34700	36450	35763

Each of the more than 4,000 WVU data records reflects emissions from a vehicle tested on one of 36 different driving cycles. Preliminary data analysis based on fuel type groupings without consideration of drive cycle indicate a very large range in emissions from any given fuel type and large deviations from the mean. However, when specific drive cycles are isolated, meaningful trends were observed. For example, transit bus emissions data collected by WVU show that CO_2 emissions are higher for diesel fueled- than for natural gas-fueled engines on the Central Business District (CBD) cycle (refer to Figures 2 and 3). This is because the rapid accelerations from idle to 20 mph, as demanded by the cycle, result in high loads on the engine, which result in better fuel economy for the natural gas engine. However, in tests using the WVU Truck Cycle, which is characterized by lighter loads and lower accelerations, the diesel engine provides better fuel economy, that is, lower CO_2 emissions.

Figure 2. Comparison of CO_2 Emissions from Diesel and CNG Engines on Central Business District Cycle

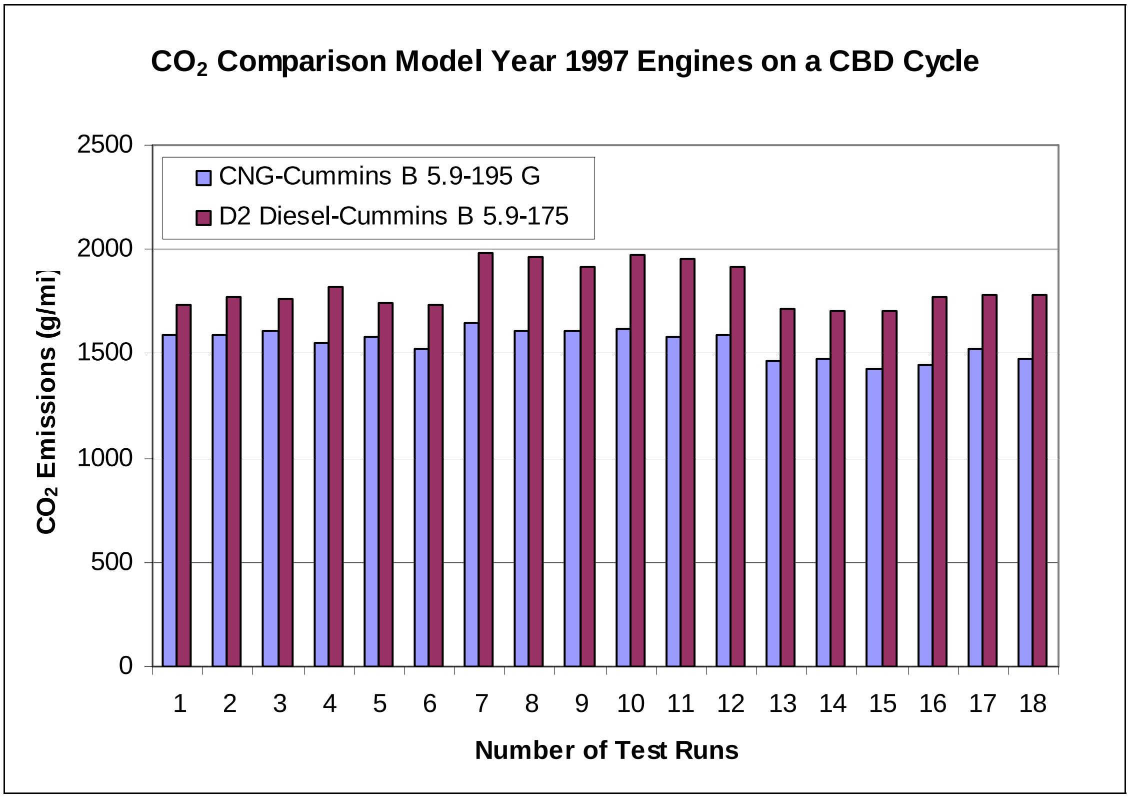
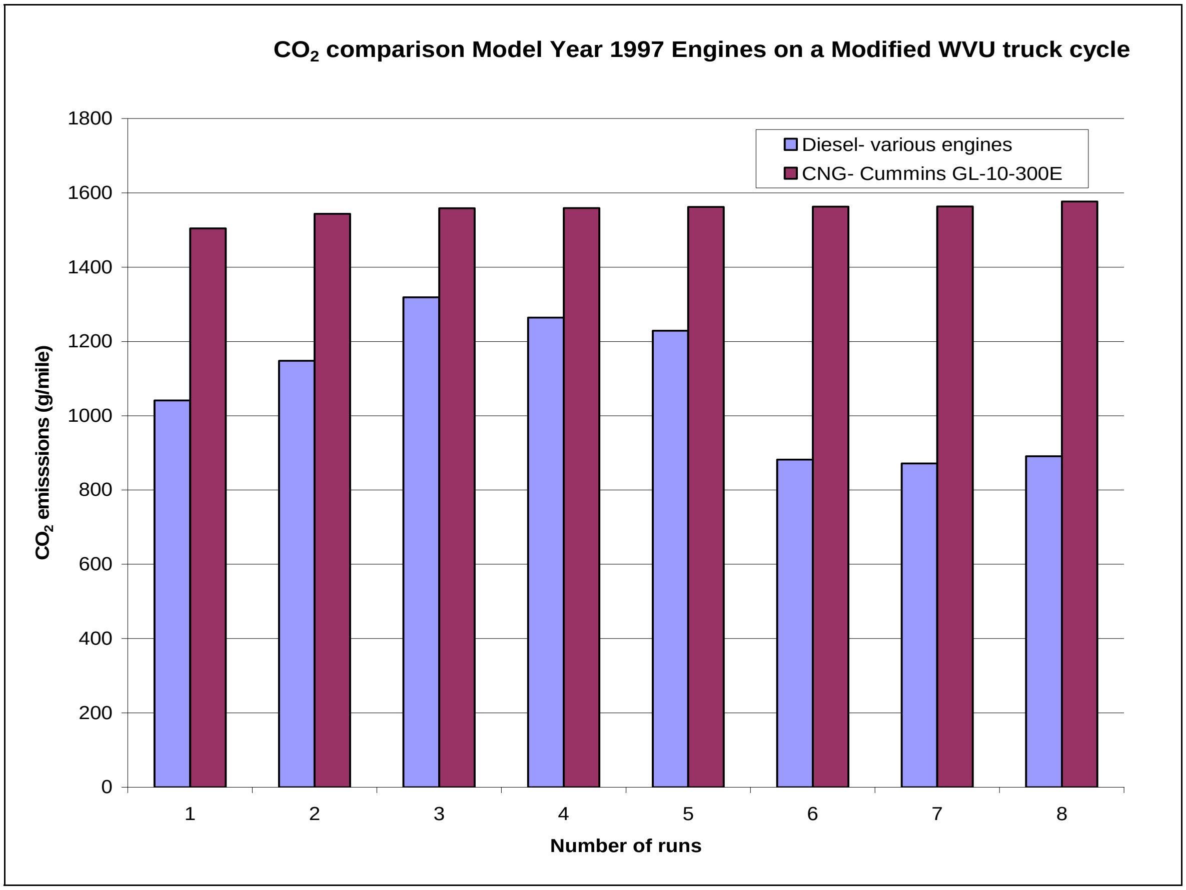


Figure 3. Comparison of CO_2 Emissions from Diesel and CNG Engines on WVU Truck Cycle



The WVU database contains emissions data from tests using several drive cycles representing the unique street network and traffic conditions of New York City (e.g., Manhattan; New York Bus Cycle; NYC Street Sweeper Cycle), in addition to other drive cycles. Emissions from vehicles tested on the New York drive cycles are typically greater than those from vehicles tested on a drive cycle developed to represent less severe driving conditions, such as in Morgantown, West Virginia.

