Air Quality Implications of Neighborhood Design: Case Study of Charlotte, NC

by

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Abstract

Mobile source emissions are a significant contributor to the problem of air pollution in urban areas. While studies have analyzed the links between neighborhood design, travel behavior, and auto emissions, most of these studies are based on simulation models. This paper attempts to analyze the affect of neighborhood design on the total auto emissions produced by persons and households using data from a household travel survey conducted in 2002 in the Charlotte, North Carolina metropolitan area. Auto emissions were directly estimated using the distance traveled and model year of the vehicle used for each trip made by households in Mecklenburg County. Trip emissions were estimated for carbon monoxide (CO), nitrogen oxides (NO_x) , and hydrocarbons (HC). Percentage of auto trips beginning with cold starts was also calculated. Emissions and cold starts were estimated at the person and household level in ordinary least squares regression models using socioeconomic variables and land use indicators aggregated at the census block group level as predictors. Controlling for socioeconomic factors, significant relationships between land use variables and predicted emissions and percentage of trips beginning with cold starts were found. Origin and destination walkability and local/regional accessibility and origin property values had the strongest relationships with person level per-trip emissions, though the relationships with origin and destination walkability and accessibility were somewhat confounding. For household-level per-trip emissions, distance from the home census block to the central business district and local/regional accessibility displayed small, positive relationships, while property values had a large negative association with predicted emissions.

1 Introduction

1.1 Mobile Source Emissions

Mobile source emissions are a leading contributor to air pollution, especially in urban areas. The term *mobile source* is used to describe vehicles and equipment that produce pollutant emissions and either move or can be moved. Emissions of three specific pollutants, hydrocarbons (HC), carbon monoxide (CO), and nitrogen oxides (NO_x), can largely be attributed to on- and non-road mobile sources. On-road mobile sources, which include passenger vehicles, light-duty trucks, heavy-duty trucks, and motorcycles, are larger contributors than non-road sources. HC, CO, and NO_x are the result of the combustion and/or evaporation of carbon-based fuels and have significant health and environmental impacts, as discussed next.

Hydrocarbons are emitted as a result of incomplete fuel combustion and fuel evaporation. Onroad mobile sources accounted for 29 percent of 1999 HC emissions in the U.S. (U.S. Environmental Protection Agency [U.S. EPA], 2006b). Volatile organic compounds (VOCs) are a type of HC and a key contributor to ground-level ozone, which can cause adverse human health effects, including difficulty breathing, lung damage, and reduced cardiovascular functioning, especially in sensitive populations, such as children, older adults, and those with heart and respiratory illnesses (U.S. EPA, 2006b). Carbon monoxide is produced through incomplete combustion of fuel. It is estimated that on-road mobile sources produce up to 95 percent of CO emissions in most U.S. cities (U.S. EPA, 2006b). When inhaled, CO reduces oxygen delivery to the body's organs and tissues, and affects both healthy and sensitive populations. Nitrogen

oxides are formed when fuel is burned at high temperatures. NO_x contributes to both groundlevel ozone and the formation of particulate matter. On-road mobile sources accounted for 34 percent of national NO_x emissions in 1999. In addition to the human health affects of NO_x emissions caused by ozone and particulates, NO_x contributes to acid rain and nitrogen loading in water bodies (U.S. EPA, 2006b).

While total emissions of all three of these pollutants decreased between 1970 and 2002, in part due to improvements in vehicle emissions control technology, vehicle miles traveled increased by 155 percent and are expected to continue increasing (U.S. EPA, 2003). Moreover, reductions in emissions have leveled off to some extent in the last decade, a large portion of the improvements having been reached between 1970 and 1995 (U.S. EPA, 2003). Thus, additional improvements in emissions control technology may not be enough to counteract the effects of increasing vehicle miles traveled.

Recent evidence suggests that compact neighborhood designs such as neo-traditional neighborhood developments reduce the number and distance of auto trips that residents take (Khattak & Rodríguez, 2005). As these types of housing developments gain popularity as alternatives to the conventional suburban neighborhood, the impacts of travel behavior in these and other types of neighborhoods on mobile source emissions must be better understood.

1.2 Study Location

The Charlotte-Gastonia-Concord North Carolina/South Carolina metropolitan statistical area (MSA) is one of the fastest growing regions in the country. The City of Charlotte, located in Mecklenburg County, lies at the heart of the MSA and covers approximately 46 percent of the county's 526 square miles (U.S. Census Bureau, 2007). Much of the recent residential growth in the county has been in sprawling, conventional suburban developments. According to the Charlotte Chamber of Commerce, between 1990 and 2003, the census tracts in the far south, north, and northeast parts of the county experienced the most growth, while central city tracts reported population losses (2007). The five fastest-growing tracts experienced population increases upwards of 400 percent. The area's population is expected to continue growing rapidly, with an estimated 43 percent increase in Charlotte's population over the next ten years, and a 38 percent increase in the county's population during the same period, resulting in year-2017 estimated populations of 950,000 and 1.2 million people, respectively (Charlotte Chamber of Commerce, 2007).

As the region prepares its plan for the next twenty-five years, it has come to a major crossroads. The MSA is already facing the problem of federal air quality standard non-attainment, having been designated as a "moderate" non-attainment area for 8-hour ground-level ozone in 2004 (U.S. EPA, 2007). The MSA has until June, 2010 to reach attainment and avoid losing federal funding for future public projects. An important aspect of its state plan to achieve federal air quality standards are its long-range transportation and land use plans. The region must decide whether to plan for growth that is "smart" or growth that maintains the status quo.

Whether or not the implementation of smart growth principles can actually improve air quality is still widely debated in the literature. It is the purpose of this master's project to contribute to the debate by helping to inform decision makers about the potential air quality benefits of growing in compact, "smart" ways. While this paper cannot account for all of the potential sources of air pollution caused by different neighborhood designs, understanding how neighborhood design affects a household's travel behavior in terms of production of air pollutants is nonetheless a key contribution to this field of research.

2 Literature Review

While numerous studies have investigated the relationship between neighborhood design and travel behavior (e.g., Cervero & Radisch, 1996; Crane & Crepeau, 1998; Handy, 1996; Khattak & Rodríguez, 2006; Kulkarni & McNally, 1997), few have extended this relationship to impacts on air quality using estimates of household emissions. Critics of the relationship between land use and air quality often claim that improvements in vehicle emissions control technology are a more important aspect of the solution to urban air quality problems than land use measures (Bae, 1993). However, in 2001, the EPA issued policy guidelines that allow metropolitan regions in non-attainment of national air quality standards to receive emission "credits" for adopting smart growth land use practices (U.S. EPA, 2001). This implies that the EPA has acknowledged that a purely technological approach to air quality management is insufficient to address the growing problem of urban air pollution and that a land use approach should be used to supplement technological measures (Stone, 2003).

