Is Smart Growth Associated with Reductions in CO_2 Emissions?

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Abstract: The transportation sector is the second largest contributor to human-generated CO_2 emissions. A key goal of the US Department of Transportation is to implement environmentally sustainable policies that can reduce carbon emissions from transportation sources. Smart growth developments are characterized by compact, mixed use, greater network connectivity and alternative mode friendly environments. These features may encourage reductions in vehicle travel and emissions. A better understanding of travel behavior in conventional and smart growth communities is needed to inform policies and make informed decisions. This study analyzes a behavioral dataset to answer whether smart growth developments are associated with lower CO_2 emissions. Using a sample of 15,213 households from a recent (2009) travel behavior survey, sample selection models are estimated to capture the conditionality of emissions on the decision to drive or not by household members on an assigned day. The study found that the activity participation needs for 12% of the responding households allow them to either use alternative modes or not travel out-of-home. The rest of the sample traveled in an automobile and hence contributed to CO_2 emissions. The study calculates CO_2 emissions based on vehicle miles traveled and the fuel efficiency of the vehicle used for specific trips undertaken by household members. The framework developed in this study models whether CO_2 emissions are associated with land use, socio-demographics, and preferences for information technology adoption. Tailpipe CO_2 emissions are lower for households that reside in more mixed land use neighborhoods with denser roadway networks and better network connections in the neighborhood (on the order of 12%). As a long-term strategy, CO_2 emission reductions from smart growth developments can be substantial.

Key words: Emissions, smart growth, Greenhouse Gas emissions, built environment, CO_2

1. INTRODUCTION

According to the United States Environmental Protection Agency, 1,745.5 Million Metric Tons CO_2 comes from transportation sources, accounting for 28% of such emissions. A key goal of the United States Department of Transportation is to implement environmentally sustainable policies that can reduce carbon emissions from transportation sources. The amount of carbon in the atmosphere has steadily increased over the years, and the increases are associated with the greenhouse effect, global warming, and to a lesser extent human health. Consistent with federal aims, the Virginia Energy Plan & Executive Order 59 aims at 30% reduction in CO_2 emissions by 2025. Reducing carbon emissions from the transportation sector is both important and urgent. Policy solutions can include higher corporate average fuel efficiency standards, promoting alternative fuel technologies, and smart growth-considering that land is being consumed for development at a rate almost three times faster than population growth, which has caused CO_2

emissions from vehicles to rise [1]. Smart growth is characterized by higher density, mixed land use, greater network connectivity, and alternative mode friendliness. This study quantifies the associations of compact, mixed use, connected and alternative mode friendly developments on tailpipe emissions of carbon dioxide (CO_2); this is achieved by analyzing behavioral data and estimating a behavioral model. Emissions are calculated based on household level VMT (Vehicle Miles Traveled) combined with MPG (Miles per Gallon) for vehicles used for specific trips. Such detailed information (about which household vehicle is used for a specific trip) is provided by the latest National Household Travel Survey (NHTS). Relatively fine spatial resolution is used to generate local land use around residential locations, which are then used as correlates to estimate the relationships between smart growth developments and household level vehicle emissions while controlling for household demographic factors.

2. LITERATURE REVIEW

From a long-term perspective, whether smart growth developments are associated with lower CO_2 emissions was answered using simulations and empirical studies. Simulations based on link level trip assignment explore the links between VMT and emissions, using contemporary emissions models that include MOBILE6/MOVES, CMEM. Additionally, to test whether smart growth is associated with reduction of emissions, travel demand models have been used in addition to statistical techniques of estimating regressions based on behavioral data. Table 1 shows a summary of relevant studies. In general, compact developments are associated with less travel and 5% to 11% lower CO_2 emissions. TOD (Transit Oriented Developments) can even reduce CO_2 emissions by 47.5% [2]. Reductions in emissions are equivalent to using alternative vehicle technologies [3] or changing driving behavior based on eco-driving information [4, 5].

Most of the studies concentrate on long-term CO_2 reductions, e.g., in next 30 years [6]. Typically, smart/compact growth scenarios were compared with no-change scenarios (business-as-usual or current trend), scenarios with different market penetration of alternative technologies [3, 7-10]. Most studies suggest that smart/compact growth is associated with lower vehicle miles traveled and CO_2 emissions. A study by Stone et al. [3] suggested decline of approximately 8% in CO_2 emissions as a result in more aggressive smart growth compared with business-as-usual scenario. Rodriguez et al. [7] suggested compact development without penetration of alternative technologies is associated with decreases CO_2 emissions by 7.1% relative to Business-As-Usual in 2050. Niemeier et al. [9] suggested that total emissions (total organic gases, CO, NO_x, PM) for controlled growth scenario is 6%-10% lower than the baseline growth scenario, but the effects of future land-use growth patterns may vary among differently sized spatial areas. Hennessy & Tynan [10] concluded that CO_2 emission would be reduced by approximately 11% if aggressive growth ratio is implemented. Studies also suggested that compact growth could achieve long-term emission reductions equivalent to or higher than using alternative technologies [3, 7].

