

S-1 Quantifying Health Effects

This section outlines the development of our assumptions for emissions (Section S-1.1), atmospheric dispersion and population exposure (Section S-1.2), and the relationship between exposure to air pollution components and the loss of QALYs (Section S-1.3).

S-1.1 Emissions

This section describes data used to quantify emissions generated by vehicle operations, emissions generated by upstream feedstock extraction and fuel production operations, and issues complicating interpretation of the data. These issues include differences between total PM and fine fraction PM (particles with an aerodynamic diameter of less than 2.5 microns, denoted "PM_{2.5}") and the impact of aging on vehicle emissions. Tables S-1, S-2, and S-3 summarize the data considered, and Table 3 in the journal manuscript summarizes our results.

Emissions Resulting From Vehicle Operation

This analysis considers published studies that reported dynamometer measurements of emissions generated by transit buses (Tables S-1, S-2, and S-3). To ensure that measurements were comparable across technologies, we restrict attention to measurements made using the dynamometer central business district (CBD) test cycle, the most commonly used cycle for bus emission measurements. Other test cycles differ from the CBD in terms of acceleration patterns and average speed, both factors that have

an important impact on emissions. Ideally, all vehicles representing each of the technologies evaluated in this analysis would have identical engine characteristics and exhaust treatment and would use the same fuel. Because the data were limited, we omit only those measurements not approximately representative of one of the technologies evaluated. Note also that the analysis affords the same statistical weight to reported measurements regardless of the number of vehicles they represent based on our judgment that variation between studies far exceeds variation among vehicles in the same study.

For conventional diesel (CD), we omit measurements from buses using ultra-low sulfur diesel, buses with two stroke engines, and buses not equipped with catalytic converters. The remaining five sets of measurements were all made on Detroit Diesel Corporation Series 50 (DDC 50) buses manufactured between 1995 and 2000 (see Table S-1). For PM and NO_x, we compute the central estimate emission rate by taking the average of the included values (0.32 g/mile for PM and 28.7 g/mile for NO_x), and assume that the low end and high end estimates equal the minimum (0.17 g/mile for PM and 23.0 g/mile for NO_x) and maximum (0.51 g/mile for PM and 37.3 g/mile for NO_x) emission values reported, respectively. Results for SO₂ are available from only one study (1) involving two vehicles. We use the average value as our central estimate (0.29 g/mile) and apply a factor of two to estimate upper and lower bounds for this parameter (0.15 and 0.58 g/mile).

We also limit emission control diesel (ECD) measurements to vehicles with four stroke engines and equipped with catalytic converters (see Table S-2). Only one such

study, with one result representing the average for two vehicles tested, satisfies these criteria. With only one value, it is not possible to construct a range of plausible values. We therefore assume that the reported value represents a central estimate (0.03 g/mile for PM), and that the full range of plausible values spans a factor of three above and below this central estimate (0.01 to 0.09 g/mile). Because the two studies that compared CD and ECD vehicles (1,2) did not find that the presence of a diesel particulate filter (DPF) substantially altered NO_x emissions, we assume that ECD NO_x emissions are equal to CD NO_x emissions. Only one study reported SO₂ emissions for ECD vehicles (1). We use the one value reported as our central estimate (0.0072 g/mile) and apply a factor of two to estimate upper and lower bounds for this parameter (0.0036 and 0.014 g/mile).

CNG measurements are limited to vehicles with closed loop technology (see Table S-3). This technology, which is available on newer CNG buses, ensures a more consistent optimal air-to-fuel ratio and has been found to reduce emissions of PM and NO_x (3). The averages of the values reported for CNG vehicles equipped with closed loop technology serve as central estimates (0.05 g/mile for PM and 16.2 g/mile for NO_x), and the ranges for these data serve as the bounds (0.02 g/mile to 0.09 g/mile for PM and 9.7 g/mile to 25.0 g/mile for NO_x). None of the studies reviewed reported SO₂ emissions for CNG buses. However, Wang (4) reported that total vehicle operation SO_x emissions for CNG automobiles were very small (0.002 g/mile). For the purpose of this study, we assume that CNG buses emit no SO₂.

Emissions Resulting from Upstream Activities

CD and CNG: Upstream activities, as described by Wang and Huang (5), include 1) production, transportation, and storage of feedstock; and 2) production, transportation, storage, and distribution of the fuel. We estimate upstream emissions associated with CD fuel and CNG from the results reported by Wang (Appendix B-1 in (4)) for the near-term passenger automobile implementations of these technologies. Wang reported BTU/mile associated with vehicle operation, and both PM and NO_x emissions (g/mile) associated with upstream activities. Our analysis calculates g/mile upstream emissions for emission component *i* ($Emit_i^{upstream}$) as

$$Emit_i^{upstream} \text{ (g/bus mile)} = Emit_i^{upstream} \text{ (g/auto mile)} \times \frac{Energy_{bus} \text{ (BTU/mile)}}{Energy_{auto} \text{ (BTU/mile)}}$$

where *Energy* is the energy consumed by vehicle operation per bus mile or automobile mile. Wang reported $Energy_{auto}$ to be 3,819 BTU/mile for diesel and 5,544 BTU/mile for CNG. Upstream PM emissions are 0.011 g/auto mile for both CD and CNG. Upstream NO_x emissions are 0.118 g/auto mile for CD, and 0.314 g/auto mile for CNG. Upstream SO_x emissions are 0.065 g/auto mile for CD, and 0.098 g/auto mile for CNG. Our estimated energy consumption per bus mile for CD (32,175 BTU/mile) has been computed from the Transportation Research Board's assumption that 1 gallon of diesel has an energy content of 128,700 BTU ((6), p. 4) and their assumption that a diesel bus travels four miles on one gallon of diesel ((6), Fuel Cost 1.0 User's Guide, p. 19).

Because CNG is 20% to 40% less efficient than diesel (6), p. 12), the energy used by a CNG bus is assumed to be between 40,200 BTU/mile and 53,600 BTU/mile. We have computed the central estimate for upstream CNG emissions by taking the average of the bounds computed using these two energy consumption values. For CD, the estimated central estimates for upstream emissions are 0.093 g/mile for PM, 0.99 g/mile for NO_x, and 0.55 g/mile for total SO_x (we assume no uncertainty in these estimates, *i.e.*, the low end and high end bounds for each emission component are assumed to equal the corresponding central estimate). Based on Lanni *et al.* (1), total SO_x is assumed to be comprised predominantly of SO₂. Hence, the SO_x emissions values serve as a surrogate for SO₂ emissions. For CNG, upstream PM emissions range from 0.080 to 0.11 g/mile, with the central estimate assumed to be equal to the midpoint of this range (0.095 g/mile). Corresponding NO_x emissions range from 2.3 to 3.0 g/mile, with the central estimate assumed to be equal to the midpoint of this range (2.7 g/mile). SO_x values (serving as a surrogate for SO₂) range from 0.71 to 0.95 g/mile (central estimate of 0.83 g/mile).