The WVU database also includes emissions data based on an “unknown” cycle, and other drive cycles that appear to produce data outliers. For example, some emissions data based on the “Background Cycle” are orders of magnitude larger than other emissions. Rather than a drive cycle, the Background Cycle was found to be a “dummy” cycle used to operate all of the necessary emissions measurement equipment to gather background emissions data prior to and following a set of tests. To ensure impartial analysis, we used a systematic approach to objectively evaluate these and other potential outliers.

Vehicle Type

Vehicle weight and operating conditions, which can characterize a vehicle type, are expected to affect CH_4 and CO_2 emissions per mile. Emission factors disaggregated by vehicle type are therefore beneficial to developers of GHG emission inventories and mitigation projects. For example, in the first step in the methodology for estimating CH_4 and N_2O emissions from mobile combustion, EPA determines vehicle miles traveled by vehicle type, fuel type, and model year (used as a proxy for control technology type).[32] The IPCC guidelines also recommend that national inventories of emissions from mobile sources be developed based on fuel consumption estimates by fuel type at a minimum and by vehicle and control technology type if data are available.[33] However, it is important to note that very few emissions tests were performed on certain vehicle types, particularly heavy duty vehicles, and IPCC recommendations therefore represent the *preferred* option in most cases, but not necessarily the most *practical* option.

Table 4 presents sample frequency of data for each fuel and vehicle type tested by WVU This table shows that only three vehicle types, specifically transit bus, tractor truck, and trash truck, were sampled using all fuel types – diesel, CNG, and LNG.

Table 4. Sample Frequency and Relative Frequency of Data for Each Fuel Type per Vehicle Type

Vehicle Type	Fuel Type	Count
Articulating Transit Bus	D1	36
	D2	4
Bus	CNG	34
Chassis Bus	CNG	118
Experimental Transit Bus	CNG	37
Hybrid Bus	CNG	6
School Bus	CNG	149
	D2	21
Tour Bus	CNG	8
Transit Bus	CNG	732
	D1	484
	D2	780
	LNG	288
Trolley Bus	CNG	25
	D2	4
Box Truck	D2	3
Dump Truck	D1	10
	D2	4
Garbage Truck	CNG	70
	LNG	151
Parcel Delivery Truck	CNG	12
Pick-up Truck	D2	1
Refuse Truck	CNG	362

32 EPA (2004).
33 IPCC/UNEP/OECD/IEA (1997).

	D1	87
	D2	109
	LNG	80
Snow Plow Truck	D1	28
	D2	6
Street Sweeper	CNG	6
	D2	6
Suburban	D2	55
Tanker Truck	D1	9
	D2	7
Tire Truck	CNG	11
	D1	9
	D2	22
Tractor	CNG	22
Tractor Truck	CNG	45
	D1	13
	D2	370
	LNG	127

Model Year

Emissions control technologies, which can be assumed based on vehicle model year, are known to influence CH_4 emissions from light- and heavy-duty gasoline- and diesel-fueled vehicles.[34] However, in this study, it was not possible to group and analyze CH_4 emissions data based on vehicle model year because of the limited number of data for each vehicle type/drive cycle/fuel type category.

Data Cleaning

The procedure to clean and prepare the data included a combination of initial exploration using standard spreadsheet software and further review using statistical software. A simple point and click approach was used to explore and clean the data. Data cleaning resulted in a reduction of data points from 4,351 to 3,602 tests. The cases in which data were deleted are outlined as follows:

1. Deleted observations with blank odometer readings;
2. All buses are grouped as transit buses except for school buses;
3. Deleted background cycle tests; and
4. Deleted unknown driving cycle tests.

The remaining 3,602 observations include diesel-, CNG-, and LNG-fueled vehicles of many types, ages, and technologies, and many different drive cycles. Because of the high number of variables in the database, the number of tests for any given vehicle, technology type, fuel type

[34] IPCC/UNEP/OECD/IEA (1997); Lipman and Delucchi (2002); EPA (2004); Gillenwater (2004).

and drive cycle were very limited. However, the existing data provides interesting insight on what prompts considerable change on the absolute value of emission factors.

2.2 Literature on Statistical Issues and Analytic Methods

A literature review was conducted to identify statistical issues and analytical methods associated with the development of emission factors for mobile sources. However, past statistical analyses of GHG emissions from mobile sources are limited. Wenzel, et al (2000), identifies a potential source of bias that stems from how, why and by whom data are collected. Sample bias could be reflected by a normal distribution. Wenzel, et al suggest that normally distributed vehicle emission test samples are "normal" because they lack any real-world variability. Bishop, et al (1996); Wenzel, et al (2000); Zhang, et al (1994); and Frey, et al (1999) note that emission test result samples typically are highly skewed and show high kurtosis values, hinting chi distributions. This means that there is typically a lack of symmetry in the distribution of the emission data analyzed and that observations for each sub-category are skewed in one direction. Skewed data make it difficult to derive statistically meaningful emission factors. Additionally, Bishop, et al (1996) concludes that most volatility, or the degree of fluctuation in each variable analyzed, is attributable to the vehicle type, its condition and driving conditions, such as use and the general environment, and not to the testing method.

Bishop, et al (1996) indicates that there are two types of outliers in vehicle emissions data specifically related to high emitters and suggests a test that can be used to identify outlier observations in emissions data sets. According to Bishop, et al, random-shock high emitters are those vehicles that emit considerably different pollutant values, randomly increased or decreased, within alternative tests undertaken on the same driving cycle. In most cases, this is due to undetected malfunctions in the vehicle. Another category of outliers can be attributed to vehicles with increasingly higher emissions over time, which indicates "trend plus drift" processes. Such high emitters signal the natural decay of a vehicle. Older vehicles have a tendency to produce more pollutants due to vehicle engine and emissions system degradation over time. Moreover, newer, cleaner technologies are more susceptible to random-shock high emitter behavior due to their inherited reliance on additional equipment. The latter of the two outlier types can be detected by monitoring control variables such as odometer readings and any supplemental information from the sponsor (e.g., vehicle care). Bishop, et al, outlines a test to detect the former by analyzing consecutive emissions data for the same vehicle under the same drive cycle (characteristics).

The analytical approach was developed with consideration of the findings of the literature review. Specifically, the statistical analysis focused on reviewing the sample selection processes to identify potential test selection bias, and identifying the skewness and volatility in the dataset to determine which WVU's emission test results can be used to develop statistically meaningful emission factors for each subcategory outlined in Section 2.1. This was accomplished by analyzing the variance in vehicle emissions data and by selecting and reviewing alternative sample subgroups of the database. Skewness and kurtosis measures were analyzed to identify potentially useful sub-groups, and the results are presented in scatter plots of kurtosis versus skewness. An outlier analysis was conducted and the skewness and kurtosis measures were reanalyzed. Further discussion of the analytic approach is below, followed by a presentation of the estimated emission factors derived from the dataset and a discussion of which of these are statistically meaningful.