Researchers have used multivariate statistical methods to explore the associations between land use and transportation emissions based on current travel behavior data. Frank et al. [11] concluded that increases in residential density, intersection density, and mixed use are associated with significant reductions in oxides of nitrogen (NO_x), hydrocarbons (HC), and carbon monoxide (CO), while controlling for socio-demographic factors. The land use characteristics are based on relatively large spatial units—the census tract. A more recent paper by Frank et al. [12] estimated multivariate linear regression models for daily household level vehicle HC and NOx emissions based on creating land use variables at one kilometer residential buffer level. The study concluded that the mix of high population density, street connectivity, and land use index were negatively associated with HC and NO_x in the Seattle metropolitan area. Also, the land use variables remained significant predictors of emissions even after vehicle miles of travel was included in the models; that is to say land use is not only associated with emissions through its relationship with travel demand (VMT), but also directly. A limitation of the study is the use of OLS (Ordinary Least Square) regression model for emissions or VMT, given that emissions are usually not normally distributed and more importantly, there can be a substantial number of zero observations in the sample. While log transform may relieve the first problem, it will not help the latter one. Vehicle emissions as a result of driving, is conditional on travelers decision to drive. Therefore, it is important to first find out whether a household drives on a particular day and if so the amount of emissions produced. Using OLS regression ignores conditionality and the associations with land use and other variables can be underestimated.

One benefit of simulations is that link-level vehicular flows can be extracted to calculate emissions, which provides needed details to accurately estimate emissions, e.g., speeds, acceleration, and congestion. Also, it can be used to anticipate future scenarios with innovative technology adoption such as eco-routing systems [13, 14], dynamic eco-driving technology [4] and intelligent transportation sytems based optimal emission pricing [15]. However, numerous assumptions must be made regarding travel behavior, VMT level, vehicles, fuel usage, regional vehicles age distribution and information technology’s market penetration in the future. This brings in high levels of uncertainty, especially when the planning horizons are 20 to 40 years in the future.

Current emissions studies measure regional emissions based on link level traffic assignment results [7, 9]. However, the link between emissions and the households who produce them is not well understood or explained. The household decision of whether or not to drive on a particular day, and if they drive, how much emissions they generate (referred to as self-selection), is unexplored. Additionally, behavioral data regarding the vehicle used for a specific trip was generally not available. This paper attempts to fill in gaps that are related to the self-selection issue.

Table 1 Summary of key studies

Paper	Data used	How emissions calculated	Scenario design	Key Findings
Stone et al. [3]	US Census 2000, 11 areas in 6 Midwestern states: IL, IN, MI, MN, OH, WI	Calculated based on VMT (NPTS) Tract level CO_2 calculated by EPA 2011 mission rate: 8887*VMT/MPG	3 scenarios: Business-as-usual (BAU) Smart-growth 1(SG1):same growth, new population reallocated to suburban & urban Smart-growth 2 (SG2): lager population growth, new population reallocated to suburban & urban	Compared to BAU, SG1 & SG2 reduce 7.2%, and 16.7% VMT, Compared to BAU, SG1 & SG2, & Hybrid Electric Vehicles reduce 4.7%, 7.8% and 18.0% CO_2 emissions in 2050;
Rodriguez et al.[7]	695,454 individuals in 235,530 households in 2000, Mecklenburg NC	TRANUS Emissions based on link level traffic assignments; Calculated emissions rates.	2 scenarios: Business-as-usual (BAU) Compact growth (CG); Alternative fuels and propulsion system achieved a 27% market penetration by 2050	CG decreases CO_2 emissions by 7.1% (no market penetration) and 10.2% (27% market penetration of alternative technologies) relative to BAU in 2050 respectively.
Niemeier et al. [9]	660,000 population growth between 2000 and 2030, Eight counties of the San Joaquin Valley region	UPlan for land use; Four-step travel demand forecast; UC Drive & MOBLIE6 model for emissions calculation	4 scenarios: Baseline growth (BG): follow current trend Controlled growth (CG): compact growth Uncontrolled growth (UG): (very) low density, roadway expansion with little transit As planned(AP): new road, high speed rail, and medium density	Emission rates: UG>AP>BG>CG. CG: total emissions 6-10% lower than BG. CG: higher residential densities contribute to development patterns that decrease regional vehicle travel and emissions.
Hennessy & Tynan [10]	US Census 1990, US Census 2000, South Carolina Population report	VMT has constant relation with GHG emissions	5 scenarios: Current trend: 5:1 “growth ratio” (land growth /population growth) 4 Compact dev. ratios: 4:1, 3:1, 2:1, 1:1 “growth ratio”	If 1:1 “growth ratio” is implemented, VMT and CO_2 emission will be reduced by approximately 11%.
Frank et al. [12]	Puget Sound Household Travel Survey 1999, Central Puget Sound Region	Speed sensitive emission rates for every link of every trip based on time of day and facility type	Linear regression	Positively associated with emissions: VMT, vehicle/HH, people/HH, & income; Negatively associated with emissions: residential densities, intersection densities, and mixed use
TRB Special Report 298 [8]	US census 2000, NHTS 2001, NPTS 1990, USA Nationwide	Calculated based on VMT EPA 2005 emission rate: 19.4 lb CO_2 per gallon gasoline	3 scenarios: Base scenario: 1.4% VMT increase Scenario 1: 25% compact growth with 12% VMT reduction; Scenario 2: 75% compact growth with 25% VMT reduction	VMT, fuel use, and CO_2 emission reduction: Scenario 1: 1-1.2% in 2030, 1.3-1.7% in 2050 Scenario 2: nearly 8% in 2030, 8-11% in 2050
Hankey & Marshall [16]	US Census 2000 142 US cities	Monte Carlo statistical distribution for future scenario, emission calculated based on VKT and depends on different technology scenario	6 scenarios: Three bounding scenarios: Infill only, Constant density, Suburban nation; Three historical decadal growth: with small (S1), average (S2), large rates (S3) 3 technology scenarios	Comprehensive compact development can reduce US 2000–2020 cumulative emissions by up to 15%–20% of projected cumulative Emissions
Xia, Barth [4]	N/A	Velocity planning algorithm Paramics	3 scenarios: Single vehicle simulation Single network simulation Multiple-lane network simulation	Efficient single vehicle reduce fuel and CO_2 emissions by 12.5% & 13.2% less fuel consumption & CO_2 emissions with short cycle length, lower volume, & higher penetration rates
Barth & Boriboonsomsin [5]	PeMS, TMC, California	Paramics simulation Real world experimentation	Two simulation scenarios: Non-eco-driving Eco-driving: 20% penetration rate of eco-driving	10%-20% CO_2 reduction without increasing travel time dramatically in congested conditions