Frank (2000) analyzed several empirical studies of the land use-transportation interaction and found that the quasi-experimental research design applied in the studies was at the heart of the controversy over the validity of research results. While the studies analyzed may lack definitive causal relationships (a common drawback in social science research), Frank found that several studies with robust research designs identified a positive relationship between density, land use mix, and connectivity and non-motorized travel, transit use, and reduction in vehicle miles traveled (VMT) due to shorter vehicle trip distances. Because of the fundamental relationship between VMT and auto emissions, a reduction in VMT associated with a specific neighborhood type would imply a reduction in emissions. However, because VMT is not the sole determinant of auto emissions, more in-depth analysis of neighborhood design with respect to its potential impact on household auto emissions is needed.

Marquez and Smith (1999) developed an integrated land use, transportation, and airshed model for Melbourne, Australia, and evaluated four growth scenarios: compact growth in inner- and middle-city suburbs, edge city or multi-nodal growth, corridor growth around key radial transportation routes, and continuation of current (1991) growth trends. The three alternative scenarios all outperformed the "business as usual" scenario in terms of total emissions and energy use. There was no clear leader among the three alternatives, however, and perhaps unsurprisingly, the compact growth scenario was among the worst for population exposure to pollutants.

Two recent studies modeled air quality in hypothetical scenarios with very different outcomes (Borrego, Martins, Tchepel, Salmim, Monteiro, & Miranda, 2006; Lam & Niemeier, 2005). Borrego et al. modeled three hypothetical cities: Compact, Corridor, and Disperse. The Corridor City demonstrated the highest emission rates due to the higher vehicle speeds assigned to this

type of city, which is characterized by growth in four corridors radiating outward from the city center with "high quality transport infrastructure (highways)" connecting nodes within the corridors. The Disperse City, characterized by low density and traditional separation of uses, had the lowest emissions per area, while the Compact City, characterized by high density and complementary activities such as housing, shopping, and offices in close proximity of one another, had the lowest emission rates per capita. They concluded that the compact cities with mixed land use have better air quality compared with other types of urban form.

A limitation of Borrego et al. and the present study is recent evidence that vehicle emissions are episodic in nature and because of this, stop-and-go traffic results in higher emissions than smooth flow traffic at higher speeds (Frey, Rouphail, & Zhai, in press). If this had been taken into account by Borrego et al., it is possible that the Corridor City would not have demonstrated the highest emissions rates. Lam and Niemeier's (2005) study, based on computer simulation of multiple hypothetical urban form scenarios, unlike Borrego et al., concluded that policies encouraging mixed-use development may actually *increase* vehicle emissions by raising housing prices and displacing existing residents, who are then forced to make longer commute trips as a result.

The review of current literature yielded two examples of the use of actual travel diary and household information to estimate household emissions and compare them to land use variables associated with each household. Frank, Stone, and Bachman (2000) found a significant inverse relationship between vehicle emissions (NO_x , CO, and VOC) and household density, work tract employment density and, for NO_x emissions only, census block density in the Central Puget Sound region of Washington. Frank, Sallis, Conway, Chapman, Saelens, and Bachman (2006) found that a walkability index (combining measures of residential and intersection density, land use mix, and retail floor area ratio) had a small but significant negative association with NO_x and VOC emissions in King County, Washington. In both cases, the authors developed a framework for estimating emissions using trip length and engine start temperatures, which emulated the technique used in EPA's MOBILE emissions modeling software. While this methodology can be repeated using travel data from other areas, the authors estimated emissions using a prototypical vehicle for all trips, thus failing to capture differences in emissions caused by different vehicle types. However, recent evidence suggests that households in conventional suburban developments are more likely to own light duty trucks (a vehicle class that includes most SUVs) than their counterparts in more compact, mixed-use neighborhoods (Cao, Mokhtarian, & Handy, 2006). A similar argument can be made for vehicle year, with older vehicles being more prevalent in neighborhoods where income is lower. Holding all else constant, the higher likelihood of finding heavier vehicles in suburban neighborhoods and older vehicles in lower income neighborhoods is likely to result in higher emissions in those neighborhoods. While this study does not incorporate vehicle type in emissions calculations, it improves upon previous studies by including vehicle model year in emissions calculations.

3 Conceptual Structure

A number of variables can influence household and person auto emissions. Most directly, auto emissions are related to vehicle miles traveled, speed and acceleration rates, engine operating

temperature, and number of trips a household takes. Number of trips is an important factor because about half of the emissions released during most trips are attributable to starting the vehicle engine (EPA, 2006a). Vehicle factors, such as model year, mileage, state of repair, and fuel efficiency, and environmental factors, such as temperature and altitude also affect emissions rates (Reynolds & Broderick, 2000). Engine load and engine displacement also affect emissions.

This study considers the most direct factors influencing household and person travel behavior and thus auto emissions; namely the socioeconomic and land use attributes that may affect the amount of auto travel (VMT and number of trips) people and households carry out. Socioeconomic characteristics are expected to affect emissions rates directly and indirectly. Attributes such as the number of people in a household and household income may directly affect auto use, but these characteristics also affect the number and attributes of cars owned by a household, which in turn affect emissions. Land use variables will also be considered in relation to household and person auto emissions. Land use is expected to affect travel behavior, which will in turn affect production of emissions. A conceptual diagram of the relationships to be investigated is shown in Figure 1.

3.1 Hypotheses

A summary of hypotheses can be found in Tables 1 and 2. First, I hypothesize that socioeconomics are related to household and person auto emissions and cold starts. I expect age, gender, income, worker status, and senior status to be related to auto emissions in the person models. In the household models, I expect

income, number of people in the household, number of vehicles owned by the household, number of workers, home type (single family residence or other), and home ownership to be related to household production of emissions and cold starts. Specifically, higher income and auto ownership are expected to be associated with higher emissions levels. There are two reasons for this: 1) higher income is associated with more household trips (Kulkarni and McNally, 1997); and 2) high auto ownership implies a need for more travel, which would result in higher emissions. I hypothesize that the number of people and number of workers in a household will influence household emissions. This follows from the tenet that transportation is a derived demand; more people mean more demand, and thus higher auto use and greater household emissions. The relationship between home type and ownership status and emissions is unclear, but will also be tested.