ECD: Beer *et al.* (7) and CSIRO (8) estimated the incremental upstream emissions associated with production of ultra-low sulfur diesel, compared to production of low-sulfur diesel. Because the Beer *et al.* analysis assumed substantially higher upstream PM emissions for low-sulfur diesel (0.26 g/mile estimated by Beer *et al.* vs. 0.093 g/mile estimated by Wang (4)), we assume that the Beer *et al.* proportional incremental increases (68% for PM and 16% for NO_x) are applicable to the United States. These assumptions yield upstream PM emissions of 0.156 g/mile and NO_x emissions of 1.15 g/mile. Whereas Beer *et al.* had assumed that production of ultra-low sulfur diesel

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would require addition of a hydrocracking unit to typical refinery operations, CSIRO concluded that such an addition would be unnecessary and hence that incremental emissions would be smaller. The CSIRO assumptions (ultra-low diesel production increases PM emissions by 3% and NO_x emissions by 27%) yield upstream PM emissions of 0.096 g/mile and NO_x emissions of 1.26 g/mile. The central estimates for these two sets of assumptions are assumed to be equal to the respective midpoints of these ranges (PM emissions of 0.126 g/mile and NO_x emissions of 1.21 g/mile). Neither Beer *et al.* nor CSIRO characterize upstream SO₂ emissions associated with the production of ultra-low-sulfur diesel. We assume that these emissions are the same as those associated with the production of low sulfur diesel used in CD vehicles.

Vehicle Age

Few studies have documented the long-term emissions performance of the ECD and CNG technologies because they are new, and few production line buses with these propulsion systems have been in service for an extended period of time.

The long-term emissions performance of ECD vehicles depends on both the durability of the DPF and the impact of wear on the engine's emissions characteristics (9), p. 24). However, electronic controls now included in diesel engines can help prevent deterioration of PM emissions performance (10). Bench tests conducted by Allansson *et al.* (11) of DPFs in service in Sweden found that engines with between 142,000 and 373,000 miles still performed well. Warren *et al.* (12) reported that even when fueled

using diesel with sulfur concentrations as high as 50 ppm (compared to the < 10 ppm sulfur used in Sweden), DPFs performed well for approximately 60,000 miles, thus suggesting that with regular maintenance, the performance of these filters can be preserved.

NO_x emissions generated by CNG vehicles may increase as an engine ages because of changes in the air-fuel ratio. On the other hand, there is reason to believe that with proper maintenance, new CNG engines can maintain stable NO_x emissions performance ((9), p. 24).

In summary, it appears that when properly maintained, both ECD and CNG engines will exhibit relatively stable emission characteristics over time. This analysis therefore assumes that vehicles will be properly maintained and hence that no adjustment is necessary to reflect the impact of aging on emissions.

Particle Size

Most studies of bus PM emissions have not specifically measured the fine particle fraction (PM_{2.5}) that may be most closely linked with mortality (13-15). However, one study (16) reported both total PM emissions (TPM) and PM_{2.5} emissions for both diesel and CNG buses. The average value of PM_{2.5}:TPM for diesel buses (N=4) was approximately 85% (range 78% to 91%). For CNG buses (N=2), the corresponding average ratio was 93%, although for one bus, the ratio exceeded unity (the ratio for the

other bus was 68%). Because $PM_{2.5}$ represents a substantial portion of TPM, the failure of most studies to distinguish between these two fractions does not introduce an important source of uncertainty. This analysis therefore makes no adjustments to address this issue.

Some scientists believe that attention should be focused on the ultrafine particle fraction (aerodynamic diameters of less than 0.1 microns). Compared to CD, ECD appears to reduce emissions of ultrafine particles (measured in terms of number of particles per unit volume) by approximately one order of magnitude or more (1,12,17,18), which is similar to its impact on the total mass of PM emitted. We are unaware of any data quantifying ultrafine PM emissions for CNG vehicles. Because available measurement data are limited and because only one epidemiological study had developed a concentration-response function for ultrafine PM at the time of our analysis (19), we do not address this issue further. However, it is worth noting that making the assumption that ultrafine particles are the relevant exposure measure could have substantial implications for the relative emissions and exposure patterns for each technology, and could therefore alter our findings.

S-1.2 Atmospheric Dispersion and Population Exposure

This section describes computation of the intake fraction (iF) parameter for primary PM, secondary PM, and ozone. As described below, because the value of the iF parameter for a pollutant varies geographically, we use the mean iF value across the U.S. as a “typical” value and also provide extreme values reflecting different meteorological

regimes, atmospheric chemistry conditions, and population patterns. In addition, for analytical reasons described below, we divide computation of the iF value for primary PM into two components – a component reflecting exposure of population members near the exposure source (the near-source contribution) and a component reflecting exposure of population members far from the exposure source (the far-source contribution). Table 4 in the journal manuscript summarizes our estimates.

Definition of Intake Fraction

An intake fraction is a unitless quantity defined as the ratio of the mass of a pollutant eventually inhaled by someone to the mass of that pollutant or its precursor emitted (20). The intake fraction concept allows one to summarize the results of past modeling studies and apply the findings to new settings with similar characteristics.

Mathematically, the total inhaled pollutant I can be defined as $I = BR \int_A C(a)p(a)da$,

where A is the area occupied by the population, BR is the breathing rate for one individual (assumed to be $20 \text{ m}^3/\text{day}$), $C(a)$ is the atmospheric concentration of the inhaled pollutant at location a , and $p(a)$ is the population density at a . The intake fraction therefore equals I divided by the emission rate of the pollutant or its precursor.

Overview of Available Information

Because our aim is to determine U.S.-average population exposures and because comprehensive national dispersion modeling is beyond the scope of our analysis, we rely

on past dispersion modeling studies. Unfortunately, only a limited number of studies have provided adequate information to estimate national-scale intake fractions for mobile sources. Wolff (21) estimated exposure associated with 20 urban mobile sources selected in a regionally stratified random sample that represented highway segments in urban areas. Using the CALPUFF atmospheric dispersion model (22) with receptors placed every 100 km across the continental U.S. and portions of Mexico and Canada, Wolff estimated iF values for primary PM, sulfates from SO_2 , and nitrates from NO_x .

In addition, Krupnick *et al.* (23) derived a region-to-region source-receptor (S-R) matrix from model runs of the Urban Airshed Model (UAM-V) for average ozone episodes. From this matrix, we derived iF values for ozone generated from NO_x , although values could be computed only for ozone episodes in the eastern half of the US. Of note, some atmospheric chemists have reported ozone production efficiencies (the number of molecules of ozone produced per molecule of NO_x emitted). For example, Ryerson *et al.* (24) reported ozone production efficiencies from power plant emissions in selected locations that range from two to seven. However, there is not necessarily any direct relationship between the production efficiency value and the iF value.

Finally, the Abt Associates *et al.* (25) S-R matrix used in past impact assessments of power plants characterizes primary and secondary PM iF values. While the Abt Associates S-R matrix for mobile sources was not available to us, Wolff's modeling study indicated that secondary PM iF values for power plants and mobile sources are

similar (21). Thus, we use the Abt Associates power plant S-R matrix to estimate secondary PM iF values.