3. HYPOTHESES

The built environment is critical to how much people drive and hence the emissions that are produced. This study emphasizes the conditional link between two processes: the decision to drive or not and the extent of resulting CO_2 emissions, given that household members drive (Figure 1). Conditionality exists because personal vehicle-based CO_2 emissions are produced if the traveler decides to drive or be driven on a particular day. If the person does not travel in a vehicle, then no emissions are produced by the personal vehicle. Therefore, a two-stage process exists in the behavioral dataset: travel by personal vehicle or not on a day, and if driving is chosen, how much emissions will be produced by driving.

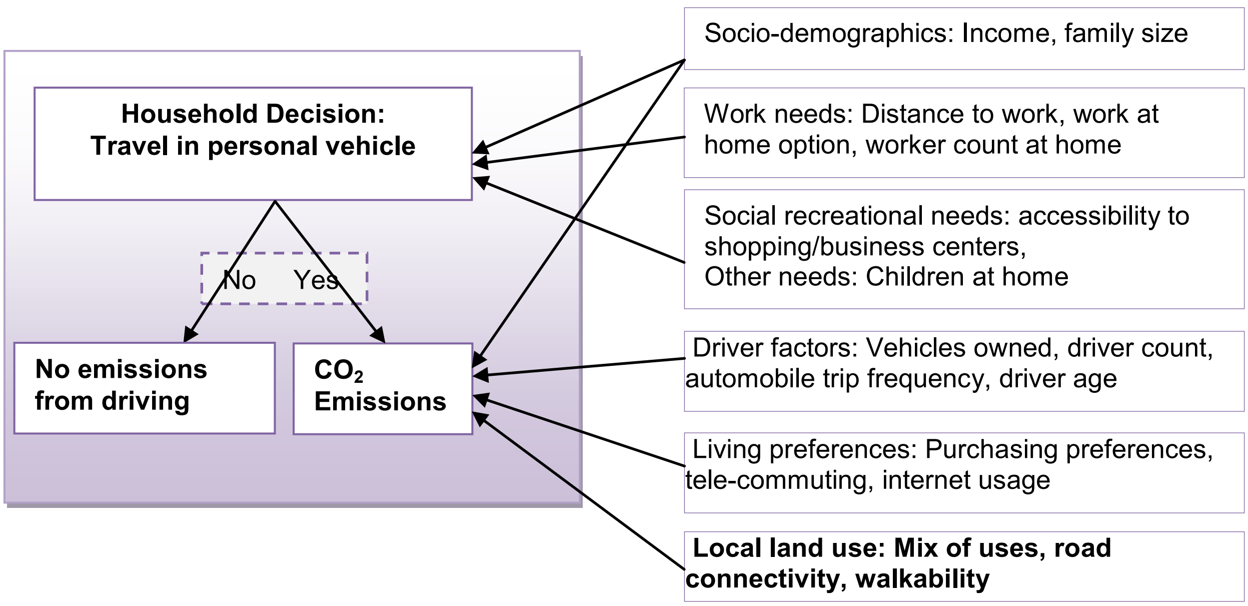

Figure 1: Conceptual framework showing conditionality between decision to drive and emissions

Factors associated with these two decision processes are conceptually different. Travelers' decision to travel by personal vehicle or not is likely associated with household socio-demographics, and the need to participate in activities (for work, shopping or social recreational purposes). Given decision to drive, emissions produced are likely associated with local land use variables, socio-demographics, driver related factors, and living preferences. Some household socio-demographic can be associated with both processes, e.g., household income, but not all of them are likely to have a direct impact on both processes. Household has children younger than 16 years can directly impact a family's driving needs, e.g. the need to drop-off or pick-up children from school. Therefore, they are included in the binary model only. Factors that may be (theoretically) weakly associated with the self-selection issue are not used in the binary drive-or-not model, e.g., local land use variables.