I hypothesize that land use will influence household and person emissions. I expect this influence to be demonstrated through differences in auto use among households in areas with different land use characteristics. Specifically, I expect emissions to decrease with increasing land use factors of walkability, local/regional accessibility, and agglomeration, because the literature suggests that these attributes are inversely related to auto use. For the same reason, I expect emissions to

increase with increasing industrial areas. The land use factor "property values" could feasibly be related positively or negatively with auto emissions. On the one hand, property values are likely to be higher in the dense, central areas of the city, which I would hypothesize to be negatively associated with auto emissions. On the other hand, property values in some conventional suburban developments (e.g., gated communities) tend to be quite high and may be associated positively with household emissions. Property values may also be correlated with income and thus vehicle age, i.e. households with higher incomes may be more likely to own newer vehicles, which correspond with lower emissions. However, I will generalize my hypothesis for all land use factors, as shown in the tables.

Table 2. Null and Alternate Hypotheses – Household Models

4 Methods

4.1 Data Description

The household and travel data used for this study was collected during a survey conducted in 2002 in ten counties (Cabarrus, Cleveland, Gaston, Iredell, Lincoln, Mecklenburg, Rowan, Stanly, Union, and York) in the Charlotte-Gastonia-Concord MSA. The survey included a telephone interview on household, person, and vehicle characteristics as well as mail-in/mailback travel diaries. The sample population is composed of 3,333 households. Eight counties were sampled in proportion to their population proportion within the region. Cleveland and Iredell Counties were sampled at a rate of 70 percent of their population proportion and only within specific zip codes; the remaining 30 percent of the sample was distributed to the other counties. Census data were used to ensure that the sample is representative of the actual population. No sample weights were used in the analysis. Because land use attributes were characterized only for Mecklenburg county, households outside of the county were eliminated from the analysis.

Wilson and Song (2006) characterized land use in Mecklenburg County by performing a factor analysis of spatial attributes within each census block group in the county. The factor analysis was performed on a number of land use variables, such as population density, median distance from houses within the block group to certain amenities (e.g., school, grocery store, park), and presence of different land use classifications (e.g., industrial, commercial) within each block

group. The factors determined during the analysis were: walkability, local/regional accessibility, property values, agglomeration, and industrial areas. The urban form and built environment variables associated with each factor and the factor loadings are shown in [Table 3](#page-7-0).

Household and person auto emissions were estimated using trip diary and vehicle information from the same survey. It is desirable to characterize vehicle emissions according to vehicle type (sedan, SUV, pick-up, etc.) and model year, as these factors heavily influence emissions and may vary substantially by neighborhood type. However, without detailed route and speed information for each trip, it is quite difficult to specify vehicle characteristics in the emissions calculations. A method incorporating vehicle model year, however, is practicable with emissions factor data from the U.S. Environmental Protection Agency (EPA), as detailed in the next section.

4.2 Emissions Estimation and Cold Starts

Auto emissions were calculated using household vehicle and trip diary information collected during the 2002 survey. Auto emissions factors for three pollutants, hydrocarbons (HC), carbon monoxide (CO), and nitrogen oxides (NO_x), were obtained from EPA (1998) (see Appendix). These factors are given as grams/mile of each pollutant based on vehicle age and mileage and were obtained using outputs from EPA's MOBILE5 modeling software. Factors are given for light-duty passenger vehicles with model years 1968-1998 for HC, 1968-1992 for CO, and 1968- 1996 for NOx, for each of seven mileage classifications: 0-24,999; 25,000-49,999; 50,000-74,999; 75,000-99,999; 100,000-124,999; 125,000-149,999; and 150,000 or more miles. Thus, there are more than 700 emissions factors in the EPA matrix. A single factor is also given for each mileage classification for all vehicles with pre-1968 model years and for all vehicles newer than the latest vehicle for which individual factors are available. The emissions factors table was published in 1998.

Each household in the survey provided make and model information on each vehicle available to members of the household. Because vehicle mileage was not collected in the survey, it was estimated by multiplying the vehicle age by 12,000 miles per year. Each household vehicle was then coded for use with the trip diaries. When a person from a household filled out a trip diary, s/he identified which household vehicle, if any, was used for the trip. The model year and estimated mileage were then matched with emissions factors from EPA to provide emissions factors for each trip. For vehicles with model years 1999-2002, the latest available factors were used. The emissions factors were then multiplied by each trip's distance in miles to obtain the mass of each pollutant, in grams, emitted during the trip.

Finally, trip emissions were aggregated at the person and household level and normalized by number of trips taken, including non-auto trips. The non-auto trips were assigned emissions values of zero so that persons who took fewer auto trips (all else being equal) would have lower per-trip emissions. These variables served as the dependent variables for ordinary least squares regression models, using person and household characteristics and land use factors as predictors for person and household production of each pollutant. To meet the assumption of normal distribution of variables in linear regression models, all emissions values were transformed by natural logarithm.

The percentage of trips beginning with cold starts was also determined for use as a dependent variable. From household trip diaries, all trips using the same household vehicle were arranged in order of departure time. The first trip for each vehicle was coded as a cold start. If the next trip began more than one hour after the previous trip ended, it was also considered a cold start (Frank et al., 2006). Thus, any trips beginning one hour or less after the end of the previous trip were considered warm starts. The percentage of each person's and household's trips beginning with cold starts was determined by dividing the number of cold starts by the number of auto trips. This variable was also modeled using ordinary least squares regression with the same independent variables (person and household variables and land use factors) as the emissions models.

4.3 Comparison of Emissions Methodologies

As discussed in Section [2,](#page-3-0) two notable research papers have used methodologies similar to the present study to estimate household auto-related emissions: Frank, Stone, and Bachman (2000) and Frank et al. (2006). [Table 4](#page-9-0) presents a summary of each methodology. The methodology developed by Frank, Stone, and Bachman employed geocoded trip origins and destinations to

specify the shortest network time-path for each trip, which allowed for estimates of both travel time and average travel speed of trips recorded in survey respondents' trip diaries. Using generalized vehicle and environmental factors for the regions studied, the authors generated emissions tables for various speeds in grams per second and multiplied these rates by the travel time of each trip to determine trip emissions. Trip start and end times were used to determine the engine operating temperature so that start emissions could be added to the per-second travel time emissions to obtain total emissions for each trip. Frank et al. (2006) updated this methodology by replacing derived average travel speed with average operating speeds for major roads as defined by the regional travel demand forecasting model of the study area. Frank et al. also used the most current MOBILE modeling software from EPA, version 6.2, to obtain emissions factors.