Primary PM – Far Source Contribution

Wolff (21) estimated the mean iF value for primary PM from urban mobile sources across the U.S. to be 9×10^{-6} . Nishioka *et al.* (26) characterized the uncertainty in this term by saying that its plausible values could range a factor of two above and below the central estimate, corresponding in our case to lower bound and upper bound values of 4×10^{-6} and 2×10^{-5} , respectively.

Wolff (21) characterized primary PM iF spatial variability by reporting that the distribution of values across 20 urban regions appeared to be lognormal with a geometric standard deviation of 1.7. Hence, we characterize this parameter's variation as having a range from approximately one-half (4×10^{-6}) to twice (2×10^{-5}) the central value. The upper bound values were generally found in dense urban areas in the Northeast (*e.g.*, New York, Philadelphia, Baltimore), while the lower values occurred in less dense areas in the West (*e.g.*, Denver, Dallas, Kansas City).

Primary PM – Near-Source Contribution

Because Wolff's analysis used relatively coarse grid spacing, it may have omitted a substantial fraction of near-source exposures. A preliminary analysis conducted by

Wolff (21) indicated that inclusion of additional near-source receptors increased total estimated exposure by 30-70%. For this analysis, we assume that the Wolff iF values for primary PM represent only longer-range exposures and that as a result, they must be supplemented by near-source modeling. However, because many upstream activities generate emissions at locations that are substantially further from populations than are emissions generated by vehicle operations, we add the near-source contribution described below only to vehicle operation emissions and not to upstream emissions.

Our near-source calculation addresses exposures among individuals within 1.5 km of the source. For primary PM, we estimate $C(a)$ over a 30×30 km region by fitting an exponential decay function to concentrations calculated using CAL3QHCD (27) at receptors within this region. We use a fitted function rather than the CAL3QHCD output directly to avoid making our results overly dependent on the chosen model receptor locations (in particular, in close proximity to the road).

For these calculations, we assume that the bus travels once each hour along the center line of the region, 24 hours per day, every day. The receptors start near the roadside and are spaced every 0.5 km out to a distance of 1.5 km from the bus route, every 1.5 km from 1.5 to 6 km from the bus route, and every 3 km from 6 to 15 km from the bus route. For simplicity, we adopt the Tier I approach (28), ignoring traffic light timing and queuing.

The fitted concentration function ($R^2 = 0.92$) is $C(D) = 2.4e^{-1.4\sqrt{D}}$, where D is the distance from the bus route. While this functional form does not directly correspond to Gaussian dispersion model equations, it is strongly predictive of the CAL3QHCD estimates with the exception of those values corresponding to receptors immediately adjacent to the road. Moreover, the iF estimates are relatively invariant with respect to other plausible formulations. The central estimate ($iF = 1 \times 10^{-6}$) reflects 1990 meteorological data from New York City and uses a population density of 5,000 people per square km at all points in the region (a value similar to that of Chicago, although lower than that of New York City and higher than that of Los Angeles).

The sensitivity analysis evaluates the impact of alternative assumptions for the value of $C(D)$. In particular, for receptors closest to the bus route, we have replaced the fitted values of $C(D)$ with the values computed by CAL3QHCD to address underestimation of the computed concentration values at those locations by the regression. This alternative assumption yielded values for iF ranging from 1×10^{-6} to 5×10^{-6} .

To characterize the extent to which the near-source iF term may vary spatially, we considered two alternative sets of meteorological data, with the first from Los Angeles and the second from Atlanta. Using these alternative data sets had a minimal impact on the estimated value of the near-source iF value and we therefore assumed that this term does not vary spatially. Taking population density differences into account would have produced a wider range of iF values, but we held this term constant for simplicity.

Because only extreme assumptions regarding population density and emission concentrations close to the road make the near-source iF term important relative to the far-source iF term (discussed above), omitting this source of geographic variation has only a limited impact on our analysis.

Secondary PM

Quantitative description of secondary PM formation is complicated by the non-linear relationships that characterize the atmospheric chemistry of sulfate and nitrate particles. These relationships depend on the relative concentrations of nitrate, sulfate, ammonia, ozone, VOCs, and other species, as well as on temperature and humidity. The fact that the models used to develop our intake fraction values for secondary PM do not explicitly account for all these relationships introduces uncertainty into the resulting estimates. To address this uncertainty, we estimate secondary PM intake fractions using the results of two models, CALPUFF and S-R matrix, that use different approaches to approximate the relevant atmospheric phenomena.

CALPUFF calculates the conversion of SO_2 to sulfate as an hourly function of relative humidity, ozone concentrations, solar radiation intensity, and atmospheric stability, with the conversion of NO_x to nitrate dependent on ozone concentrations, atmospheric stability, and plume NO_x concentrations. However, CALPUFF has limited characterization of background concentrations, with fixed ammonia levels and no nitrate/sulfate characterization beyond that formed from the modeled sources. In

contrast, S-R matrix uses a simplified chemical conversion mechanism to generate its “first-guess” model outputs (the sulfate formation rate is assumed to depend only on relative humidity, while nitrate formation is assumed to occur at a constant rate of 2% per hour) but allows for a richer characterization of background conditions. Moreover, S-R matrix calibrates its initial outputs based on ambient monitoring data and determines incremental ammonium sulfate and nitrate concentrations using a post-processing step that captures many of the non-linear characteristics of the sulfate-nitrate-ammonium system. While significant uncertainty remains, we obtain similar intake fraction values with both models, a finding that provides some indication that our intake fraction estimates are reasonable.

While other models that treat the non-linear behaviors of secondary aerosols with greater sophistication are available (*e.g.*, (29)), these models have generally focused on maximum concentrations within pollutant episodes given large perturbations in emissions. In contrast, the phenomena we are concerned with include only small changes in emissions. Moreover, the results of our analysis are sensitive to changes in long-term average PM concentrations, rather than to short-term changes in maximum PM concentrations.

For the NO_x – secondary PM *iF* value (defined to be the incremental nitrate inhaled per unit of NO_x emissions), Wolff (21) provides a central estimate for urban motor vehicles of 2×10^{-8} . However, Wolff assumed that the CALPUFF model outputs overestimated particle nitrate formation, an assumption that may be valid in some

locations but is likely to be invalid in many others. Removing the adjustment factor used by Wolff yields an iF value of 1×10^{-7} . By comparison, using the Abt Associates *et al.* (25) S-R matrix produces a mean NO_x – secondary PM iF estimate (for power plants) of 5×10^{-8} . Although it is difficult to compare estimates across models, the fact that this value falls between the adjusted and unadjusted Wolff estimates is consistent with the possibility that the adjustment may be valid only in selected geographic locations. We therefore use 5×10^{-8} as our central estimate.