Factors related with emissions may include local land use and contextual characteristics, driver related attributes, and living preference variables such as use of information technology and working from home. Residential density, land use mix, and local roadway connectivity are important indicators of smart growth residential neighborhoods. This is because higher mix of residential and commercial land use can increase the ease of satisfying activity participations needs with fewer and/or shorter trips, enhancing the work-life balance which in turn can lower VMT and decrease the transportation emissions. Driver factors can have a direct relationship with emissions. These variables include the number of drivers at home, vehicles available, frequency of automobile trips and how much the vehicles are driven. Studies have shown empirical evidence linking driving behavior with emissions, e.g., if they drive aggressively, then higher emissions are expected [17]. Considering data availability and the fact that the model is based on household level, the age of household head is used as explanatory variable. For instance, generally a household with an average age of 60 years can drive differently compared with a household with average age of 30 consisting of only young couples.

The discussion above leads to two specific hypotheses to be tested in this paper: 1) travelers' drive or not is associated with household socio-demographics, and need to participate in activities (for work, shopping or social recreational purposes); 2) given the decision to drive, emissions produced is correlated with local land use variables, as well as socio-demographics, driver related factors, and living preferences.

4. Model structure

To capture the two-stage process in the behavioral database, i.e., drive or not and how much emissions are produced if driving, regression techniques such as Tobit model and Heckman sample selection model are appropriate. Heckman selection model is used in this study given a limitation of the Tobit model that assumes the same variables are associated with both processes. Based on the conceptual structure, a set of common as well as unique set of variables are likely associated with the two stages. The Heckman selection model separates the model into two parts: A linear regression model for emissions and a binary probit model for the decision to drive. The detailed model specification is presented below:

$$y = \boldsymbol{\beta}'\boldsymbol{x} + \varepsilon \quad \text{(linear regression model)} \tag{1}$$

$$z^* = \boldsymbol{\alpha}'\boldsymbol{v} + u \quad \text{(binary probit model)} \tag{2}$$

In the model, y is the dependent variable (how much emissions are produced by driving a personal vehicle), which is observed only if a criterion, $z = 1$ is met (drive). The dependent variable y is related to independent variables $\boldsymbol{x}$ with the error term ε. And z^* is unobserved; it can be estimated by independent variables $\boldsymbol{v}$, with the error term, u. Here z^* is not observed and has an observed counterpart z, which is determined by:

$$z = 1 \text{ if } z^* > 0 \text{ and } z = 0 \text{ if } z^* \leq 0 \tag{3}$$

$\boldsymbol{x}$ and $\boldsymbol{v}$ are two sets of explanatory variables that could contain either the same or different variables. In this paper, a demographic variable, household income, is common in both $\boldsymbol{x}$ and $\boldsymbol{v}$; variables related with the needs for working, and whether household has children at home are used in $\boldsymbol{v}$; variables capturing local land use, living preference, and driver factors are only included in $\boldsymbol{x}$. The model reports an index, ρ, to represent the correlation between the unobserved variables in the two equations. A statistically significant estimate for ρ indicates that modeling the two processes simultaneously is superior to modeling them separately.

5. DATA DESCRIPTION

5.1 Data Sources

The behavioral data analyzed in the paper are from the Virginia Add-on survey of NHTS conducted in 2009 (survey period covered April 2008 through May 2009). A total of 15,213 households were included in the sample after cleaning out data with unclear location information. The sample covers about 12 CBSAs (Core Based Statistical Areas) in Virginia, representing various land use types and populations. To ensure that the survey is representative of the State's population (approximately 8 million) and their daily activity-travel patterns, geographic and demographic distribution goals for the sample were achieved. The survey relies on the willingness of households to 1) provide demographic information about the household, its members and its vehicles, and 2) have all household members record all travel-related details for a specific 24-hour period, including information about the miles traveled and the vehicle used for each trip. The database has detailed fuel economy compared with previous surveys, including MPG for the vehicles owned and gasoline price information. The database contains three different levels of data: personal data; household data, and trip data. The survey's response rate is reasonably high at 25%.

A unique database was created by adding other data from various sources. This includes:

1) Publicly maintained roadway centerline shape files (Tiger files).
2) Population data from Census 2010 (census block boundary).
3) Employment data from the 2009 LEHD (Longitudinal Employer-Household Dynamics) database.