2.3 Analytical Approach

Univariate analysis of potential data classes, as suggested by Browning (2004), was used to estimate candidate emission factors.[35] Univariate analysis is a data analysis methodology that considers only one factor or variable at a time - the analysis of single variables as distinct from relationships among variables. The univariate analysis tools were applied to subsets of measured data to see if different data subsets generate significantly different emission factors. Control variables such as fuel type were used to define such subsets. The potential identification of significantly different emission factors would inform us about two important characteristics of the variance in emissions tests:

- Information about the chosen control variables can explain the volatility in emission factors, and;
- As a result, multivariate analysis tools could be used to parameterize (measure) how control variables influence emission factors.

In other words, the univariate analysis was used to determine if enough information is available to describe how emission factors change when variables, such as vehicle type, are considered.

Additional analytical methods were also used to evaluate WVU's emissions data, such as interactive outlier analysis to review estimate robustness. If certain outliers were determined to be indicative of an error or an anomaly not representative of the population, they were eliminated and estimates recomputed.

Emission Factor Volatility and the Source of Bias

The analysis included an investigation of emission factor intra- and inter-temporal volatility and the source of bias. Average emission results of a subject test (a vehicle) can show two forms of volatility; random and a mean with drift. Several potential sources of bias in vehicle emissions tests can lead to volatility, including the vehicles and the vehicle survey process. The vehicle selection process could create so much bias in an observed emission factor that it could be deemed useless for representing real-world emissions. Outlier detection processes suggested by Bishop, et al (1996) were used to refine possible emission factors.

To evaluate potential test selection bias, understand the context of the tests, and interpret any possible bias, the WVU test sponsors objectives and purpose for the emissions testing were reviewed, including the mix of sponsors. The potential impact of test selection bias, such as the observation of a "normal" but not representative population distribution, is suggested by Wenzel, et al (2000). The following questions were thus examined:

[35] Browning (2004).

1. Who were the public or private sponsors of the emissions tests? If proprietary, how many unique public and private sponsors are associated with the emissions data?
2. Was there a defined purpose of the sponsorship(s) (e.g., for academic research and learning, to improve emissions inventories, to compare emissions from different fleet vehicles, to compare emissions from different fuel types)? For example, the CRC E55/59 study had multiple sponsors (i.e., CARB, CRC, NREL, EMA, SCAQMD, and EPA) and a stated objective (i.e., to improve the on-road vehicle emissions inventory of regulated pollutants from diesel engines; generate emission factors; improve source profiles).
3. How were the vehicles recruited by WVU? Is it possible to connect each individual test to the appropriate data collection method? Alternatively, is it possible to use a reference proxy to establish some relationship between test groups and data collection methods?
4. Are there any rewards or punishments for complying or not complying? For example:
    - Did WVU or any of the tests sponsors provided some reward from having the vehicles tested?
    - Did any of the sponsors threaten test candidates if they failed to report to the test site?
    - Was there a sense, from the test candidate's perspective, that the emissions test's outcome would carry any positive or negative consequence?
5. Was the vehicle's condition a factor in determining if the vehicle should be tested or not, and/or was the vehicle fixed before the test was made?

WVU reported that emissions data were collected over a 15-year period from 1989 to 2004. WVU populated the database with the results of 49 separate projects sponsored by 33 unique organizations and collaboratives. WVU identified and associated each sponsor and project with one or more objective for the vehicle emissions testing conducted by WVU using their mobile emissions testing laboratory. Just a few examples of sponsoring organizations include:

- U.S. Department of Energy;
- National Renewable Energy Laboratory;
- South Coast Air Quality Management District;
- North Carolina Department of Transportation; and
- Undisclosed private sponsors

Each project had one or more of the following six objectives:

1. Emissions Evaluation;
2. Engine Technology Evaluation;
3. Exhaust After-treatment System Evaluation (Emissions Related);
4. PM Sizing;
5. Emissions Inventory; and/or
6. Repair/Maintenance Related Issues.

The research into the sponsors' purpose for the emission tests suggests that the test results may not be representative of the U.S. vehicle population as a whole. To the extent that these tests where tailored to the sponsors' specific needs, the less representative these tests will be of the population. For example, while a test to determine the emissions inventory of a sponsor's fleet (objective 5) may provide a representative factor for that fleet, the fleet and their characteristics may not be representative of other similar vehicles on different roads, cities, and driving patterns.

Based on the analysis of test selection bias, we further tested the underlying properties of the available data. Alternative skewness and kurtosis measures were reviewed to shed light into the distribution of each vehicle population. Zhang, et al (1994) suggests simple rules of thumb to determine a population distribution:

- A normal distribution has skewness and kurtosis values of zero.[36]
- An exponential distribution has skewness and kurtosis values of one.
- A chi distribution has correlated skewness and kurtosis values (i.e., same value and sign).
- Skewness and kurtosis values of different signs do not represent a distribution and they are said to represent white noise.

Statistical Methodology

Alternative sample subgroups of the database were reviewed for skewness and kurtosis values. The estimated skewness and kurtosis measures for CO_2 and CH_4 emissions data are presented in Figures 4 and 5, respectively. We assume that the distribution of CO_2 and CH_4 can be expected to display the same distribution characteristics as local air pollutants studied in the literature, which is consistent with Zhang, et al. Figures 4 and 5 contain scatter plots of skewness and kurtosis measures for 76 and 40 unit random samples within the database subset as described in Zhang, et al.[37]

[36] The kurtosis for a standard normal distribution is 3, but is normalized to zero.
[37] Zhang plots skewness and kurtosis measures for more than 60,000 emission tests and obtains 45 degree plots. Additionally, he plots skewness and kurtosis measures against time and shows how volatility augments with technology.

Figure 4. Kurtosis Versus Skewness of CO_2 Emissions Data to Test for Chi Distribution of Vehicle Emissions