To determine spatial variability, we evaluate the NO_x – secondary PM iF values computed using both the Abt Associates *et al.* S-R matrix and the results from Wolff (21). For urban settings, Wolff reported iF values ranging from 1×10^{-8} to 2×10^{-7} . For the power plants specified in the Abt Associates *et al.* S-R matrix, iF values ranged from 4×10^{-9} to 2×10^{-7} . Because the lowest values in the S-R matrix often correspond to power plants on the East Coast, where a portion of the emissions is transported out to sea, they are likely to understate the iF values for mobile sources, including even those in the same general location. Thus, we assume that the iF value range reported by Wolff represents geographic variation, with lower values reflecting conditions in the Northeast and higher values reflecting conditions in the West.

In addition to exhibiting geographic variability, our NO_x – secondary PM iF value is also very uncertain because of substantial uncertainties related to atmospheric chemistry, issues related to our interpretation of Wolff's estimate, and because of our use of power plant-based values from Abt Associates *et al.* S-R matrix. Although decreases

in NO_x emissions have been found to increase net nitrate formation under some conditions (29), neither model identifies any scenarios in which decreasing NO_x emissions increases net nitrate formation on an annual average basis. This finding may reflect limitations of our atmospheric models or our focus on annual average intake fractions rather than on pollution episodes of relatively limited duration. We follow a recent subjective assessment of Wolff's *iF* estimates (26) and assume that the average *iF* value for the U.S. has a plausible range extending from one-fifth to five times its central estimate. Applying this factor of five to the central estimate of 5×10^{-8} yields bounds of 1×10^{-8} and 3×10^{-7} . Although this interval is somewhat arbitrary and although it is unclear whether it overstates or understates the actual uncertainty, it is not possible at this time to address the multiple sources of uncertainty quantitatively.

To estimate the SO₂ – secondary PM *iF* value (defined to be the incremental secondary PM inhaled per unit of SO₂ emissions), we must consider both the impact of SO₂ on sulfate levels and its potential impact on nitrate concentrations. Although a decrease in SO₂ emissions will reduce sulfate concentrations, it might increase ammonium nitrate levels. This behavior stems from the fact that ammonium preferentially reacts with sulfate over nitrate. As a result, a reduction in sulfate levels can (under some circumstances) make ammonium available to react with nitrate, thereby increasing particulate nitrate.

The Wolff (21) analysis estimates the impact of SO₂ emissions on only sulfate exposure, and not the impact of SO₂ emissions on nitrate exposure. His central estimate

for the SO₂ – sulfate *iF* (defined to be the incremental sulfate inhaled per unit of SO₂ emissions) was 1.2×10^{-7} . The Abt Associates *et al.* S-R matrix provides estimates for both the SO₂ – sulfate *iF* value (power plant mean value of 3.4×10^{-7}) and the SO₂ – nitrate *iF* value (power plant mean value of -5×10^{-8}). Our central estimate for the SO₂ – secondary PM *iF* value is the sum of these two values, which rounds to 3.0×10^{-7} .

As described above for the NO_x – secondary PM *iF* value, we develop bounding estimates for the SO₂ – secondary PM *iF* value from the range of SO₂ – sulfate *iF* values reported by Wolff (21) and the range of SO₂ – secondary PM *iF* values computed using the Abt Associates *et al.* S-R matrix. For the 20 urban highway segments examined by Wolff, SO₂ – sulfate *iF* values ranged from 4×10^{-8} to 2×10^{-7} , with lower values reflecting conditions in the West and higher values reflecting conditions in the East. SO₂ – secondary PM *iF* values for power plants calculated from the S-R matrix ranged from 6×10^{-8} to 7×10^{-7} . As was the case with the NO_x – secondary PM *iF* values discussed above, many of the lower SO₂ – secondary PM *iF* values calculated from the S-R matrix correspond to coastal power plants and are therefore not relevant to our mobile source analysis. As a result, we assume that mobile source SO₂ – secondary PM *iF* values range from 1×10^{-7} to 7×10^{-7} due to geographic variation. Unlike the NO_x – nitrate *iF* value, which was highest at locations in the East, the highest SO₂ – secondary PM *iF* values correspond to locations generally in the Industrial Midwest.

Nishioka *et al.* (26) characterized the SO₂ – sulfate *iF* value as somewhat less uncertain than the NO_x – nitrate *iF* value because the latter is complicated by more

atmospheric chemistry issues. We adopt their conclusion that a factor of three above and below the central estimate for the SO₂ – sulfate *iF* value adequately characterizes its uncertainty, yielding bounds of 1×10^{-7} and 9×10^{-7} . We note that the Nishioka *et al.* uncertainty bounds we use for both the NO_x – nitrate *iF* value (factor of five in either direction) and the SO₂ – sulfate *iF* value (factor of three in either direction) are both somewhat broader than the corresponding bounds developed in a recent analysis by Carrothers *et al.* (30) (factor of three and 2.25 in either direction for the NO_x – nitrate *iF* value and SO₂ – sulfate *iF* value, respectively). However, the ratio of the two uncertainty factors estimated by Nishioka *et al.* is similar to the corresponding ratio of the two uncertainty factors estimated by Carrothers *et al.*

Ozone

Calculation of a “typical” ozone *iF* value is complicated by the highly non-linear chemistry involved in ozone formation. Ozone concentrations depend on both the concentrations of NO_x and volatile organic compounds (VOCs), and on ultraviolet radiation intensity. In addition, although many geographic regions are thought to be NO_x-limited (*i.e.*, additional ozone production depends on the availability of additional NO_x), some regions are VOC-limited, implying that additional NO_x production could reduce ozone concentrations. Given the structure of our analysis, we focus only on the impacts of NO_x emissions on ozone formation, using the average U.S. value to characterize a “typical” setting, and reporting a range that reflects both NO_x-limited and VOC-limited regimes.

As indicated above, we can derive NO_x – ozone iF values from the S-R matrices reported by Krupnick *et al.* (23). These matrices consist of six source regions and seven receptor regions, and were meant to represent average ozone episodes. We follow the approach in Toy (31) to derive iF values. That approach involved using 1999 county-level population data and assuming that ozone formation occurs during six months of the year, with negligible ozone formation during the rest of the year. Given these assumptions, the average iF value across all source regions was 2×10^{-6} . Values ranged from -1×10^{-6} for sources in eastern Pennsylvania and New Jersey to 4×10^{-6} for sources in Tennessee and northern Alabama and Georgia. Krupnick *et al.* did not report values for regions to the west of the Mississippi River.

Clearly, this quantity varies substantially across settings and for reasons stated earlier, it is also very uncertain. A simple calculation serves as a check of our central estimate's plausibility. The ratio of total ozone inhaled annually by all members of the U.S. population (20 m^3 air per day $\times 40 \text{ } \mu\text{g}/\text{m}^3$ estimated average ozone concentration $\times 365$ days/year $\times 2.8 \times 10^8$ individuals, or $8 \times 10^{13} \text{ } \mu\text{g}/\text{year}$) to annual national NO_x emissions ($2 \times 10^{19} \text{ } \mu\text{g}/\text{year}$ (32)) is 4×10^{-6} . This value is reasonably close to our computed average value of 2×10^{-6} for this quantity, especially given the fact that ozone scavenging is more likely to occur in dense urban areas. Hence, our central NO_x – ozone iF estimate appears to be plausible. However, because of our simplified modeling approach, the uncertainty surrounding this estimate could be substantial (on top of the variability reported above, which encompasses negative values). Following our approach

for nitrates, we assume that a factor of five in either direction is a reasonable first-order approximation of uncertainty (given data from only one study with limited temporal and geographic coverage).