¹Destination block group considered for person-level analysis only

5 Results

5.1 Descriptive Statistics

To give the reader an overall sense of the data set, descriptive statistics for each variable are shown below. [Table 5](#page-11-0) shows descriptive statistics for the person-level models and [Table 6](#page-12-0) displays descriptives for the household models. The pollutant weights (in grams) were transformed by natural logarithm for use in the regression models, but descriptive statistics are provided for both non-transformed and log-transformed emissions weights. In both person and household models, carbon monoxide (CO) was the largest contributor to air pollution (in mass) of the three pollutants studied. The average percentage of auto trips beginning with cold starts was slightly higher for persons than households, at roughly 72 percent and 70 percent, respectively.

Four socioeconomic variables plus three indicator variables for income were used in the person models. The variables for gender, worker status, and senior status were indicator variables with values of one or zero. The mean values for these variables indicate that within the sample,

approximately 46 percent are male, 75 percent work on a regular basis, and 12 percent are 65 years old or older. The sample includes only persons aged 18 or older, with an average age of about 46 years. The three indicator variables for income represent three ranges of annual household income: 0-\$29,999, \$30,000-\$74,999, and \$75,000 and above. The lowest income category was used as the base case in the models, with approximately 9 percent of the sample in this category. The middle range accounted for about 52 percent of the sample, while the remaining 39 percent fit into the highest income category. An additional variable not included in the models but included in the descriptives tables for reference, IMPUTEINC, represents the number of persons and households for which income had to be imputed due to non-reporting of income. Households had slightly more imputed values than persons, with 16 and 15.7 percent of the cases imputed, respectively.

Households were characterized by five socioeconomic variables plus the three indicator variables for income described above. Among the sample of 1,334 households, the average household had 2.2 people, 1.3 workers, and 1.9 vehicles. About 83 percent of households owned their home, and about 80 percent of the households in the sample resided in single family detached houses. Approximately 11, 54, and 35 percent of households had incomes in the low, middle, and high income categories, respectively.

The descriptive statistics for the land use variables used in the regression models are not especially informative for two reasons: first, they have been aggregated at the block group level, and second, the majority of the land use variables are the results of factor analysis and represent a variety of measured land use values for households in the sample. The statistical models discussed in the next section are more illustrative of the land use variables used in this study. One note regarding the land use variables in the person models is that both home and destination block group land use variables were included. Destination block group refers to the block group in which each worker's place of employment is located or the most-often visited block group for those who did not work at the time of the survey. For non-workers with more than one mostvisited block group, the land use factors for the most-visited block groups were averaged.

5.2 Regression Analysis

Four ordinary least squares regression models were evaluated for both persons and households in the study area (one for each of three pollutants, HC , CO , and NO_x , plus percentage of trips beginning with cold start), for a total of eight models. The general formats of the regression models estimated in the analysis are:

where *Y* represents per-trip emissions of a particular pollutant in grams or percentage of trips beginning with a cold start and x_1 through x_n are household and land use variables. The results of person and household models are discussed in the next two sections.

Table 5. Descriptive Statistics - Person Models

(a) Home land use variables calculated for census block group in which person resides.

(b) Destination land use variables calculated for census block group in which person works or most-often visited block group of non-workers

Table 6. Descriptive Statistics - Household Models

(a) Land use variables calculated for census block group in which household resides.

5.2.1 Person Models

As shown in [Table 7](#page-14-0) through [Table 10,](#page-17-0) all three models for emissions of pollutants showed significant relationships between all five of the socioeconomic variables and per-trip emissions. Gender, age, and worker status have significant positive relationships with per-trip emissions, though the relationship is weaker and of much smaller magnitude for age than for the other two variables. The predicted increase in emissions of all three pollutants was upwards 40 percent for males, significant at the 99 percent confidence level. (Recall that gender is an indicator variable equal to one for males and zero for females.) For persons who work regularly, the model predicts approximately 24 percent higher emissions of all three pollutants. Senior status and income had significant negative relationships with all three pollutants. For seniors, the model predicted 30-32 percent lower emissions than non-seniors, while the middle income category reduced predicted emissions by about the same percent, and high income category reduced predicted emissions by about 54 percent when compared with the low income category.

Home land use variables varied in their significance and direction of relationships with predicted per-trip emissions. Median distance to the central business district and factors of agglomeration and industrial uses had either weakly significant (<90 percent) or insignificant positive relationships with emissions. Walkability and local and regional accessibility factors had positive significant relationships with emissions; a unit increase in the walkability factor resulted in predicted emissions increase of approximately 4.5 percent for HC and NO_x and an increase in per-trip CO emissions of 6.4 percent. A unit increase in the local and regional accessibility factor was associated with a predicted increase in emissions between 18 and 22 percent, significant at the 99 percent confidence level. It should be noted, however, that the local and regional accessibility factor is associated with a number of *median distance of homes within the block group to X* variables, where X can represent various amenities such as primary roads, parks, and commercial land uses. Thus, when the factor increases, it is associated with increases in these distance variables and thus the factor may be a better measure of local and regional *inaccessibility*. Thus, the large positive coefficients associated with this factor are not surprising. The final home block group land use factor of significance is property values. This factor had a strong negative association with emissions of all three pollutants, decreasing the predicted emissions of each by approximately 45 percent.

Finally, destination land use variables were added to the models. Of the five factors, local and regional accessibility and property values showed consistent, significant relationships for all three pollutants. Walkability was significant at greater than 90 percent confidence only in the NO_x model. An interesting aspect of the walkability, accessibility, and property values factors is that the signs are opposite of those for the home location block group. While the magnitude of walkability coefficients is of the same order for both home and destination, the negative access coefficient is approximately 9 percent, or about half of the magnitude of the home block group access coefficient, and the destination property values coefficients are a fraction of their home block group counterparts (3 percent change versus -45 percent change, respectively).