Both the population and employment data are at the Census block level which is the finest geographic unit available for public use, providing reasonable details about residences and employment. The employment data in LEHD also provides employment information based on NAICS (North American Industry Classification System) categories, which is very useful for grouping employment by different type which can be used as a proxy for land use types.

5.2 Calculating Key Variables

CO_2 emissions

The CO_2 emissions were calculated for each household using VMT data from NHTS. A key improvement in the 2009 NHTS is that it provides information on MPG (miles per gasoline-equivalent gallon estimate) for each vehicle driven on a particular trip. Note that vehicles with alternative fuels are considered in this calculation since their MPGs are substantially different compared with regular gasoline vehicles. The amount of CO_2 created from burning one gallon of fuel depends on the amount of carbon in the fuel. EPA suggests using 8,887 grams of CO_2/gallon. The CO_2 emissions are calculated by using the equation recommended by EPA:

$$CO_2 \text{ emissions per mile} = \frac{CO_2 \text{ per gallon}}{MPG} = \frac{8887}{MPG} \text{ grams}$$

The total CO_2 emissions for each trip are equal to CO_2 emissions per mile multiplied by VMT for each trip, and then the emissions for each trip are aggregated to the household level.

Mix of land use

Entropy was used as an index to represent land use diversity. This index is used frequently to define the mixture of employment and residences [18], land use balance [19], and mixture of different types of land uses [12]. In this study, the entropy score is a normalized index which varies between 0 and 1, with 1 signifying maximally mixed and full balance of land uses, and 0 signifying a maximally homogeneous used. Seven land use types are considered in the calculation of land use mix entropy index, including residential, commercial, service, office, institutional, industrial, and agricultural land uses. The employment densities for each of these land uses were exacted from Census LEHD and calculated at the Census block level. There are two types of land use entropy, “balanced” and “blended.” Higher values on balanced entropy represents neighborhoods with a balanced combination of residential, commercial, service, office and institutional land uses, which can provide better access for activity participation. Blended entropy represents neighborhoods where residential land use is mixed with industrial and agricultural land use. Higher values of blended entropy will be typically associated with lower levels of accessibility (especially alternative mode connections). The entropies are calculated in the following equation:

$$\text{Entropy} = -\sum_j \frac{P_j \times \ln(P_j)}{\ln(J)}$$

Where P_j is the proportion of density in the j^{th} land use type.

J is the number of land use types, which is equal to 5 for balanced entropy and 3 for blended entropy.

Measures of local transportation network

Studies of spatial analysis, often use circular buffers around residences to measure land use around a residence, including buffers with a radius from 0.25 miles to 1 mile [20]. Note that the NHTS and its add-on data do not release the exact location of each residence. Therefore, to obtain accurate residential buffers, a geo-imputation method was applied to assign each residence an exact location (latitude and longitude) within their census block. All sampled residences are assigned to roadways excluding freeways, ramps, bridges, and tunnels. A 0.75-mile buffer (equivalent to a 45-60 minutes walking distance) is created for each geo-imputed residence (shown in Figure 2) to capture the local land use characteristics in the neighborhood. Research has shown that using a 0.75-mile buffer around a geo-imputed residence can produce local land use variables with reasonable accuracy [21]. The following network measurements are based on this buffer and are meant to capture accessibility of the local network.

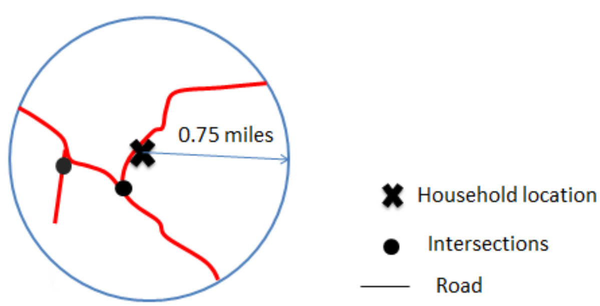

Figure 2: A land use buffer surrounding a residence

Network Connectivity

Connected Node Ratio (CNR) was selected to represent the connectivity of roadway network. It is calculated using the number of all intersections divided by the number of intersections plus cul-de-sacs. The maximum value is 1.0, which means all the intersections in a buffer were 4-way or 3-way intersections; implying that the roadway network is in a perfect grid. Generally, higher CNR means higher level of connectivity.

The Link-Node Ratio (LNR) was selected to represent the connectivity of roadway network. Link-Node Ratio is equal to the number of links divided by the number of nodes within a buffer. Links are defined as roadway segments between two nodes. Nodes can be intersection or cul-de-sacs. A perfect grid has a ratio of 2.5. Ewing [22] suggests that a link-node ratio of 1.4 is a good target for network planning purposes.

Roadway length within residential buffer

Note that CNR and LNR do not account for roadway length in a residential buffer. The roadway length within a buffer can be used to represent the density of roadway in a neighborhood. Also the average length per node was used to represent the separation between nodes, which is a coarse indicator of walkability. Lower roadway length per node is expected to be better for walking while longer roadway length per node is preferred for driving.