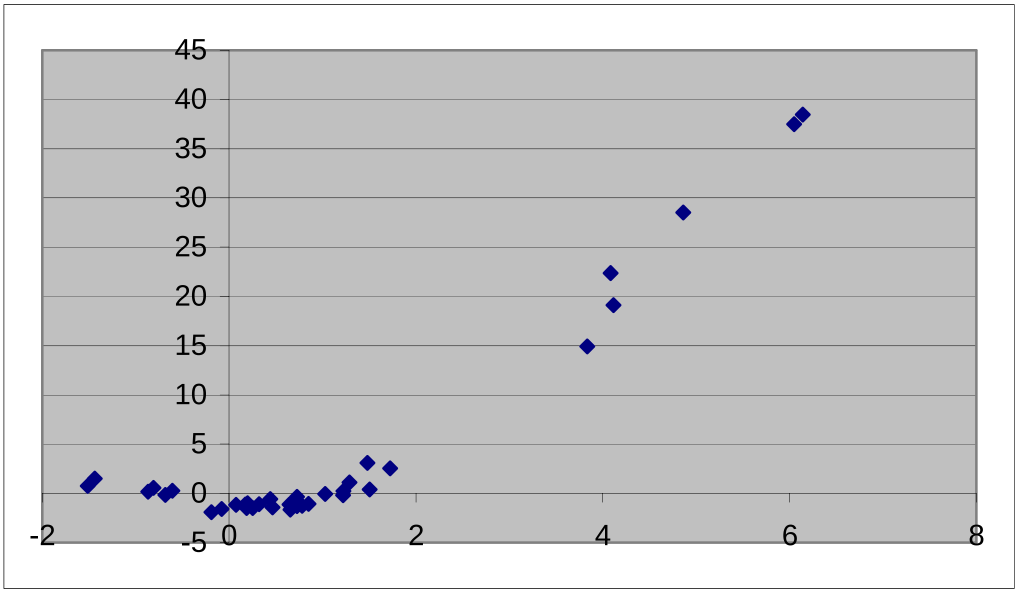
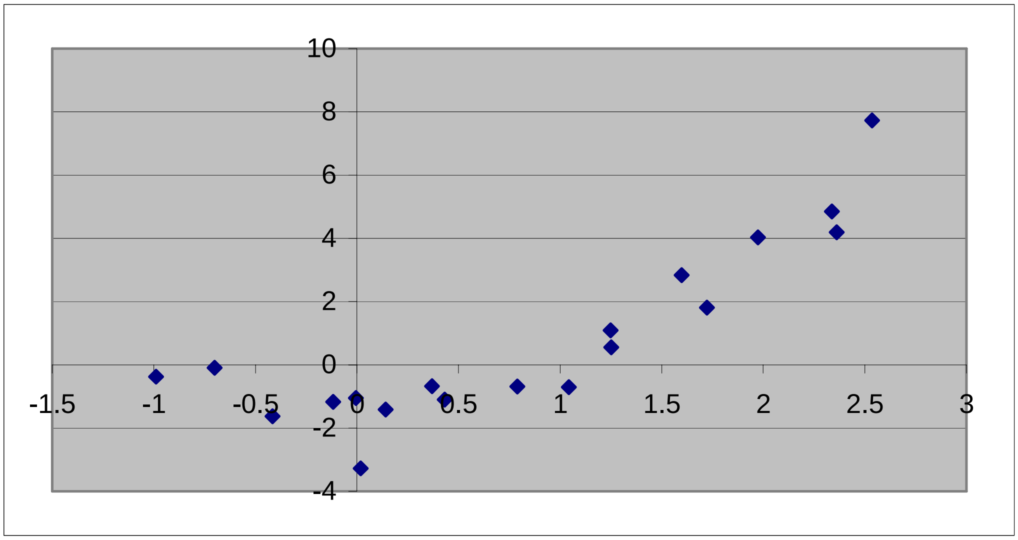


Figure 5. Kurtosis Versus Skewness of CH_4 Emissions Data to Test for Chi Distribution of Vehicle Emission



The skewness and kurtosis tests were repeated for each variable/subcategy identified for analysis in Section 2.1, including fuel type, vehicle type, driving cycle, and vehicle model year. The figures show that the skewness and kurtosis measures are not equal since the data in the scatter plots do not fall in the 45-degree line. These results were similar for every variable identified as a focus of analysis. Moreover, plots of skewness and kurtosis measures against time show no correlation between volatility and technology.

Outlier Analysis

The outlier analysis test selected the 25th and 75th percentile of each vehicle emissions values for which four or more tests were taken. Any set of observations with at least one emission value larger or smaller than the 25th or 75th percentiles was deleted from the sample. Using these tools, we identified 153 outliers in the WVU data set. The outlying observations were deleted and the distribution tests for skewness and kurtosis were recomputed. However, the robustness of the resulting emission factors did not improve significantly and use of this tool to eliminate outliers did not change the underlying conclusions of this report.

3. RESULTS AND CONCLUSIONS

The WVU data are insufficient to draw universal conclusions about the emission benefits of natural gas relative to diesel in heavy duty vehicles because WVU database does not have enough emission test data for similar subcategories of diesel and natural gas vehicles to enable a comparison across fuel types. Moreover, a review of the population distribution within each vehicle subcategory indicates that most emission factors that could be developed from the WVU data set are not statistically robust enough to be representative of any population. This is attributed to the limited number of emission tests taken for each subcategory of different vehicle types and driving cycles. However, the observed emission factors may still be useful for estimating emissions from certain populations of heavy duty vehicles, where more robust, less disaggregated emission factors are not available.

The mean emission values derived from the analysis and illustrated in the following data tables reflect emissions from vehicles that span a wide range in model year and weight categories. This contributes to the lack of statistical certainty of the emission factors.

Owing to the few emission tests for each vehicle subcategory relative to the high number potential variables, emission factors could not be developed for certain useful subcategories of data, such as vehicle weight, number of axles, number of cylinders, or model year. Instead, emission factors were only identified for the variables of fuel type, vehicle type, and drive cycle, but could not be subdivided further. Figures 6 through 9 provide an example of the effects of the large number of variables on emissions. Specifically, the scatter plots show the results of a linear regression analysis to determine whether engine model year or gross vehicle weight had a large enough impact on CO_2 emissions to outweigh the effects of the drive cycle and other variables in the database. For the regression analysis, SAIC grouped the WVU data by fuel type but did not group by any other test parameters. The R^2 value indicates how well the data are correlated. A strong correlation would be indicated by a high R^2 value, close to 1.0. These charts indicate R^2 values close to 0, which means the data set, which includes many variables, some of which have a strong impact on emissions, do not reflect any correlation between age of the engine or vehicle weight and increased CO_2 emissions. This does not mean that there is no correlation, but rather that given the large number of variables, it is not possible to identify a trend in CO_2 emissions as a function of weight or age without normalizing for other variables. The strong impact of the drive cycle may outweigh the effect of vehicle weight and other variables in some cases (e.g., a

2005 light heavy-duty vehicle operating on a New York drive cycle may emit more than a 1995 heavy heavy-duty vehicle operating on a West Virginia drive cycle). Later, after normalizing for drive cycle and vehicle type, it was determined that the data set contained too few data to further disaggregate beyond three levels of subcategories: fuel type, drive cycle, and vehicle type. To address these limitations of the data set, further research is recommended to identify additional unpublished heavy duty vehicle emissions data sets and additional emissions testing based on statistical samples. Despite the limitations of the data, several useful results were observed.