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Table 7. Person per-trip emissions of Hydrocarbons [Ln(g)]

	Model 1		Model 2		Model 3		Model 4		Final Model	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t -stat
Constant	$3.237***$	19.013	$0.435***$	2.468	$0.598***$	3.066	$0.584***$	3.004	$0.569***$	3.051
Socioeconomic Variables										
GENDER	0.422 ***	6.767	0.424 ***	6.916	0.429 ***	7.037	0.425 ***	6.979	0.426 ***	7.003
AGE	$0.005*$	1.847	$0.005*$	1.898	$0.005*$	1.719	$0.005*$	1.789	$0.005*$	1.773
WORK	0.362 ***	4.491	0.386 ***	4.859	0.352 ***	4.422	0.244 ***	2.943	0.246 ***	2.973
SENIOR	-0.331 **	-2.468	$-0.299**$	-2.256	$-0.311**$	-2.359	-0.320 **	-2.442	-0.321 **	-2.446
MIDINC	-0.300 ***	-2.699	-0.360 ***	-3.268	-0.322 ***	-2.927	-0.325 ***	-2.966	-0.329 ***	-3.011
HIGHINC	-0.523 ***	-4.560	-0.604 ***	-5.275	-0.534 ***	-4.594	-0.550 ***	-4.737	-0.553 ***	-4.783
Home Land Use Variables										
MED_DIST_CBD			0.033 ***	4.220	0.011	0.738	0.013	0.890	0.015	1.270
WALKABILITY					0.034	1.169	0.051 *	1.657	$0.044*$	1.665
LOCALREGACC					0.167 ***	3.043	0.195 ***	3.528	0.186 ***	4.215
PROPVAL					-0.446 ***	-3.659	-0.465 ***	-3.828	-0.455 ***	-3.891
AGGLOM					0.009	0.285	0.004	0.120		
INDUSTRIAL					0.020	0.638	0.022	0.700		
Destination Land Use Variables										
D WALKABILITY							-0.044	-1.444	-0.045	-1.610
D LOCREGACC							-0.091 ***	-2.561	-0.095 ***	-3.460
D PROPVAL							$0.031**$	2.118	$0.031**$	2.110
D_AGGLOM							0.006	0.197		
D INDUSTRIAL							0.024	1.345	0.025	1.414
Summary Statistics										
N	1,779		1,779		1,779		1,779		1,779	
F-statistic	18.221		18.310		13.015		10.657		12.915	
R^2	0.058		0.067		0.081		0.093		0.093	
Adjusted _{R²}	0.055		0.064		0.075		0.085		0.086	

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Table 9. Person per-trip emissions of Nitrogen Oxides [Ln(g)]

	Model 1		Model 2		Model 3		Model 4		Final Model	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Constant	$0.656***$	4.046	$0.417**$	2.457	$0.582***$	3.098	$0.567***$	3.031	$0.551***$	3.069
Socioeconomic Variables										
GENDER	0.409 ***	6.895	0.407 ***	6.904	0.412 ***	7.027	0.408 ***	6.959	0.409 ***	6.979
AGE	$0.005*$	1.864	0.005 *	1.788	0.004	1.615	$0.004*$	1.689	$0.004*$	1.673
WORK	0.361 ***	4.703	0.383 ***	4.995	0.349 ***	4.555	0.242 ***	3.042	0.244 ***	3.072
SENIOR	-0.329 ***	-2.572	-0.284 **	-2.223	-0.296 **	-2.331	-0.305 **	-2.418	-0.305 **	-2.418
MIDINC	-0.284 ***	-2.682	-0.336 ***	-3.173	-0.300 ***	-2.830	-0.303 ***	-2.869	-0.307 ***	-2.913
HIGHINC	-0.484 ***	-4.431	-0.570 ***	-5.170	-0.502 ***	-4.485	-0.518 ***	-4.635	-0.522 ***	-4.684
Home Land Use Variables										
MED_DIST_CBD			0.034 ***	4.533	0.011	0.802	0.014	0.963	0.016	1.390
WALKABILITY					0.037	1.317	$0.053*$	1.814	0.047 *	1.818
LOCALREGACC					0.166 ***	3.148	0.194 ***	3.648	0.184 ***	4.324
PROPVAL					-0.438 ***	-3.735	-0.456 ***	-3.894	-0.445 ***	-3.954
AGGLOM					0.007	0.227	0.003	0.086		
INDUSTRIAL					0.020	0.665	0.022	0.712		
Destination Land Use Variables										
D WALKABILITY							-0.045	-1.525	-0.045 *	-1.662
D_LOCREGACC							-0.092 ***	-2.689	-0.094 ***	-3.548
D PROPVAL							0.028 *	1.941	0.027 *	1.935
D_AGGLOM							0.003	0.103		
D_INDUSTRIAL							0.024	1.419	0.025	1.495
Summary Statistics										
N	1,779		1,779		1,779		1,779		1,779	
F-statistic	18.311		18.804		13.374		10.931		13.250	
R^2	0.058		0.069		0.083		0.095		0.095	
Adjusted R ²	0.055		0.066		0.077		0.087		0.088	

ality Implications of Neighborhood Design E. Yasukochi Air Qu

	Model 1		Model 2		Model 3		Model 4		Final Model	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t -stat	Coeff.	t-stat	Coeff.	t-stat
Constant	66.027 ***	21.34	65.570 ***	20.17	$67.079***$	18.53	$67.223***$	18.55	66.164 ***	21.99
Socioeconomic Variables										
GENDER	$1.942*$	1.701	1.941 *	1.7	$1.918*$	1.682	1.862	1.626	$2.034*$	1.788
AGE	-0.113 **	-2.179	$-0.113**$	-2.188	-0.121 **	-2.335	$-0.122**$	-2.349	-0.104 **	-2.509
WORK	15.790 ***	10.61	15.827 ***	10.62	16.107 ***	10.75	15.567 ***	9.971	15.846 ***	11.11
SENIOR	1.084	0.438	1.166	0.47	1.262	0.509	1.368	0.551		
MIDINC	-1.460	-0.727	-1.565	-0.774	-1.925	-0.946	-1.947	-0.957	-2.147	-1.063
HIGHINC	-2.926	-1.41	-3.094	-1.468	-4.008 *	-1.866	-4.107 *	-1.906	$-4.192**$	-1.982
Home Land Use Variables										
MED_DIST_CBD			0.067	0.46	-0.021	-0.074	-0.041	-0.147		
WALKABILITY					-0.080	-0.146	-0.164	-0.287		
LOCALREGACC					0.465	0.46	0.535	0.523		
PROPVAL					5.650 **	2.473	5.300 **	2.312	5.697 ***	2.66
AGGLOM					0.649	1.131	0.453	0.774		
INDUSTRIAL					0.577	0.99	0.626	1.065		
Destination Land Use Variables										
D WALKABILITY							0.519	0.906		
D LOCREGACC							0.172	0.257		
D PROPVAL							$0.532**$	1.953	$0.532**$	1.99
D_AGGLOM							0.688	1.281		
D INDUSTRIAL							0.156	0.474		
Summary Statistics										
N	1,779		1,779		1,779		1,779		1,779	
F-statistic	29.629		25.416		15.810		11.570		27.112	
R^2	0.087		0.087		0.092		0.095		0.092	
Adjusted R ²	0.084		0.083		0.086		0.087		0.089	

Table 10. Person percentage of trips beginning with cold start

Because this result is somewhat confounding, total per-trip emissions have been calculated for persons with home-destination combinations in five representative block groups in the county. [Table 11](#page-18-0) gives a description of each block group's characteristics, including factor scores for the five land use factors used in the regression models.