5.3 Descriptive Statistics

Table 2 presents the descriptive statistics of relevant variables. On average, the sampled Virginia household traveled 74 miles per day, including all vehicles used. The conditional variable drive or not drive is binary. Only 12% of respondents reported that they did not drive on the assigned travel day. For those who drive, the average CO_2 emissions produced are about 29 kilograms (or 64 pounds). For those who did not drive, zero emissions are produced from their household vehicles. Given that the emissions variable is skewed, it was log-transformed before using it as dependent variable.

For household characteristics, the average driver count per household is 1.8, and the average vehicles owned is 2.2. About 4% of households own hybrid vehicles. Analysis shows that the average CO_2 emissions of the households who own hybrid vehicles are slightly higher than others. This result is unexpected. However, further analysis confirms that hybrid vehicle owner households travel more. Specifically, on average households who own hybrid vehicles are higher income families, have more drivers at home (2.0 vs. 1.8), make more daily trips (8.5 vs. 7.9 trips per day, on average), and have higher VMT (87 vs. 73 miles per day). This suggests that consumers buying more fuel efficient vehicles may have greater travel needs. Given that whether hybrid vehicles were driven has been considered in the MPG (i.e., calculation of CO_2 emissions—the dependent variable), it was not used in the model specification.

The household income coded in the dataset is categorical; the categorical income in this paper is recoded with the average income of each category, where income=5 if family income is less than $10,000, income=$7.5 if family income is between $10,000 and $15,000, etc. Those who did not answer the income question were replaced by the mean of household income which is $57,500. On average, 22% of sample households have children younger than 16 years old. Nearly 7 daily trips per household are done using the automobile.

For work related factors, the average worker per household is about 1, the home to work distance (one way derived distance calculated based on home and work address) between home and work is about 10.8 miles, if there are more than one person working in the family, the maximum distance among all working family members is reported in this measure.

For living preferences, on average, the internet use frequency by all family members is 33 times per month; the purchase delivery frequency by all family members during a month is 2.2 times, and the frequency of working from home during past month is 0.44. These variables to some extent can represent the adoption of technology by households.

In terms of local land use variables at the residential neighborhood level, Virginia residents in the sample on average have 17.5 miles roadway in their 0.75 miles circular buffer. The average connected node ratio for local road is 0.72 and the average link node ratio is about 1.4. The average number of cul-de-sacs in the neighborhood is 37. The average balanced entropy score is about 0.51 and the score of blended entropy is about 0.34. Descriptive statistics also show a substantial variation in residential environments of survey respondents, as indicated by relatively large ranges and standard deviations of the variables.

Table 2: Descriptive statistics for variables in the database

Variable Description	Name	N	Mean	Std. Dev.	Min	Max
CO_2 emissions (grams)	CO_2 (uncensored)	13371	29,170.97	31112.95	61.29	780913.6
	CO_2 (pooled)	15213	26, 021.62	31001.14	0	780913.6
Log-transformed CO_2 emissions	$LNCO_2$	13371	9.82	1.09	4.12	13.568
Did not drive (binary)	NODRIVE	15213	0.12	0.33	0	1
Vehicle miles traveled	VMT	15213	73.84	82.18	0	2468.3
Socio-Demographic Variables						
Household vehicle count	HHVEH	15213	2.25	1.217	0	27
Own hybrid vehicle (binary)	HYBRID	15213	0.04	0.193	0	1
Family income ($x1000)	INCOME	15213	57.48	29.548	5.00	100
Household workers count	WRKCNT	15213	0.98	0.897	0	5
Distance between home and work	DISWH	15213	10.81	66.561	0	2473.19
Having children younger than 16	HAVEKID	15213	0.22	0.413	0	1
Driver-Related Variables						
Auto trip frequency	TAUTO	15213	6.80	5.685	0	52
Household driver count	DRVRCNT	15213	1.82	0.759	0	8
Age of household head	AVGAGE	15213	58.14	15.06	18	92
Living Preference Variables						
Internet use during past month	INTERNET	15213	33.34	27.49	0	186
Product delivery during past month	DELIVERY	15213	2.20	4.43	0	115
Freq. of work from home past month	FWKFH	15213	0.44	2.22	0	40
Local Land Use Variables						
Roadway length (miles)	LENGTH	15213	17.52	11.521	0.07	76.35
Connected node ratio	CNR	15213	0.72	0.135	0.00	1.00
Link node ratio	LNR	15213	1.37	0.262	0.00	5.00
Number of cul-de-sacs	NDANGLE	15213	36.68	31.361	0.00	309
Length per node (miles)	LENGPN	15213	0.21	0.247	0.029	3.756
Mix of land use entropy-Balanced	ENTROPY_BA	15213	0.512	0.180	0.00	0.954
Mix of land use entropy-Blended	ENTROPY_BE	15213	0.338	0.131	0.00	0.837

6. MODEL RESULTS

After examining correlations among variables and conducting several test runs, the final model specification was selected. The variable LNR was dropped from the specification since it was highly correlated with CNR, and it offered limited value [23]. Two models are shown in Table 3: the Heckman sample selection regression (Model 1), and a conventional OLS regression (Model 2). The Chi-Square test and F-test show that both the Heckman and OLS regression models are statistically significant, overall.