S-1.3 Health Effects

This section describes the computation of γ_j , which is the number of QALYs lost per year per million people exposed per $\mu\text{g}/\text{m}^3$ of pollutant j . Table 5 in the journal manuscript summarizes our estimates.

The Impact of PM on All-Cause Mortality

We have established bounds on the association between PM concentrations and all-cause mortality using the time-series and cohort mortality literature. The time series data indicate a smaller impact on mortality incidence and fewer QALYs lost per death compared to the cohort evidence.

Cohort Studies: For the cohort literature, we rely on the recent Pope *et al.* (33) follow-up analysis of the American Cancer Society (ACS) study (34). This study included a much larger number of participants and locations and is hence likely to be more representative of the U.S. population than the two other major cohort mortality studies (35,36). Our estimate reflects the Pope *et al.* analysis that used the average of $\text{PM}_{2.5}$ concentrations at the start and end of the follow-up period and adjusted for numerous hypothesized confounders (see Table 2 in (33)). Pope *et al.* estimated that a 10

$\mu\text{g}/\text{m}^3$ increase in annual $\text{PM}_{2.5}$ concentrations is associated with a mortality relative risk of 1.06. By analyzing the Cox proportional hazards results from the original ACS study, Leksell and Rabl (37) estimated that a $1 \mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ would result in the loss of 600 years of life for every one million people exposed. We have adjusted this loss downwards to 500 years of life because their estimate is based on a slightly higher relative risk than that reported in the follow-up study.

Time Series Studies: Samet *et al.* (38) used data collected as part of the National Morbidity, Mortality, and Air Pollution Study (NMMAPS), pooling information from the 90 largest cities in the U.S. Recently, the statistical methodology used in this study was revised, resulting in a lower estimate than previously reported (39). Using the revised statistical approach, Samet *et al.* estimated that a $10 \mu\text{g}/\text{m}^3$ increase in PM_{10} (particles with an aerodynamic diameter of less than 10 microns) increases mortality by 0.27%. We have divided this estimate by 0.6 to reflect our assumption that the $\text{PM}_{2.5}$ fraction is responsible for mortality and our assumption that $\text{PM}_{2.5}$ typically comprises 60% of the PM_{10} fraction. To one significant digit, the resulting slope is a 0.05% change in mortality per $\mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ concentrations. Multiplying this slope by the baseline mortality rate (omitting accidents, suicides and homicides) of 8,102 per million (40) yields four deaths per million people exposed per $\mu\text{g}/\text{m}^3$ of $\text{PM}_{2.5}$. Recent studies (41,42) have demonstrated that the mortality detected in the time-series studies is not a “harvesting” phenomenon, and concluded that the lost longevity associated with each such death must be at least 60 days. Because of seasonal effects, losses longer than 60 days were not possible to evaluate. However, other researchers (43,44) have assumed

that this value might fall somewhere in the range from six months to six years. We use a central estimate value of 2 years lost per time series death, which yields a total of eight lost life years per million people exposed per $\mu\text{g}/\text{m}^3$ $\text{PM}_{2.5}$.

Conversion of Life Years to QALYs: Individuals who die due to PM exposure probably suffer from pre-existing coronary or respiratory disease. Stinnett *et al.* (45) estimated that each life year for individuals with coronary disease is worth 0.8 QALYs. This decrement reflects the finding that such individuals suffer from a reduced quality of life. Based on this finding, we assume that each year of life lost due to PM-induced mortality is worth 0.8 QALYs. Hence, the cohort findings suggest a loss of 400 QALYs per $\mu\text{g}/\text{m}^3$ change in $\text{PM}_{2.5}$, while the corresponding change suggested by the time series data is 6 QALYs. Because our baseline assumption is that the effect observed in the cohort studies reflects a causal relationship, we use the cohort-based estimate as our central estimate for this parameter. A formal analysis of the likelihood of this outcome is warranted and would influence the value of the central estimate.

Ozone Mortality

Because evidence for a cohort mortality effect for ozone is scant (46), only the time-series literature provides evidence of a non-zero effect. In recent reviews of the ozone time-series literature (46,47), there is some evidence of a small but statistically significant effect in studies that adequately control for temperature and other pollutants. Levy *et al.* (46) found that these data imply that a $10 \mu\text{g}/\text{m}^3$ increase in 24-hour average

ozone concentrations increases the incidence of death by 0.5%. Because there is no evidence available suggesting that different pollutants shorten life by different lengths of time, we assume that ozone mortality is associated with the loss of two years of life (*i.e.*, the same loss assumed for PM-induced mortality inferred from time series data), and that each year of life is worth 0.8 QALYs. This estimate may be an upper bound because ozone may affect respiratory endpoints more than cardiovascular endpoints and because loss of life due to chronic obstructive pulmonary disease exacerbation may result in the loss of only several months (42). As a result, a $1 \mu\text{g}/\text{m}^3$ increase in the ozone concentration results in the loss of approximately 6 QALYs ($0.05\% \times 8,100$ annual baseline deaths $\times 2$ years per death $\times 0.8$ QALYs per year lost). We use this value as our central estimate because it represents the best current synthesis of the literature. Because there is no specific evidence indicating that ozone has a bigger impact on mortality, we have not identified an alternative upper bound. Because of the limited number of studies and potential issues related to residual confounding, zero is a plausible lower bound.

Ozone Morbidity

Because there is no evidence for cohort mortality from ozone, it is likely that morbidity outcomes will contribute relatively more to the lost QALYs resulting from ozone exposure than it will to the lost QALYs resulting from PM exposure. We evaluate the development of asthma, which is likely to be a significant contributor to QALYs lost due to ozone morbidity because of the chronic nature of the disease.

Because many studies investigating the potential association between ozone exposure and the development of asthma have failed to find a positive effect (*e.g.*, (48,49)), we assume that the lower bound QALY loss for this effect is zero. However, the Adventist Health Study of Smog (AHSMOG) conducted by McDonnell *et al.* (50) did find such an association, with findings corresponding to a 23% increase in the asthma incidence rate (the baseline rate is 0.22%) among non-smoking adult males per $10 \mu\text{g}/\text{m}^3$ increase in 20-year average ozone concentrations (although there was no effect observed in females). Our central risk estimate for this health effect is based on the Levy *et al.* (46) conclusion that a reasonable central estimate for the impact of ozone on the incidence of asthma is a 6% increase in the incidence rate per $10 \mu\text{g}/\text{m}^3$ increase in the annual average concentration.