Figure 6. CO_2 Emissions (g/mi) from Diesel Vehicles by Engine Model Year

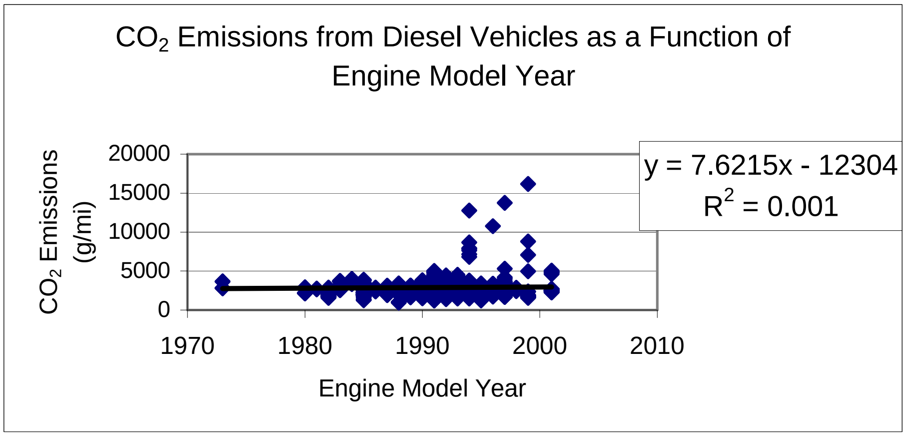


Figure 7. CO_2 Emissions (g/mi) from CNG Vehicles by Engine Model Year

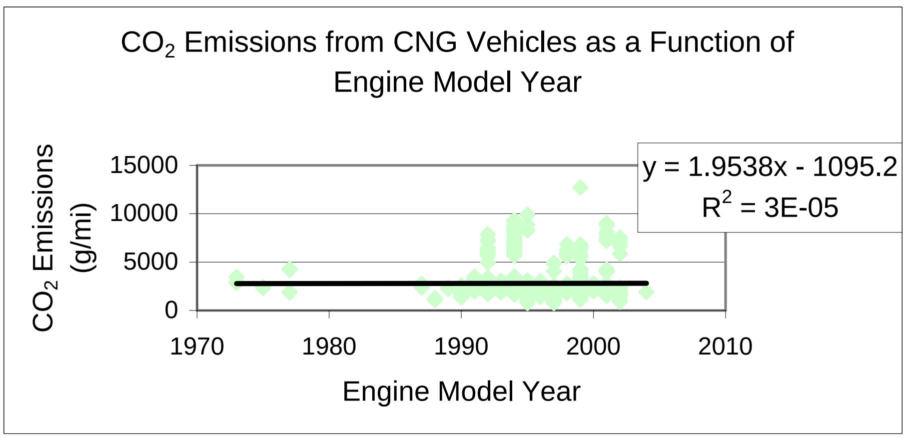


Figure 8. CO_2 Emissions (g/mi) from Diesel Vehicles by Gross Vehicle Weight (lbs)

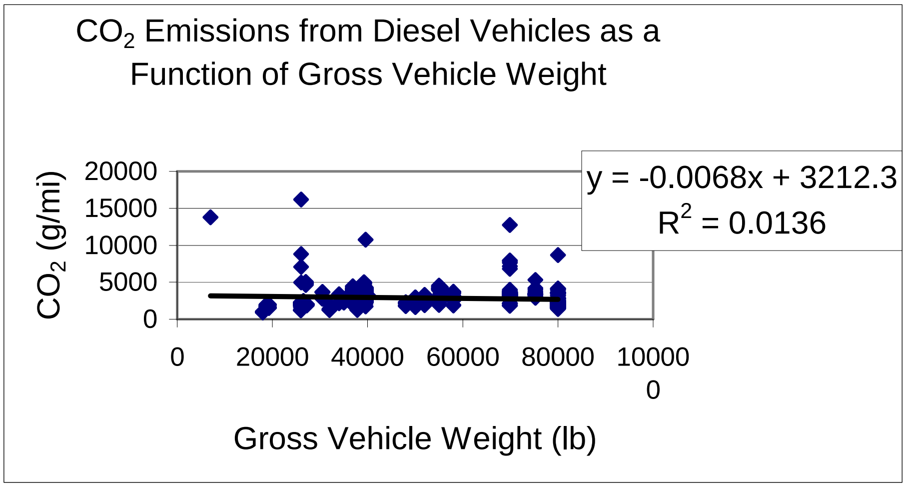
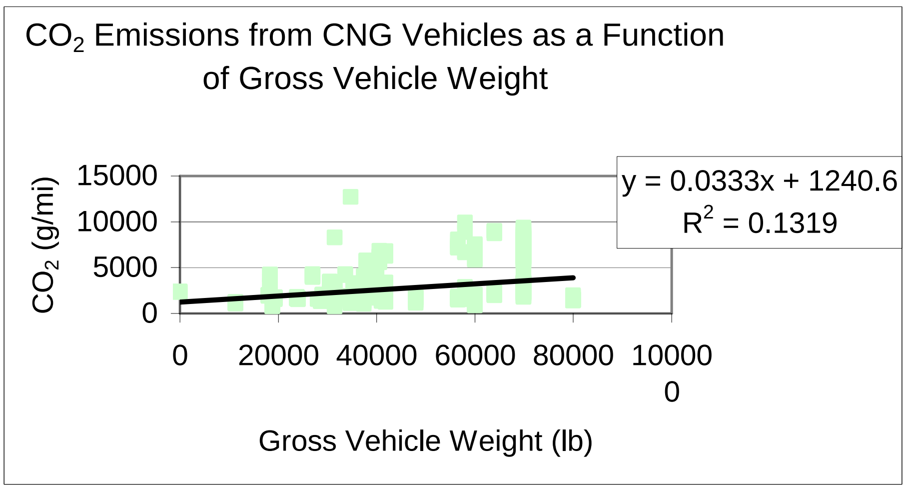


Figure 9. CO_2 Emissions (g/mi) from CNG Vehicles by Gross Vehicle Weight (lbs)



Major findings are illustrated in Tables 5 through 10. Although not statistically significant, the CO_2 and CH_4 data results for CNG buses tested by WVU are generally consistent with the results of recent emission tests on some of the same vehicle types, fuel types, and drive cycles,[38] as shown in Table 5. Table 5 also emphasizes the strong impact of the operating conditions, as indicated by the drive cycle, on both CO_2 and CH_4 emissions from heavy duty vehicles. Table 6 compares selected results of SAIC's analysis of heavy duty vehicle emission test data to other published emission factors. Table 7 presents selected results of SAIC's analysis of WVU's heavy duty vehicle emission test data.

Although the resulting emission factors were not found to be statistically significant, the available data shown in Tables 8 and 9 suggest that for refuse trucks and school buses operating

[38] Emission testing of three New Flyer CNG buses conducted by the Emissions Research and Measurement Division (ERMD) of Environment Canada in partnership with the New York City Transit Authority (NYCTA).

in conditions similar to the central business district driving cycle, total GHG emissions from natural gas-fueled vehicles may be equivalent or greater than diesel-fueled vehicles.

The statistical analysis produced two very similar, possibly significant CH_4 emission factors for CNG- fueled vehicles (refer to Table 6). It should be noted that CO_2 emission factors in units of distance traveled, while useful for comparing emissions across fuel types, driving cycles, or vehicle types, are not recommended for developing CO_2 emissions inventories. CO_2 emissions are most accurately estimated based on the total carbon content of the fuel consumed.[39]

Emission factors from normal distributions and emission factors from chi distributions are evaluated as follows:

- **Emission factors from normal distributions**. These were tests tailored for individual sponsors. These are a source of bias in our study since they do not represent a larger population but reflect only the individual vehicles tested.
- **Emission factors from chi distributions**. Our analysis indicates that these values are relevant since the sample units seem to represent some population, albeit "noisy." However, conventional tools cannot confirm their significance since we do not have other variables to control the volatility of the vehicle emission data. The robustness of the majority of the emission factors in this category are therefore inconclusive since they represent emissions factors that were normalized to an individual's needs or interests and not to represent a major sub-group of a population.
- **Mean emission rates not representative of a population.** The statistical analysis indicates that the mean CO_2 and CH_4 emission rate for the majority of data categories is not representative of a population, and therefore inconclusive. However, although the data are insufficient to produce statistically significant emission factors, the results do provide important information about the high variability of vehicle emissions among and across fuel types, drive cycles, and vehicle types.