	Land Use Characterization		Land Use Factors							
Block Group		Miles from CBD	Walk- ability	Local/ Regional Accessibility	Property Values	Agglomer- ation	Industrial Areas			
	City Center	0.41	0.513	-3.443	0.061	3.851	1.730			
2	Urban	2.48	0.219	-1.153	-0.410	-0.140	1.320			
3	Rural Greenfield	5.10	-0.080	-0.413	0.688	1.432	6.066			
4	Inner Suburb	5.87	-0.555	0.247	0.054	0.117	-0.287			
5	Outer Suburb	13.64	4.739	-1.602	0.260	-2.019	0.939			

Table 11. Representative Block Group Descriptions

[Figure 2](#page-18-1) shows the total predicted emissions for each home-destination pair of the representative block groups described above. The sample's median values for socioeconomic variables were used and thus the "person" for whom emissions were estimated is a 46-year-old female worker with an annual household income between \$30,000 and \$74,999. The values shown in the figure are in grams of total emissions (HC, CO, and NOx). Carbon monoxide makes up the bulk of each figure, representing 84-88 percent of total emissions shown. Note that the models used to calculate the emissions shown in [Figure 2](#page-18-1) do not predict emissions at the trip level; the emissions values in the figure represent the predicted per-trip emissions for persons who live in the home block group and travel most frequently to the destination block group.

Destination Block Group

An interesting result of the representative emissions exercise is that it predicts that persons who live in the outer suburb (5) will create fewer emissions per trip than persons living in the inner suburb (4) for each combination of home and destination block groups, even though the outer suburb in this case is more than twice the distance to the city center. This could be an indication that persons living in outer suburbs are traveling to destinations closer than the central business district for work and other purposes than persons living in the inner suburb block group. A second interesting result supports this theory: the model also predicts lower emissions for persons living in the outer suburb than persons living in the urban block group for all homedestination pairs.

Another interesting result of this exercise is that it implies that persons who work or travel often to the city center block group have the highest per-trip emissions regardless of the home block group in which they live. This could be indicative of a couple of trends: first, that most people working in the CBD use the auto mode to get to the CBD; and second, that most home locations are somewhat distant from the CBD.

A corollary to the previous finding and a final interesting note is that persons who live in the city center block group have the lowest per-trip emissions, regardless of their most-often visited destination block group. In fact, the models predict that the lowest per-trip estimate of emissions was for persons living in the center city block group and working in the outer suburban location. This is somewhat unexpected considering that this daily commute is one of the longest commutes of all individuals in the example. However, it may be an indication that persons living in the center city are more likely to use modes other than personal auto to make non-work trips, thus reducing their per-trip auto emissions.

The regression model predicting percent of person trips beginning with a cold start had somewhat different results from the emissions models. The final model includes all but the senior status socioeconomic variable and included only the property values factor from the home and destination block group land use variables. Worker status had the largest and most significant relationship of the socioeconomic variables, increasing the predicted percentage of trips beginning with cold starts by more than 15 percent, while a unit increase in the home property values factor increased the predicted percent of trips beginning with cold starts by 5.7 percent. Gender (male) and destination property values had small positive relationships, while the income indicators had small negative relationships with predicted percentage of trips beginning with cold starts. [Table 12](#page-20-0) provides a summary of the final model coefficients for each of the models estimated. The emissions model coefficients have been adjusted to represent percent change in the prediction of the dependent variable given a unit increase in the independent variables.

While the F-statistic for each final model was sufficiently high, the explanatory power of the models was low. The adjusted R-square values for the models ranged from 0.082 to 0.089, indicating that the independent variables included in the models explained between 8.2 and 8.9 percent of the variation observed in the data.

Note : ***, **, * Significant at the 99, 95, and 90% level of confidence, respectively.

5.2.2 Household Models

Six socioeconomic variables were considered in the models estimating per-trip household emissions and percent of trips beginning with cold starts: number of workers in the household, number of people greater than 4 years of age in the household, number of vehicles in the household, homeownership status, home type, and household income. Homeownership status is indicated by the value of one, while renting households are assigned the value of zero for this variable. Home type is an indicator variable assigned the value of one if the home is a single family detached residence and zero otherwise. Income is represented by two indicator variables that are identical to those used in the person models. Six land use variables, matching the home land use variables in the person models, were evaluated in the household models. The results of the individual household models can be found in [Table 13](#page-21-0) through [Table 16.](#page-22-0)

All of the socioeconomic variables except for homeownership status showed relationships with per-trip household emissions of all three pollutants that were significant at greater than 95 percent confidence. Number of workers and vehicles and single family residence status all had positive relationships with emissions. Each additional worker in the household increased the predicted amount of each pollutant by nearly 16 percent, while each additional household vehicle increased predicted per-trip emissions by 28–30 percent. The number of people aged five and above in the household and increasing income categories had negative relationships with emissions. For each person over five years old in the household, predicted per-trip emissions

Note: *** ** * Significant at the 99, 95, and 90% level of confidence, respectively.

Note: *** ** * Significant at the 99, 95, and 90% level of confidence, respectively.

Table 16. Household percentage of trips beginning with cold start

decreased by about 22 percent. Belonging to the middle income category decreased predicted emissions by 31–33 percent compared to the lowest income category, while belonging to the highest income category decreased predicted per-trip emissions by 54–58 percent.

With respect to land use variables, median distance to the central business district (CBD) and local and regional accessibility had small positive and significant relationships with per-trip household emissions of all three pollutants. For every additional mile of median distance of households within the block group to the CBD, predicted emissions increased by between 2 and 3 percent, while a unit increase in the accessibility factor (recall it would more aptly be called an *inaccessibility factor*) is associated with a 7 percent increase in predicted emissions. As in the person models, property values had a large, significant negative relationship with predicted household per-trip emissions, hovering around 29 percent for all three pollutants.