An increase in the asthma incidence rate results in a loss of QALYs because this condition adversely affects quality of life. Although U.S. EPA has not estimated the value in QALYs of avoiding a single case of asthma, the Agency has estimated the monetary value of avoiding such a case to be \$25,000 (32). We have estimated the corresponding QALY value by comparing this monetary value to the monetary value of avoiding a case of chronic bronchitis, estimated by U.S. EPA (32) to be \$260,000. Hammitt *et al.* (51) estimated that avoiding a single case of chronic bronchitis is worth 2.5 QALYs. As an approximation, we assume that the QALY value of avoiding a single case of chronic asthma is proportional to its monetary value, or 0.25 QALYs.

Because the epidemiological evidence for this effect is limited, our lower bound estimate for the number of QALYs lost is zero. Our high-end estimate is based on the assumption that ozone increases the incidence of new cases among all members of the population, yielding a loss of 3 QALYs per $\mu\text{g}/\text{m}^3$ increase in the ozone concentration per million individuals exposed (0.6% change in the incidence \times 0.22% baseline incidence \times 0.25 QALYs per case \times 1 million individuals). The central estimate (loss of 1 QALY) is based on the assumption that the increased incidence is applicable only to adult males (about 1/3 of the population) because they were the only group among whom an association between ozone exposure and asthma has been observed empirically.

Cancer

U.S. EPA (52) reviewed the evidence suggesting that diesel exhaust causes cancer. The hypothesis that diesel exhaust causes cancer consists of the following evidence. First, constituents of both the gas phase and the particle phase of diesel exhaust have been demonstrated to exhibit mutagenic behavior. At occupational levels of exposure, diesel exhaust causes an increase in the frequency of DNA adducts in humans. Second, exposure of rats to diesel exhaust via inhalation is associated with an increased incidence of lung tumors. Finally, epidemiology studies generally indicate a modest association between occupational exposure to diesel exhaust and an elevated risk of lung cancer mortality (OR \approx 1.4). Meta-analyses have found that the positive associations are unlikely to be due to chance (*e.g.*, Bhatia *et al.*, (53), as cited in U.S. EPA (52)).

We have computed central and upper estimates for this risk's magnitude using the Dawson and Alexeeff (54) reanalysis of exposure data from the Garshick *et al.* (55) study of railroad workers. The Garshick *et al.* data have been used to develop the most prominent quantitative estimates of lung cancer mortality risk for diesel (*e.g.*, the 1998 analysis conducted by the state of California (56)). The reanalysis, which fit a seven-stage model to these data, suggested that depending on the pattern of historical diesel exhaust exposure assumed for these workers, increasing average lifetime exposure to diesel PM by $1 \mu\text{g}/\text{m}^3$ increases the lifetime risk of lung cancer mortality by between 1.4×10^{-4} and 3.5×10^{-4} (95% upper confidence limit of 2.1×10^{-4} to 5.5×10^{-4}). Our central estimate equals the average of the central estimates reported by Dawson and Alexeeff (2.1×10^{-4}) and our upper bound estimate equals the maximum value they reported (5.5×10^{-4}).

Other evidence suggests that use of the Garshick *et al.* data to estimate risk is inappropriate. In particular, the supporting rat bioassay studies may not be relevant because the lung tumors in rats occurred only at concentrations sufficiently high to cause lung particle overload, a phenomenon not likely to be applicable to humans at either ambient or occupational exposure levels (Nonetheless, it is not known if other mechanisms that may be relevant to humans also contribute to the incidence of lung tumors in laboratory animals, albeit at a lower and statistically undetectable rate). Regardless of the relevance of the rat bioassay data, several commentators have questioned the validity of using the Garshick *et al.* data to estimate diesel's impact on cancer risk (57,58). Crump suggested that the observed association in the Garshick *et al.*

data was likely to be due to confounding by lifestyle factors. In particular, he noted that while exposed railroad workers (train riders) have a higher mortality risk than unexposed workers (clerks and signalmen), there is a negative dose-response within the group of exposed workers. Crump argued that this pattern was consistent with the possibility that membership in the exposed worker group was confounded by some other risk factor. He also criticized the biological plausibility of the Dawson and Alexeeff analysis in particular because it implies that cancer risk depends on diesel exposure occurring 10 years earlier, but does not depend on exposures either prior to or subsequent to that time. Dawson and Alexeeff (59) responded to Crump, stating that 1) inclusion of unexposed workers in epidemiological analyses is standard practice, and that 2) the form of the multistage model they used is biologically plausible. They also pointed out that several other modifications to the analysis suggested by Crump did not substantially alter their results. In recognition of the possibility that diesel exhaust exposure does not cause lung cancer, our lower bound estimate for this risk is zero.

Next, we have estimated the number of QALYs lost due to mortality. Using methodology analogous to the approach described by Cohen *et al.* (60), we estimate that each lung cancer death results in the loss of 11 life years. Making an approximate adjustment for the assumption that each year of life is worth something less than one QALY, we conclude that each lung cancer death results in the loss of 10 QALYs. QALY losses associated with non-fatal cases of lung cancer are likely to be small because the vast majority of lung cancer cases are fatal (61) and because the total QALY loss per non-fatal case is substantially less than the loss associated with fatal cases.

Assuming that the average lifetime is 70 years and that exposure to diesel exhaust imposes cumulative risk at a constant rate, the central risk estimate suggests that a single year of exposure to an additional $\mu\text{g}/\text{m}^3$ of diesel exhaust results in an incremental loss of $\frac{1}{70} \times 2.2 \times 10^{-4} \times 10$ QALYs per person, or approximately 30 lost QALYs per million people exposed per $\mu\text{g}/\text{m}^3$. The corresponding upper bound estimate is 80 QALYs per million people exposed per $\mu\text{g}/\text{m}^3$.

It should be noted that the contribution of cancer to lost QALYs may have been double counted to some extent. In particular, the epidemiology studies of the association between PM exposure and all-cause mortality may also reflect the association between exposure to diesel PM and the incidence of lung cancer. The extent of this overlap depends on the proportion of PM exposure attributable to diesel exhaust.

Despite a lack of direct evidence of CNG's carcinogenicity, we might infer such effects if it contains the same toxic agents assumed to be responsible for diesel's putative carcinogenicity. If we assume that particle-bound PAHs are the cancer-causing agents in diesel exhaust (a reasonable but unproven assumption), we would have to compare PAH concentrations per μg diesel PM to PAH concentrations per μg CNG PM. Unfortunately, reliable data to make this comparison are not available. Some studies (62) have found PAH emissions to be substantially larger in diesel vehicles, while others (63) found similar PAH emissions per mile traveled, implying greater PAH concentrations per μg CNG PM. Furthermore, the latter study indicated that CNG exhaust is more mutagenic

than diesel exhaust (per μg) and that CNG vehicles emit more benzene and 1,3-butadiene than diesel vehicles, both of which are considered human carcinogens. However, none of these studies evaluated the precise technologies in our analysis, and resolving this issue is beyond the scope of our analysis.