Table 5 compares the results of this study for CNG-fueled transit buses to a Canadian study in which in partnership with NYCTA, the ERMD of Environment Canada performed emissions testing on three 1999 New Flyer CNG bus operated without an oxidation catalyst. Exhaust emissions were measured while the buses were operated over the Central Business District (CBD) and New York Bus Cycle (NYBUS) cycle. There are two major conclusions that can be drawn from this comparison:

- Although the mean CH_4 and CO_2 emission values produced by SAIC's analysis of the WVU data on CNG transit buses for the CBD and NYBUS cycles are not statistically significant, they are meaningful since they indicate consistency with another recent study of the same vehicle type, fuel type, and drive cycle, which provides some validation of each of the studies.
- The operating condition, as indicated by the drive cycle, has a major impact on both CH_4 and CO_2 emissions, as illustrated by the huge difference between emissions from the CBD Cycle and the NYBUS Cycle.

[39] IPCC/UNEP/OECD/IEA (1997) and IPCC (2005).

Table 5. Comparison of Emission Results for CNG-Fueled Bus on CBD and NYBUS Cycles

Fuel Type	Vehicle Type/Control Technology	Drive Cycle	Source	Mean CH_4 Emissions (g/mi)	Mean CO_2 Emissions (g/mi)
CNG	Transit Bus	CBD	***This study***	16.8	2,502
			ERMD (2001)	16.4	2,287
		NY BUS	***This study***	53.6	6,077
			ERMD (2001)	54.5	5,609

Notes: Neither CH_4 nor CO_2 data results from this study indicate chi or normally distributed populations.
SAIC calculated the CH_4 mean for the ERMD study as the difference between THC and NMHC.
SAIC calculated the mean for the ERMD study from the reported average of samples for 3 buses.
Sources: This study on behalf of DOT that analyzes data from WVU emissions database; and ERMD (2001): Emissions Research and Measurement Division (ERMD) of Environment Canada, in partnership with the New York City Transit Authority (NYCTA), ERMD Report #01-34

Table 6 presents the three CH_4 factors produced by the WVU data, the corresponding CO_2 emissions mean for the same sample group, and for comparison, other studies' heavy-duty vehicle CH_4 and CO_2 emissions factors. The three CH_4 factors produced by the WVU data were found to be representative of a chi distributed population. It was determined that the CO_2 data were not representative of a population. Interesting observations include:

- The relative CH_4 emissions from various heavy-duty vehicle types, fuel types, and drive cycles are sometimes consistent and other times inconsistent with previous studies and theory. For example, EPA's recently updated emission factor for CH_4 from the CNG-fueled, generic heavy duty vehicle category is relatively close to the values produced in this study for transit buses and garbage trucks on different drive cycles. However, EPA's recently updated CH_4 factor for a CNG transit bus was higher than the WVU value for a bus. EPA's CH_4 factor for a LNG-fueled unspecified heavy-duty vehicle was much lower than what this study found for transit bus emissions on the arterial cycle. Much of the differences may be attributed to differences in drive cycles. The arterial cycle is intended to represent driving conditions on arterial roads, which include state roads with relatively high mobility (i.e., greater mobility than local or collector roads, but less mobility than freeways). Greater mobility generally means higher speeds and less start-stop driving patterns, which would suggest higher fuel efficiency and therefore lower CO_2 emissions per mile. If the EPA value was developed from vehicles tested on urban driving cycles, such as the CBD cycle, one would expect greater emissions per mile from the less efficient driving patterns.
- The statistical analysis produced very similar, possibly significant (i.e., chi distributed) CH_4 emission factors for CNG-fueled heavy duty vehicles, specifically garbage trucks and transit buses, despite the tests being conducted on different drive cycles.
- There are no normal populations in the CH_4 data.

Table 6. Comparison of Reported Emission Rates for CH_4 from Heavy-Duty, CNG-, LNG-, and Diesel-Fueled Vehicles, and Corresponding CO_2 Emission Rates from Same Vehicle Samples

Fuel Type	Vehicle Type/Control Technology	Drive Cycle	Source	Mean CH_4 Emissions (g/mi)	Mean CO_2 Emissions from Same Sample (g/mi)	GWP-[d] Weighted Emissions CO_2E (g/mi)
LNG	Heavy-duty (HD) vehicles	Not specified	EPA (2004)	6.857	Not reported	Not available
	Transit Bus	Arterial cycle	***This study***	11.8 [a]	1,717 [a]	1,988
CNG	Garbage Truck	AQMD Compactor cycle	***This study***	9.9 [a]	1,689 [a]	1,917
	Transit Bus	Triple Length CBD	***This study***	9.5 [a]	2,495 [a]	2,714
	Buses (1999 DDC Series 50G)	CBD cycle	ERMD (2001)	16.4 [b]	2,287 [c]	2,664
	Buses (1999 DDC Series 50G)	NY BUS cycle	ERMD (2001)	54.5 [b]	5,609 [c]	6,863
	Buses	Not specified	EPA (2004)	12.416	Not reported	Not available
	HD vehicles	Not specified	EPA (2004)	9.629	Not reported	Not available
Diesel	Advanced HD vehicles	FTP cycle	Browning (2004)	0.004	1,588	1,588
	Moderate HD vehicles	FTP cycle	Browning (2004)	0.004	1,627	1,627
	Uncontrolled HD vehicles	FTP cycle	Browning (2004)	0.004	1,765	1,765

Notes: [a] CH_4 factors represent chi distributed population. CO_2 data do not reflect chi nor normally distributed populations. [b] We calculated the CH_4 mean for the ERMD study as the difference between THC and NMHC. [c] We calculated the mean for the ERMD study from the reported average of samples for 3 buses. [d] GWP-weighted emissions in units of CO_2 equivalent grams per mile were estimated by weighting CH_4 value by GWP value of 23 for methane and adding to CO_2 value. For the GWP-weighting, diesel vehicles are assumed to produce no CH_4 emissions. Diesel vehicles are known to emit relatively low levels of CH_4 emissions. For this analysis, CH_4 data are not available because they were not collected by WVU for diesel vehicles. Comparison does not account for differences in N_2O emissions.
Sources: WVU emissions database; EPA (2004): Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2002, Table 3-19; ERMD (2001): Emissions Research and Measurement Division (ERMD) of Environment Canada, in partnership with the New York City Transit Authority (NYCTA), ERMD Report #01-34; and Browning (2004): "Update of Methane and Nitrous Oxide Emission Factors for On-Highway Vehicles." For full citations, see References section.

Table 7 presents the nine CO_2 factors produced the WVU data that represented a chi or normal distribution, and the corresponding CH_4 emissions data from the same sample group even though they do not represent a population. Observations from SAIC's analysis of CO_2 emissions from heavy-duty, CNG-, LNG-, and diesel-fueled vehicles provide the following important findings:

- The only observations of GWP-weighted emissions being greater for natural gas-fueled vehicles than for the single diesel-fueled vehicle group, were the two New-York based drive cycles. Based on the limited number of potentially significant results, the available data are insufficient to draw any universal conclusions about the benefits of natural gas-fueled vehicles relative to diesel-fueled heavy-duty vehicles. Based on these results, the selection of a heavy-duty vehicle fuel type to reduce GWP-weighted GHG emissions should continue to be made on a case-by-case basis, and should consider the vehicle application and operating conditions. Still, available data do not always provide sufficient information to make these case-by-case decisions.