Similar to the person model, the household model for percent of trips beginning with cold starts is somewhat different from the emissions models. Number of workers, number of people over age five, and single family residence status are the only socioeconomic variables significant at greater than the 90 percent confidence level. For each additional worker, percent of trips beginning with cold starts is predicted to increase by 6.8 percent, while each additional person decreases predicted percentage of trips beginning with cold starts by 4.9 percent. Residing in a single family detached home decreases the predicted percentage of cold starts by 3.6 percent. Of the land use variables, the property value and agglomeration factors both had small but significant relationships with the dependent variable. Unlike with the emissions models, property values showed a positive relationship with predicted percentage of cold starts, increasing the predicted percentage by nearly four percentage points. A unit increase in the agglomeration factor increased predicted percentage of trips beginning with cold starts by less than one percent.

Like the person models, the F-statistics of the four models used to predict household per-trip emissions of HC, CO, and NO_x and percentage of trips beginning with cold starts were sufficiently high, but the explanatory power of the models is low—lower in fact than the person models. The adjusted R-square values of the household models ranged from 0.068 to 0.072, indicating an explanatory power of 6.8 to 7.2 percent of the data's variation. [Table 17](#page-24-0) provides a summary of the final model coefficients for each of the household models estimated. The emissions model coefficients have been adjusted to represent percent change in the prediction of the dependent variable given a unit increase in the independent variables.

	НC	CO	NO _x	% Cold
	(% change)	(% change)	(% change)	starts
Constant	70.57 ***	328.37 ***	68.91 ***	76.26 ***
Socioeconomic Variables				
WORKERS	15.83 ***	15.62 ***	15.68 ***	6.79 ***
PEOPLE	-22.19 ***	-21.82 ***	-22.53 ***	-4.88 ***
NUMVEH	29.83 ***	29.19 ***	27.94 ***	
OWNHOME				
SFR	17.58 **	18.54 **	17.90 **	-3.58 **
MIDINC	-33.23 ***	-32.42 ***	-30.77 ***	-0.97
HIGHINC	-57.11 ***	-57.83 ***	-53.56 ***	-2.07
Land Use Variables				
MED DIST CBD	2.54 ***	2.36 **	$2.70***$	
WALKABILITY				
LOCALREGACC	$7.06*$	$7.02*$	$6.83*$	
PROPVAL	$-29.51**$	-28.62 **	-29.04 **	$3.92*$
AGGLOM				$0.83*$
INDUSTRIAL				
Summary Statistics				
N	1,334	1,334	1,334	1,372
F-statistic	12.276	11.850	12.676	15.372
R^2	0.077	0.075	0.079	0.073
Adjusted R^2	0.071	0.068	0.073	0.068

Table 17. Summary of Final Household Model Coefficients

Note : ***, **, * Significant at the 99, 95, and 90% level of confidence, respectively.

6 Limitations

6.1 Data Limitations

There are a number of limitations inherent in the data set. First, the land use data is at the block group level, which means that some amount of variation is lost in the aggregation process, e.g., population density and measures of street network, which are more meaningful at the neighborhood level than at the block group level. There may also be an issue of self-selection of households into different types of neighborhoods, which has been widely discussed in the recent literature on the topic of smart growth and new urbanist developments. A third limitation is that the survey data, especially the trip diaries, involve the recording of meticulous details, which can easily result in human error and omission.

6.2 Methodological Limitations

A number of methodological limitations are reflected in this study, the largest of which is the emissions estimation methodology. Emissions data are extremely complex and depend on a number of factors. These include individual vehicle characteristics (make, model, and year, maintenance history, engine type and size, mileage, and emission reduction devices), fuel quality, driver behavior, operating conditions (start temperature, average speed, load, trip length, frequency of trips), traffic conditions, climate conditions, and topography (Reynolds and Broderick, 2000). Emissions rates also depend on operational mode (acceleration, deceleration, or cruise) and speed (Unal, Frey, & Rouphail, 2004; Frey, Rouphail, & Zhai, in press).

Although vehicle information for each trip taken by each person (vehicle make/model and model year) was available, only the model year and trip distance were taken into account in the

emissions estimate. All of the other vehicle factors, trip characteristics, and environmental factors were assumed to be the same for all trips. Therefore, it is important to note that while the figures calculated give some idea of the emissions produced by the auto trips recorded in trip diaries, they are by no means a definitive assessment.

Another limitation of this study is that it takes into account only auto emissions. There are additional emissions sources implicit in mixed-use and compact neighborhoods that are not usually contained within conventional neighborhoods. These include additional mobile source emissions from buses and delivery vehicles and point source emissions from services such as dry-cleaning that may be located in the neighborhood. These could have important implications for residents' exposure to air pollution. It is also important to note that household and person emissions are not synonymous with neighborhood aggregate emissions. Very little of the total vehicle emissions contributed by residents of neighborhoods is actually contained within the neighborhood unless trips take place entirely within its boundaries.

7 Conclusions

Promoters of smart growth would have their cause strengthened if its environmental benefits could be clearly shown. In areas of the United States that are growing at a rapid pace, such as the study area where the data for this paper originated (Mecklenburg County, North Carolina), it is particularly important to understand the potential benefits and negative impacts of building new developments in a specific fashion, such as the new urbanist style. Because mobile source emissions play such a large role in overall air quality, it is imperative to understand the relationship between urban form, transportation behavior, and auto emissions.

The initial analysis conducted here provides some evidence that the travel behavior of residents in more mixed-use communities may lead to air quality benefits. This relationship was stronger and of larger magnitude when trip information was aggregated at the person level rather than at the household level. The regression models revealed that, controlling for socioeconomic variables, land use factors explained an additional 0.3 to 3.3 percent of variation in the models for both emissions and cold starts (see [Table 18\)](#page-26-0). The most important land use variables in the emissions models for persons were home and destination walkability, local and regional accessibility, and property values, though the magnitude and strength of home block group factors were generally greater. The most important land use variables in the household emissions models were median distance of houses within the block group to the central business district, local/regional accessibility, and property values. Other land use variables investigated were not significant or were weakly significant and small in magnitude. In general, land use was stronger in predicting emissions than percentage of trips beginning with cold starts for both persons and households. The property values factor was the only land use factor that was consistently significant for both emissions and percentage of trips beginning with cold starts.

Table 18. Change in Adjusted R-square Values from First to Final Models

¹First model includes socioeconomic variables only.