Given the available information, our central estimate for CNG's carcinogenicity is zero. However, due to the prevailing uncertainties and recent mutagenicity evidence, our upper bound for CNG's carcinogenicity reflects the assumption that its carcinogenicity per μg PM is the same as diesel's. In any case, as noted above, our sensitivity analysis (journal manuscript Section 3.2 and Table 6) indicates that the carcinogenicity assumptions have only a small impact on our results.

S-2 Greenhouse Gas Emissions

Greenhouse gases (GHGs) emitted from buses include CO_2 , CH_4 , and N_2O . In order to compute their combined effect, CH_4 and N_2O emissions are expressed in terms of the amount of CO_2 resulting in the same global warming potential (GWP). This analysis uses GWPs of 21 for methane and 310 for N_2O (the GWP of CO_2 is 1), as suggested by the Intergovernmental Panel on Climate Change (p. 9 in (5)).

GHG emissions stem from both vehicle operation and upstream activities. To quantify emissions associated with vehicle operation, we have used measurements from the same vehicles identified in Section 2.1.1 of the primary manuscript for the purpose of quantifying PM and NO_x emissions. None of the selected studies reported CH_4 or N_2O

emissions for either CD or ECD vehicles, although values reported by Ahlvik and Brandberg (2) indicate that they are small enough to ignore even after adjustment for GWP. No N₂O emissions were reported for CNG vehicles. Because there is no reason to believe that ECD GHG emissions differ substantially from corresponding CD emissions, data for these two technologies were combined (five CD values and one ECD value). The data appear in Table S-4, along with the average values used in this analysis. The average CO₂ emissions among the diesel vehicles is approximately 2,600 g/mile, while the corresponding value for the CNG vehicles is approximately 2,500 g/mile. Adding the CO₂ equivalent average value for CNG CH₄ emissions yields approximately 2,800 g/mile for CNG vehicles.

This analysis estimates GHG emissions associated with upstream fuel activities using the lifecycle analysis developed by Wang (4) and the estimates reported by Beer *et al.* (7). The GHG emission estimates developed for CD and CNG using the Wang *et al.* data are calculated in a manner analogous to calculation of PM₁₀ and NO_x emissions (see Section S-1.1). Total CO₂ equivalent emissions amounted to 550 g/mile for the production of diesel fuel and from 960 to 1,300 g/mile for CNG. Beer *et al.* evaluated the impact of reducing diesel sulfur levels on upstream GHG emissions. That analysis found that upstream CO₂ emissions associated with the manufacture of ultra-low sulfur diesel were 20% (580 g/mile) greater than the corresponding emissions associated with production of standard diesel fuel and that upstream CH₄ emissions associated with ultra-low sulfur diesel production were 6% higher (70 g/mile CO₂ equivalent). There was no reported difference in N₂O emissions.

Total CO₂ equivalent emissions (the sum of vehicle operation and upstream emissions) amount to 3,200 g/mile for CD (no quantified uncertainty), 3,300 g/mile for ECD (no quantified uncertainty), and 3,800 to 4,100 g/mile for CNG. Because this range is small in relative terms compared to uncertainty introduced by the range of plausible values for the economic cost of these emissions (see below), the remainder of this analysis assumes total CNG GHG emissions are approximately 4000 g/mile.

This analysis has estimated the monetary value of the damage resulting from GHG emissions by assuming that it equals the value of the optimal carbon tax on GHG externalities. Tol (64) has reported the most updated summary of studies estimating the optimal tax (see Table S-5). Several key assumptions contribute to substantial differences among the reported estimates, including: 1) the impact of CO₂ on equilibrium surface temperatures (used as an index of climate change); 2) the relationship between changes in average temperature and changes in human welfare; 3) the discount rate; and 4) the baseline scenario, *i.e.*, the level of emissions that the tax is designed to generate. Based on these results, this analysis assumes that the economic cost of emitting one ton of CO₂ ranges from \$2 to \$22 per ton. The geometric mean of these bounds (approximately \$7) serves as the central estimate for this parameter.

Note that the taxes in Table S-5 are designed to generate an “optimal” level of emissions (or close to optimal), *i.e.*, an emissions level at which marginal costs just equal marginal benefits. In order to achieve a more stringent reduction in emissions (*e.g.*, those

specified by the Kyoto Protocol on Climate Change), a larger tax would be necessary.

Estimates of the marginal cost to the U.S. of meeting the Kyoto targets are on the order of \$100 per ton of carbon emitted (p. 8 in (65)), a value that corresponds to \$27 per ton of emitted CO₂.

Assuming a bus travels 40,000 miles per year, the incremental annual monetary cost of GHG emissions for ECD buses ranges from \$8 to \$88 (central estimate of \$28). For a CNG vehicle, the corresponding incremental cost ranges from \$64 to \$704 (central estimate of \$224). These costs turn out to be far smaller than the transit agency costs described in the following sections.

S-3 Transit Agency Costs

This section estimates transit agency costs, including vehicle procurement costs (Section S-3.1), infrastructure costs (Section S-3.2), and operational costs (Section S-3.3). These costs are expressed as dollars per vehicle year. The time horizon for the analysis is the expected life of a transit bus, which is assumed to be 12 years, an assumption used by the Los Angeles County Metropolitan Transportation Authority (LACMTA) (p. 30 in (66)). The real discount rate (*i.e.*, after inflation) is assumed to be 3%. Table 6 in the journal manuscript summarizes our estimates.

S-3.1 Vehicle Procurement

ECD

The DPF for transit buses is not yet manufactured in production quantities. As a demonstration product, its cost is \$7,500 (67). When produced in substantial quantities (e.g., 500,000 units per year), that cost is expected to fall to \$1,500 (\$150 per year at a discount rate of 3%). However, that level of demand is unlikely until more stringent diesel emissions standards go into effect in 2006. This analysis assumes that the cost per unit is \$7,500 (annualized cost of \$750).

CNG

At this time, CNG vehicles cost approximately \$36,000 more than CD vehicles (66), which amounts to an annualized cost of \$3,600. Motta *et al.* (68) argued that this difference will decrease as CNG production volumes increase. Nonetheless, it is unlikely that this difference will disappear completely because some CNG bus components, especially fuel tanks, appear to be inherently more expensive than the corresponding diesel bus components, increasing vehicle cost by around \$20,000 (p. 18 in (68)). This analysis assumes that the incremental cost of a CNG vehicle compared to CD is between \$20,000 and \$36,000, with a central estimate of \$28,000. The corresponding annualized costs range from \$2,000 to \$3,600, with a central estimate of \$2,800.

S-3.2 Infrastructure Costs

In addition to purchasing buses, a transit agency must also ensure that the necessary fueling, maintenance, and bus storage facilities are available. Because natural gas is a vapor at room temperature, special steps must be taken to reduce the risk of an

explosion in these facilities (68). Moreover, because natural gas is delivered from municipal distribution systems at relatively low pressure (several pounds per square inch, or psi), compressors must be used so that large quantities of gas can be loaded into each vehicle's fuel tanks. To incorporate infrastructure capital costs into the analysis, we amortize them over the expected life of such facilities (assumed to be 50 years) and use the resulting annualized costs.