Table 7. Mean CO_2 Emissions from Heavy-Duty, CNG-, LNG-, and Diesel-Fueled Vehicles, and Corresponding CH_4 Emission Rates from Same Vehicle Samples

Fuel Type	Vehicle Type/Control Technology	Drive Cycle	Mean CO_2 Emissions (g/mi)	Notes on Population Distribution of CO_2 Data	Mean CH_4 Emissions from Same Sample (g/mi)	GWP - Weighted Emissions CO_2E (g/mi)
LNG	Transit Bus	CBD Cycle	2,374	Chi	11.3	2,634
CNG	Chassis Bus	Arterial Cycle	1,937	Normal	10.4	2,177
	Refuse Truck	CBD Cycle	2,844	Chi	14.6	3,179
	Refuse Truck	New York Garbage Truck Cycle	6,810	Normal	48.3	7,922
	School Bus	CBD Cycle	2,008	Normal	18.5	2,434
	Street Sweeper	NYC Street Sweeper Cycle	4,079	Chi	26.2	4,681
	Tractor Truck	City Suburban Route	2,018	Chi	41.7	2,977
	Transit Bus	Triple Length CBD	2,495	Chi	9.5	2,713
Diesel	Refuse Truck	WHM Cycle	3,314	Chi	Not tested	3,314

Notes: CH_4 values do not reflect chi nor normally distributed populations. GWP-weighted emission in units of CO_2 equivalent grams per mile were estimated by weighting CH_4 value by GWP value of 23 for methane and adding to CO_2 value. For the GWP-weighting, diesel vehicles are assumed to produce no CH_4 emissions. Diesel vehicles are known to emit relatively low levels of CH_4 emissions. For this analysis, CH_4 data are not available because they were not collected by WVU for diesel vehicles.
Sources: This study on behalf of DOT that analyzes data from WVU emissions database.

Comparison of Emissions from Select Fuels and Vehicles on CBD Cycle

Tables 8 through 10 provide information on comparative emissions from each fuel type from various vehicle types on the CBD drive cycle. These emission values are provided for comparative purposes only, as they were determined to be inconclusive, with few data points and high variance in the underlying data. Nevertheless, these available data suggest that for refuse trucks and school buses operating in conditions similar to those represented by the central business district driving cycle, total GHG emissions from natural gas-fueled vehicles may be equivalent or greater than diesel-fueled vehicles.

Table 8. Comparison of Refuse Truck Emissions on CBD Cycle

Fuel	Number of Samples	CO_2 Mean (g/mi)	CH_4 Mean (g/mi)	GWP -Weighted Emissions CO_2E (g/mi)
CNG	165	2,844	14.6	3,180
Diesel	153	3,223	*Not tested*	3,223
LNG	5	2,919	*Not tested*	*Not available*

Note: GWP-weighted emission in units of CO_2 equivalent grams per mile were estimated by weighting CH_4 value by GWP value of 23 for methane and adding to CO_2 value. For the GWP-weighting, diesel vehicles are assumed to produce no CH_4 emissions. Diesel vehicles are known to emit relatively low levels of CH_4 emissions. For this analysis, CH_4 data are not available because they were not collected by WVU for diesel vehicles.

Table 9. Comparison of School Bus Emissions on CBD Cycle

Fuel	Number of Samples	CO_2 Mean (g/mi)	CH_4 Mean (g/mi)	GWP -Weighted Emissions CO_2E (g/mi)
CNG	68	2,008	18.5	2,434
Diesel	18	2,001	*Not tested*	2,001

Note: No LNG vehicle data available. GWP-weighted emission in units of CO_2 equivalent grams per mile were estimated by weighting CH_4 value by GWP value of 23 for methane and adding to CO_2 value. For the GWP-weighting, diesel vehicles are assumed to produce no CH_4 emissions. Diesel vehicles are known to emit relatively low levels of CH_4 emissions. For this analysis, CH_4 data are not available because they were not collected by WVU for diesel vehicles.

Table 10. Comparison of Tractor Emissions on CBD Cycle

Fuel	Number of Samples	CO_2 Mean (g/mi)
Diesel	8	3,449
LNG	16	2,559

Notes: No CNG vehicle data available. CH_4 emissions were not sampled.

Suggestions for Future Research to Reduce Uncertainty

The literature suggests two different main sources of uncertainty in emission factors. One of these sources is the data collection technology (i.e. the device); the other one is the data collection technique (i.e. surveying). To reduce uncertainty, we suggest collecting additional vehicle exhaust emissions data based on a sampling plan.

Options to further reduce uncertainty of emission factors include additional emissions testing, either using dynamometer test labs or on-board data collection systems (e.g., portable or mobile emission monitors). Most existing emission factors for GHGs and criteria pollutants are based on emission tests conducted by dynamometers based on drive cycles that simulate real-world operating conditions. In recent years, on-board emission measurement devices have been developed that collect exhaust data through tailpipe chemical sensors with flow monitors linked to an on-board electronic data acquisition system. These devices provide an opportunity to test emissions as vehicles drive through traffic and accelerate and decelerate in the actual environment.

To characterize GHG emissions from “real-world” driving conditions, and to better understand and appropriately use the available GHG emissions data, which until recently have only been collected in fixed laboratories using dynamometers, future research could include collecting and comparing GHG emissions data from a sample of road vehicles using two different measurement systems:

- **Chassis dynamometers** - The dynamometer measures emissions as the vehicle is operated over a specified driving cycle, which is intended to represent the on-road driving conditions for a certain test case and allow for repeatable conditions, such as acceleration, deceleration, steady state for that test case.
- **Portable on-road emissions systems** - Not commonly available at this time, a portable or mobile system is installed on-board the vehicle and directly measures the specific gas(es) using a sensor that penetrates the tailpipe while the vehicle is operated on highways.

Existing labs, such as WVU, running either measurement system would have the capability to measure CO_2 emissions and Clean Air Act criteria pollutants (NOx, CO, PM). Off-the-shelf CH_4 and N_2O emissions collection equipment is available to incorporate into any existing dynamometer lab. Although off-the-shelf CH_4 and N_2O portable emissions systems may not be readily available, it is likely that labs may have recently incorporated, or are capable of incorporating, commercially available CH_4 and N_2O sensors into available portable emissions systems.

There are many possible variations of vehicle emissions testing projects. Research would be tailored to address the different needs identified by an analysis of the population distribution. The following list includes suggestions for filling gaps and further reducing uncertainty of GHG emissions from heavy duty vehicles:

- Testing of N_2O and NOx to determine whether there is a correlation for certain vehicles, fuel types, and/or driving cycles. Because NOx is regulated, it is much better characterized from different vehicle types and driving conditions. Previous studies of existing data have not identified a consistent relationship between the gases, even though they are known to be related to catalyst activity. If additional vehicle testing could uncover a correlation under certain conditions, this would allow GHG analysts to take advantage of the wealth of data available on NOx emissions to estimate N_2O.
- Testing of CH_4 and non-methane hydrocarbons (NMVOC) or total hydrocarbons (HC) to better understand the relationship between the two gases. In absence of measured CH_4 data, analysts infer methane emissions as the difference between total HC and NMVOC, which are regulated and therefore more commonly tested. Some studies have reported estimates of CH_4 as a fraction of THC, which have been used by inventory agencies.
- Although CO_2 is most accurately estimated based on the carbon content of fuel consumed, some researchers and policy analysts might have interest in CO_2 per mile. This could be used as an indication of energy efficiency of different vehicle types and advanced technologies (hybrid fossil-electric) on different drive cycles/real-world driving applications (highway freight transport, urban refuse collection).
- Further research and comparison of CH_4 and CO_2 emissions from natural gas and diesel vehicles, to better learn which applications are better suited to each fuel type with regard to fuel efficiency and GHG gas emissions. Additional emissions data

from further testing will help further reduce the uncertainty about the resulting emission factors.