In Model 1, 1842 samples are censored with zero driving trips, producing zero CO_2 emissions from their vehicles. The upper half of the table shows log-transformed OLS regression coefficients; the bottom half of the table shows the probit regression coefficients. The correlation of the residuals in the selection and outcome equations, ρ, is statistically significant (5% level). This indicates that the sample selection structure is preferable to estimating two separate models, and that the selection is non-random with respect to the amount of emissions.

Table 3 Results from Heckman sample selection models of (log-transformed) CO_2 emissions

	Model 1 (Heckman)			Model 2 (OLS regression)		
	β	$e^{(\beta)}$	P>z	β	$e^{(\beta)}$	P>z
CO_2 Emissions model						
Auto trip frequency	0.094	1.099	0.000	0.284	1.328	0.000
Household income	0.003	1.004 *	0.000	0.010	1.010	0.000
Household vehicle count	0.049	1.050	0.000	0.177	1.194	0.000
Driver count	0.058	1.060	0.000	0.268	1.307	0.000
Roadway length	-0.008	0.992	0.000	-0.020	0.980	0.000
Connected node ratio	-0.149	0.862	0.042	1.510	4.527	0.000
Length per node	0.182	1.200	0.000	-0.387	0.679	0.000
Number of cul-de-sacs	-0.001	0.999	0.093	0.004	1.004	0.001
Balanced mix of land use	-0.125	0.882	0.070	-0.392	0.676	0.054
Blended mix of land use	0.024	1.024	0.800	0.437	1.548	0.115
Avg. house head age (years)	0.009	1.009	0.005	0.075	1.078	0.000
Square of avg. house head age	-0.0002	1.000	0.000	-0.001	0.999	0.000
Internet usage freq.	0.002	1.002	0.000	0.001	1.001	0.634
Delivery freq.	0.0001	1.000	0.970	-0.006	0.994	0.245
Work from home freq.	0.007	1.007	0.033	-0.002	0.998	0.823
Constant	8.979	7934.693	0.000	3.071	21.563	0.000
Probit model for decision to drive						
Household income	0.008	0.001 **	0.000			
Distance to work	0.001	0.0002 **	0.145			
Worker count	0.490	0.086 **	0.000			
Have children <16 years	0.164	0.029 **	0.000			
Constant	0.391		0.000			
Summary Statistics						
Observations=15213, Censored Observations=1842 Log likelihood = -21303.26 Prob. >Chi-squared=0.000 ρ= -0.208 Prob. >Chi-squared=0.001				Observations=15213 Prob.>F=0.000 R-squared =0.382		

Notes: *Inverse mills ratios of income are calculated for exp(income), since income is included in both the emissions model and the selection drive-or-not-drive probit model.

**Marginal effect of probit drive or not drive model.

The findings reaffirm the advantage of the sample selection model. That is, by estimating a model with two processes different factors associated with the two processes can be captured separately providing a clearer assessment of CO_2 emissions. The model with sample selection is methodologically sophisticated and provides a more nuanced interpretation. Note that the magnitudes and signs of variables from the OLS Model 2 without sample selection are not close to that from Model 1; therefore, ignoring sample selection in the data may generate misleading conclusions about associations.

Several variables in the binary probit model are notable for answering which factors are associated with driving and hence carbon emissions from personal vehicle use. In line with expectations, the probability of driving on the assigned travel day is higher when a household has higher income, there are more workers, and there are children younger than 16 years. One more worker at home is associated with 9% higher possibility of driving; households with children younger than 16 years have a 3% higher possibility of driving compared with households that do not have children.

The key question is whether smart growth is correlated with lower CO_2 emissions. Not all the variables used to describe mix of land use, density and road network characteristics within the 0.75 miles residential buffer are statistically significantly associated with CO_2 emissions. The model results show that CO_2 emissions are negatively associated with a good mix of land use (shown by balanced entropy), roadway length and the number of cul-de-sacs surrounding a residence, and connected node ratio; emissions do not show statistically significant associations with blended entropy. CO_2 emissions are positively associated with roadway length per roadway node; this makes sense since longer roadway links generally favor driving. Smart growth neighborhoods are characterized by greater land use mix, higher density, denser roadway networks, and higher connectivity or accessibility by various modes. The results confirm that residences located in smart growth areas in Virginia are associated with lower CO_2 emissions, on average. A neighborhood with a "balanced" land use mix (excluding industrial and agricultural land use) is associated with 12% lower CO_2 emissions compared with a single land use, while controlling for other variables. The blended entropy variable does not show statistically significant association with CO_2 emissions. A 0.1 mile increase in average roadway length per node (means larger separation between roadway intersections) in a neighborhood is associated with nearly 2% higher CO_2 emissions, all else being equal. As for connected node ratio- the indicator of grid street patterns, ten percent additional intersections that are not cul-de-sacs (a 0.1-unit increase in connected node ratio) are associated with a 1.4% decrease in CO_2 emissions. The marginal effect of number of cul-de-sacs is too small to be counted although it shows a statistically significant association with CO_2 emissions.