Table S-6 summarizes the available infrastructure cost data for CNG facilities (we assume that ECD does not require any additional infrastructure). The data indicate that costs can vary substantially. Factors contributing to this variation include climate (which determines if the facility is outdoors or indoors), and the availability of land (which determines if facilities can be built on a single level, substantially simplifying ventilation). Interpreting the data is complicated by the fact that most sources have not reported the incremental cost of new CNG facilities, but instead have reported either total new facility cost or facility conversion costs.

For a low-cost setting, we use the costs reported for LA County (annualized cost of \$326 per bus for the fuel facility) and the costs reported by Motta *et al.* (68) (annualized costs of \$300 per bus for the maintenance facility and \$325 per bus for the storage facility). Totaling these costs yields approximately \$950 per year. To estimate costs for a high cost setting, we have used the information reported by NYCT. Fuel facility costs reported by NYCT amounted to an annualized value of \$957 per bus. Annualized costs for storage and maintenance facilities can range from \$957 to \$9,575

per bus. These values serve as bounds for this parameter, and the average of these bounds (\$5,266) serves as the central estimate.

S-3.3 Operating Costs

Operating costs consist of fuel, bus maintenance, and facility maintenance.

Fuel

To estimate fuel costs for CD vehicles, this analysis uses prevailing prices from 1999, or \$1.15 per gallon (Figure 112 in (8)). Assuming the vehicle travels four miles on a gallon of fuel, the per mile cost is \$0.29.

U.S. EPA has estimated that reducing sulfur concentrations to 15 ppm would cost four cents per gallon (Federal Register, v65, n 107, p. 35430, June 2, 2000). NYCT reported ultra-low sulfur diesel (≤ 30 ppm) costs 12 cents more per gallon than does low sulfur diesel (350 to 500 ppm) (18). This analysis assumes that the per gallon incremental cost of ultra-low sulfur diesel ranges from \$0.04 to \$0.12, with a central estimate of \$0.08. The per mile costs are \$0.01 to \$0.03, with a central value of \$0.02.

To calculate fuel costs for CNG, we have multiplied the cost of diesel by two parameters: 1) the relative cost of CNG compared to diesel per unit heat energy; and 2) the relative efficiency of diesel vehicles compared to CNG vehicles, *i.e.*, the distance traveled per unit energy. Quantifying the cost of CNG is complicated by the fact that

cost can vary by location (p. 14 in (68); p. 12 in (69)) and can depend substantially on the nature of the contract between the transit agency and the local utility (68). This analysis sidesteps these complications and instead assumes constant fuel costs over time. In its most recent evaluation, the Department of Energy (8) stated that it does not anticipate that real prices for natural gas will change substantially over the next 20 years. U.S. GAO (69) estimated that per BTU, the cost of CNG is 80% of the corresponding cost of diesel. To this result, the cost of compression must be added. The National Research Council estimated that it costs \$0.11 to compress CNG with the same heat content as a gallon of diesel. Hence, the total cost of CNG with the same heat content as a gallon of diesel is $(80\% \times \$1.15) + \0.11 , or \$1.03. The cost of CNG with the same heat energy as diesel sufficient to propel a bus one mile is $\$1.03 \div 4$ miles, or \$0.26.

Diesel vehicles are far more efficient than CNG vehicles for three reasons (6). First, CNG engines cannot achieve as high a compression ratio as diesel engines and hence do not convert as much of the fuel's heat energy into kinetic energy driving the pistons. Second, because CNG engines regulate air intake with a throttle, they have higher so-called "pumping losses," a phenomenon that results in the over-fueling of the engine at low loads (*e.g.*, when idling). Finally, CNG buses are heavier than diesel buses because of their fuel tanks (6). The net impact of these factors is a reduction in energy efficiency of between 20% and 40% (p. 12 in (6)). As a result, the cost per mile for CNG buses is \$0.26 (the cost of CNG with the same heat energy as a quantity of diesel sufficient to propel a bus one mile) divided by either (1-20%) or (1-40%), or \$0.32 to \$0.43.

Vehicle Maintenance

ECD: Although there has been no extensive study documenting the cost of maintaining DPFs, Johnson Matthey has stated that the only maintenance necessary for these devices is removal of ash generated by lubricating oils every 60,000 miles (70). This task takes from two to four hours and is estimated to cost approximately \$200. This cost amounts to 0.3 cents per mile.

CNG: Although several reports have compared maintenance costs for diesel and CNG buses, extrapolation of the findings is complicated by a variety of factors (*e.g.*, the vehicles are not the same age, the engines differ in performance, or the cost estimates fail to reflect repairs made under warranty). For example, the 1999 analysis conducted by LACMTA criticized a Pacific Gas and Electric (PG&E) report that concluded that CNG buses in the city of Sacramento reduced maintenance costs because the study compared new CNG buses to diesel buses that were between eight and thirteen years old (p. 11 in (66)). LACMTA presented its own repair data indicating that model year 1995-1996 CNG buses in its own fleet had annual maintenance costs that exceeded by \$6,000 the costs of diesel buses acquired in the late 1980's. However, Arcadis Geraghty & Miller (AG&M) (71) claimed that the Cummins L-10G engines powering the LACMTA buses are not as reliable as other bus engine models. AG&M criticized data from NYCT on the same grounds, stating that the 1995 model year Cummins L-10G engines powering the CNG buses was not as reliable as the Detroit Diesel Corporation (DDC) CNG counterpart

to the DDC Series 50 engine powering the NYCT diesel buses. Nonetheless, the NYCT study is superior to many other studies on this topic because the CNG and CD vehicles were the same age. The NYCT study found that maintenance costs for CNG buses exceeded the corresponding costs for CD vehicles by \$0.30/mile. Because it is plausible that there is no difference between CNG and CD maintenance costs, this parameter has bounds from \$0.00 to \$0.30/mile, and a central estimate of \$0.15/mile.

Facility Maintenance

We assume that ECD requires no incremental facility maintenance. However, natural gas compressor maintenance can be an important cost. LACMTA (p. 26 in (66)) estimated that over a ten-year period, maintenance and compression at a 200 bus facility will cost \$4,544,500 (*i.e.*, the costs are \$454,450 per year, or \$2,272 per bus per year). However, compression costs must be subtracted from this total in order to isolate the cost of maintenance. These costs are difficult to calculate without knowing the number of miles driven by the buses served by this facility and the assumed price of the energy used for compression in this particular case. NYCT is now paying \$900,000 to \$1,000,000 per year to an outside contractor for maintenance at a 215 bus facility (approximately \$4,000 per bus per year) and estimated that even if the work were brought in house, it would still cost nearly \$2,400 per bus per year. Other estimates for maintenance costs have been substantially less. For example, the Transportation Research Board estimated that compressor station maintenance costs amount to 3% of plant costs annually (p. 20 in (6)). Given the \$5 million price of the new fueling station in the Bronx, that would amount to

\$150,000 per year, or \$600 per bus per year. This analysis assumes that the incremental cost of maintaining CNG fueling facilities amounts to between \$600 and \$4,000 per bus per year.