Suggestions for Future Statistical Sampling

Among the surveying sources of uncertainty are a vehicle's type, fuel and engine technology as well as its driving conditions. The literature suggests that vehicle type and use follow socioeconomic patterns. For example, while emission factor uncertainty is highly linked to vehicle maintenance; maintenance is highly correlated to income. In addition, demographic factors such as population density, a measure of urbanization, considerably influence emission factor estimates.

Minimizing emission factor uncertainty requires large emission databases that would include many vehicle types on different driving cycles. Creating such a database would require significant investment, attributed to the high costs of lab testing or portable emission monitoring. An alternative statistical tool to reduce costs would be to use survey sampling applied to large vehicle databases such as the U.S. Census's vehicle inventory survey and commuter data from the American Community Survey to determine a sample size that would minimize uncertainty and cost. For example, to improve national emission inventories and emissions test data for heavy-duty vehicles, population density data and commuter information could be researched to help understand what type of driving cycle best fits given areas of the country. Additionally, data on vehicle inventories could also be used to determine how different vehicle types are distributed across the country.

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APPENDIX: GLOSSARY OF STATISTICAL TERMS

This appendix outlines commonly available definitions of statistical concepts that have been used in this paper. The definitions below were obtained from various sources in the statistical literature and the internet.

- **Bias -** In statistics, a deviation of the expected value of a statistical estimate from the quantity it estimates. The word bias has at least two different senses in statistics, one with negative connotation referring to something considered prejudiced or the result of systematic error introduced into sampling or testing by selecting or encouraging one outcome or answer over others, the other referring to something that can at times produce results more useful and closer to the truth than an insistence on being "unbiased."

- **Intra-temporal -** Within a sampling period.

- **Inter-temporal -** Across sampling periods.

- **Kurtosis -** Kurtosis is a measure of the heaviness or fatness of the tails in a distribution, relative to the normal distribution. A distribution with negative kurtosis (such as the uniform distribution) is light-tailed relative to the normal distribution, while a distribution with positive kurtosis (such as the Cauchy distribution) is heavy-tailed relative to the normal distribution. A fat-tailed distribution has higher-than-normal chance of a big positive or negative realization (outlier). Kurtosis should not be confused with skewness, which measures the fatness of one tail. Kurtosis is sometimes referred to as the volatility of volatility.

- **Population Distribution -** The patterns of settlement and dispersal of data, such as emission measurement data. The actual distribution(s) of data for the entire population is/are unknown to the researcher. A population distribution may be described as normal, chi-squared, or exponential.

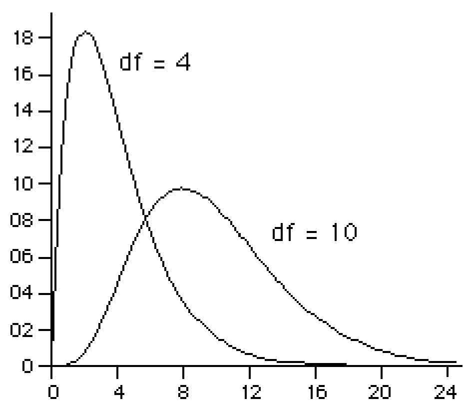
    - **Normal Distribution -** The normal or Gaussian distribution is one of the most important probability density functions, not the least because many measurement variables have distributions that at least approximate to a normal distribution. It is usually described as bell shaped, although its exact characteristics are determined by the mean and standard deviation. It arises when the value of a variable is determined by a large number of independent processes. Many statistical tests assume that the data come from a normal distribution. Careful review of the emission factor literature advises against this assumption, owing to the high volatility of emission measurement data.

    - **Chi-squared distribution -** The Chi Square distribution is a mathematical distribution that is used directly or indirectly in many tests of significance. The most common use of the chi square distribution is to test differences between proportions. Although this test is by no means the only test based on the chi square distribution, it has come to be known as the chi square test. The chi square distribution has one parameter, its degrees of freedom (df). It has positive skewness; the skewness is less with more degrees of freedom. The mean of a chi square distribution is its df. The mode is df - 2 and the median is approximately df -0 .7. as the dfs augment the chi distribution develops into a normal distribution.

This paper assumes that the emission measurements reflect a chi-squared distribution, since few emission measurement observations are used. As the number of observations grows, the influence of un-observed data on emission factors would diminish, allowing observed data to describe volatility in emission data. As the degrees of freedom grow the influence of un-observed data diminishes.

- **Exponential Distribution -** An exponential distribution is a skewed probability distribution with right tail extending to infinity and having the density function. The exponential distribution is an extreme case of a Chi-squared distribution.

  The diagram below shows a hypothetical example of how a Chi-squared distribution transforms into a normal distribution as the degrees of freedom augment.



- **Outlier -** A data point (or points) that lie far outside most of the rest of the points in the data set.

- **Percentile -** A ranking scale ranging from a low of 1 to a high of 99 with 50 as the median score. A percentile rank indicates the percentage of a reference or norm group obtaining scores equal to or less than the test-taker's score. A percentile score does not refer to the percentage of questions answered correctly, it indicates the test-taker's standing relative to the norm group standard.

- **Skewness -** Skewness is the lack of symmetry in a distribution in which the values are concentrated on one side of the central tendency and trail out on the other side. Data from a positively skewed distribution (skewed to the right) have values that are bunched together below the mean, but have a long tail above the mean. Distributions that are forced to be positive, such as annual income, tend to be skewed to the right. Data from a negatively skewed distribution (skewed to the left) have values that are bunched together above the mean, but have a long tail below the mean.

- **Univariate Analysis -** Univariate analysis is a data analysis methodology that considers only one factor or variable at a time; the analysis of single variables as distinct from relationships among variables. In this paper, univariate analysis tools are applied to subsets of emission measurement data to see if different data subsets generate significantly different emission factors. Control variables such as fuel type and vehicle type are used to define such subsets.

  The identification of significantly different emission factors would inform us about two important characteristics of the variance in emission measure data:

  - Information in the chosen control variables can explain the volatility in emission factors; and
  - As a result, multivariate analysis tools could be used to parameterize (measure) how control variables influence emission factors.

  For example, this paper tests if enough information is available to describe how emission factors change with vehicle weight. This paper concludes that control variables can explain volatility in emission factors; however, the data are insufficient to define significantly different emission factors and parameterize how control variables influence emission factors.

- **Volatility -** Volatility refers to the degree of fluctuation in a variable. For example, in this paper, volatility refers to the range of fluctuation of emission measurement data. The higher the volatility, the greater the fluctuations across emission measurement data. Regarding emission measurement data, volatility is a function of observed and unobserved data such as the control variables outlined in the paper (observed) and vehicle maintenance habits (unobserved).