In the CO_2 emissions model, positive associations are observed with higher income, more drivers at home, more vehicles owned, and more automobile trips. One additional vehicle owned is associated with 5% higher CO_2 emissions. This percent is 10% for one additional automobile trip and 6% for one additional driver. Since income is the variable used in both the drive and emissions models, the coefficient of income in the emissions model must be adjusted before calculating the percent change in emissions. An inverse mills ratio of income is calculated before taking the exponent of this variable. After adjusting, an additional ten thousand dollars of household income is associated with 4% higher CO_2 emissions. The association between average age of household head and CO_2 emissions is modeled as non-linear, showing an inverted-U shape.

For the relationship between living preferences and CO_2 emissions, internet usage frequency and working from home frequency are both statistically significantly associated with higher CO_2 emissions; while the product delivery frequency does not correlate with CO_2 emissions significantly. Note that working from home and greater internet use frequency are expected to be associated negatively with driving, this result is somewhat counter to expectations. However, possible explanation can be the time saving due to telecommunication can be used to make more out of home activities which can result in more driving trips. Similarly, studies [24, 25] also suggested the use of ICT (Information and Communications Technologies) may generate additional time use for out-of-home recreational activities therefore increasing trip-making propensity.

7. LIMITATIONS

The emissions analyzed in this paper is limited for CO_2 emissions only, therefore other emissions (NO_x, VOCs, and CO) are not analyzed. The results are based on a self-reported trip diary from a behavioral survey, where people may not accurately report all their trips. Another limitation of the method used in this study is that traffic conditions, e.g., congestion, vehicle speeds and variations are not taken into account. Due to data availability restrictions, the regional accessibility, local walkability, and public transit variables were not included in the emission model but they remain in the conceptual framework. If such data becomes available for Virginia, then it can be used to potentially improve model specification.

The study is also limited due to cross-sectional nature of the data. As such it represents a snapshot of households during a time of change, with a relatively high unemployment rate and high energy prices. Exploring the dynamics of travel behavior and resulting carbon emissions will need panel type surveys. Finally, the focus is on smart growth developments, which is a long-term strategy, but we recognize that other solutions (e.g., new vehicle technologies and new forms of eco-information) may also effectively deal with the emission problem.

8. CONCLUSIONS

In the context of increasing carbon emissions from transportation and the goal of implementing environmentally sustainable policies that can reduce such emissions, it is important to understand how different strategies perform, i.e., smart growth, behavioral change through eco-information/ eco-driving technology, alternative vehicle technologies, and fuel efficiency standards. This research focused on the influence of land use and associated travel behavior on the production of CO_2 emissions, and explicitly captures the conditionality inherent in calculation of CO_2 emissions based on household members' decision to use personal automobile at the household level. Analysis of behavioral data coupled with land use data allows in-depth investigation of how smart growth developments may be associated with tailpipe CO_2 emissions. Detailed spatial land use characteristics representing the mix of land use, local roadway density and connectivity on a relatively small geographic scale were generated using geographic information systems. To some extent availability of data constrains the model specification and the implications—although key variables were available for use in the model specification.

The answer to the key question of whether smart growth is correlated with lower CO_2 emissions is a "yes." Specifically, the results confirm that several indicators of smart growth developments, especially balanced mix of land use and roadway connectivity, in Virginia are associated with lower CO_2 emissions. A neighborhood with a "well-balanced land use mix" (i.e., good jobs-housing balance but excluding industrial land uses) is associated with 12% lower CO_2

emissions compared with a single land use; ten percent additional intersections that are not cul-de-sacs (a 0.1-unit increase in connected node ratio) are associated with a 1.4% decrease in CO_2 emissions, while controlling for other variables. As expected, more mixed use and connected developments also show lower VMT. It is notable that the study could not find statistical evidence for a direct association between higher density and lower carbon emissions, perhaps due to correlation with other variables in the model.

The effect of balanced mixed land use (12%) is similar to the findings in related smart growth literature, e.g., compact growth in future years (2030-2050) can reduce CO_2 by 5% to 11.0% compared with no-built scenario [3, 7, 8]. Such long-term strategies may be coupled with short-term strategies of applying dynamic eco-driving technology and alternative vehicle technologies, where 10% to 20% reduction of CO_2 can be expected with different penetration rates of technologies and different congestion levels on roadway [4, 5]; additionally, hybrid electric vehicles are associated with substantial reduction (18%) in CO_2 emissions [3]. However, a key question to be answered by policy makers is whether multiple strategies for reducing carbon emissions can be additive? And how can multiple policies be implemented resulting in greater carbon reductions?

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