While the results of this study have shown that the land use variables considered here have significant relationships with the dependent variables, the single land use variable consistently important in all models is property values. The magnitude and significance of the inverse relationship between property values and the dependent variables in the emissions models may simply be indicative of the fact that newer cars have lower emissions rates and homes in block groups with higher property values are more likely to have newer vehicles (and conversely, households in block groups with lower incomes are more likely to have older, more polluting vehicles). Because vehicle model year and mileage were the only vehicle factors taken into consideration in this study, it is difficult to say with certainty that the land use variable of property values is truly indicative of a relationship between land use and person or household emissions. If vehicle type choice were to be considered in the emissions estimates, the suburban household propensity for larger vehicles may result in higher emissions for wealthy, suburban block groups rather than lower emissions, as was demonstrated here.

Moreover, the consistently high percentage of trips beginning with cold starts for both persons and households may diminish any potential impacts of compact, mixed use urban form on emissions. That the average percentage of trips beginning with cold starts was 72 percent for individuals and 70 percent for households highlights the importance of cold starts in total person and household emissions. This being the case, trip distance (and by proxy, urban form) matters little in total trip emissions. More important in the equation of total person and household emissions may be the aspect of mode choice. Further analysis in the form of more sophisticated modeling should be done to see whether the high percentage of trips beginning with colds starts affects the emission levels estimated here and the independent variables' significance in relationship to them.

Finally, this study does not take into account the added mobile source emissions created by transit that is typically more prevalent in mixed-use neighborhoods and added commercial vehicles that may occur more frequently in mixed-use areas. More study is needed to determine if the potential air quality benefits of smart growth lead to fewer mobile source emissions both within the neighborhood and at a regional level.

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References

- Borrego, C., Martins, H., Tchepel, O., Salmim, L., Monteiro, A., & Miranda, A.I. (2005). How urban structure can affect city sustainability from an air quality perspective. *Environmental Modelling & Software, 21*, 461–467.
- Cao, X., Mokhtarian, P.L., & Handy, S.L. (2006). Neighborhood design and vehicle type choice: Evidence from Northern California. *Transportation Research Part D, 11*(2), 133–145.
- Cervero, R., & Radisch, C. (1996). Travel choices in pedestrian versus automobile oriented neighborhoods. *Transport Policy, 3*(3), 127–141.
- Charlotte Chamber of Commerce. (2007). Demographics and economic profile. Retrieved March 2, 2007, from: http://www.charlottechamber.com/index.php?submenu=Demo graphicsEconomicProfile&src=gendocs&ref=DemographicsEconomicProfile&category= eco_dev
- Crane, R., & Crepeau, R. (1998). Does neighborhood design influence travel? A behavioral analysis of travel diary and GIS data. *Transportation Research Part D*, *3*(4), 225–238.
- Frank, L.D. (2000). Land use and transportation interaction: Implications on public health and quality of life. *Journal of Planning Education and Research, 20*(1), 6-22.
- Frank, L.D., Sallis, J.F., Conway, T.L., Chapman, J.E., Saelens, B.E., & Bachman, W. (2006). Many pathways from land use to health: Associations between neighborhood walkability and active transportation, body mass index, and air quality. *Journal of the American Planning Association, 72*(1), 75–87.
- Frank, L.D., Stone, B., & Bachman, W. (2000). Linking land use with household vehicle emissions in the central Puget Sound: Methodological framework and findings. *Transportation Research Part D, 5*(3), 173–196.
- Frey, H.C., Rouphail, N.M., & Zhai, H. (in press). Speed- and facility-specific emission estimates for on-road light duty vehicles based on real world speed profiles. *Transportation Research Record*.
- Handy, S. (1996). Methodologies for exploring the link between urban form and travel behavior. *Transportation Research Part D, 1*(2), 151–165.
- Khattak, A.J., & Rodríguez, D. (2005). Travel behavior in neo-traditional neighborhood developments: A case study in USA. *Transportation Research Part A, 39*(6), 481–500.
- Kulkarni, A., & McNally. M.G. (1997). Assessment of influence of land use-transportation system on travel behavior. *Transportation Research Record, 1607*, 105–115.
- Lam, T., & Niemeier., D. (2005). An exploratory study of the impact of common land-use policies on air quality. *Transportation Research Part D, 10*(5), 365–383.
- Marquez, L., & Smith, N. (1999). A framework for linking urban form and air quality. *Environmental Modelling & Software, 14*, 541–548.
- Reynolds, A.W., & Broderick, B.M. (2000). Development of an emissions inventory model for mobile sources. *Transportation Research Part D, 5*(2), 77–101.
- Stone, Jr., B. (2003). Air quality by design: Harnessing the Clean Air Act to manage metropolitan growth. *Journal of Planning Education and Research, 23*(2), 177-190.
- Unal, A., Frey, H.C., & Rouphail, N.M. (2004). Quantification of highway vehicle emissions hot spots based upon on-board measurements. *Journal of the Air & Waste Management Association, 54*(2), 130-140.
- U.S. Census Bureau. (2007). North Carolina QuickFacts. US Census Bureau state and county QuickFacts. Retrieved March 2, 2007, from: http://quickfacts.census.gov/qfd/states/ 37000.html
- U.S. Environmental Protection Agency. (1998). Appendix H: Highway mobile source emission factors, in *AP-42: Compilation of Air Pollutant Emission Factors*. Retrieved January 20, 2006, from: http://www.epa.gov/otaq/ap42.htm
- U.S. Environmental Protection Agency (2001). *EPA guidance: Improving air quality through land use activities* (Publication No. EPA 420-R-01-001). Washington, D.C.: Author.
- U.S. Environmental Protection Agency. (2003). *Latest findings on national air quality: 2002 status and trends* (Publication No. EPA 454/K-03-001). Research Triangle Park, NC: Author.
- U.S. Environmental Protection Agency. (2006a). Ozone action day information. Retrieved April 19, 2006, from: http://www.epa.gov/reg5oair/naaqs/o3info.htm
- U.S. Environmental Protection Agency. (2006b). Mobile source emissions past, present, and future. Retrieved March 2, 2007, from: http://epa.gov/otaq/inventory/overview/ pollutants/index.htm
- U.S. Environmental Protection Agency. (2007). 8-Hour ground-level ozone designations. Retrieved March 25, 2007, from: http://www.epa.gov/ozonedesignations/index.htm
- Wilson, B. & Song, Y. (2006). Developing built environment typology for Charlotte. Unpublished mimeo. Chapel Hill, NC.

 $H-5$

TABLE 1.1B.1 DATE: JUNE 30, 1995

EXHAUST EMISSION RATES FOR
LOW ALTITUDE
LIGHT DUTY GASOLINE POWERED VEHICLES
AT VARIOUS MILEAGE LEVELS
(ADJUSTED FOR INDUSTRY AVERAGE FUEL. RATES INCLUDE TAMPERING)

