HOW DOWNTOWN RESIDENTS DELIVER MORE TRANSPORT DAMAGES: SELF-SELECTION AND AVIATION EMISSIONS

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ABSTRACT

As demand for air travel rises and climate change becomes more severe, understanding trade-offs between urban form and travel choices becomes even more relevant for transportation planners and researchers. This paper uses travel data from 129,696 US households (923,572 individual trips) to quantify the carbon emissions and climate impacts of ground-based plus air travel by Americans in 2016 and 2017 as a function of demographics, land use patterns, and other variables. Controlling for self-selection in home neighborhood choices, using a hurdle model for air travel on the survey day, and recognizing that air travel adds radiative forcing (from contrails and other atmospheric impacts), results suggest that increasing population density of one's neighborhood by 1,000 persons per square-mile lowers average American's daily driving distance by 0.57 miles (-1.71%) and air travel distance by 1.23 miles (-4.92%).

Simple averages of per-person CO2e emissions from travel average 54 lb per person-day in rural settings, 43.8 in exurban settings, 53.7 in suburban settings, and 44 in urban core zones; but they jump to 58.7 lb/person-day in the highest-density Urban neighborhoods. Importantly, after controlling for demographics - but not self-selection in one's location choice, predicted emissions for comparable individuals living in the highest-density Urban neighborhoods fall to 42 lb per person-day. In other words, those who choose to live in US dense urban areas are big flyers, more offsetting any driving reductions such settings tend to offer the average American. Econometric controls suggest that 43% of observed emission differences (in CO2e from motorized travel, by ground and air) are due to one's residential location and 57% can be attributed to self-selection.

Key Words: Transportation emissions, air travel versus ground travel, residential self-selection, urban form, National Household Travel Survey

INTRODUCTION

Transport produces about 15% of the world's greenhouse gas (GHG) emissions and 28% of U.S. GHG emissions (IEA, 2025; EPA, 2024). GHGs are gases like carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) that trap heat in the atmosphere, causing the planet to warm up (EPA, 2024). The United Nations defines an urban area by a combination of population size and density, typically settlements with at least 1,500 people per square kilometer or a total population above 20,000 (UN DESA, 2018). By this definition, 58% of the global population lived in urban areas in 2025 (Urban Institute, 2025). Ewing and Cervero (2010) combined results from more than 200 empirical studies of U.S. cities and reported that doubling neighborhood density is linked to about a 25–30% reduction in per-capita vehicle miles travelled (VMT). Similarly, land-use mix, intersection density, and transit access together can shorten VMT through shorter trips, easier walking and cycling, and a larger share of transit trips. The Urban Institute (2025) reported that a neighborhood with 40% higher density has, on average, 9% lower per-capita VMT, and that households five miles from downtown drive about 32% less than those ten miles out. Using parcel-level data for Austin with a self-selection correction, Zhou and Kockelman (2008) suggested that residents in dense neighborhoods drove about 14% fewer daily miles than similar households in low-density areas.

However, less ground travel in a city does not always mean lower total travel emissions, because people who live in dense urban areas tend to fly more often. Using International Air Transport Association data across 100 countries, Gössling and Humpe (2020) found that aviation demand is heavily concentrated: only about 11% of global population flew in 2018, and just 1% of the global population caused 50% of aviation CO2 emissions. Using the 2015 European Household Budget Survey (covering 275,614 households across 27 European countries), Büchs et al. (2023) reported that the top 10% of households by income emit about 5 to 7 times more per person from aviation than the bottom 10%, and the top 1% emit more than 20 times as much. Winkler et al. (2023) estimated that an 81% cut in car-kilometers by Londoners would deliver a 70.5% cut in their travel emissions, thanks to rebound or offsetting emissions from alternative modes, including long-distance flights.

The relationship between residential location and long-distance flying is important for land use planning and sustainable transport decisions. Zhao and Oke (2025) studied 349 U.S. metropolitan areas using census, land-use, and transit data and found that per-capita mobile GHG are driven by the interaction of transit access and density rather than density alone. Mattioli et al. (2021) suggested that urban residents fly more due to better airport accessibility and dispersed social networks. Using radiative transfer modelling for global commercial aviation between 2000 and 2018, Lee et al. (2021) showed that high-altitude nitrogen oxides, water vapor, and contrail formation deliver a total radiative forcing about 2.1 times the CO_2-only value. Graver et al. (2020) used the International Council on Clean Transportation's Global Aviation Carbon Assessment model to allocate each flight's fuel burn among passenger classes in proportion to the floor area each seat occupies, and found that a first- or business-class seating is responsible for 2.6 to 4.3 times more CO2 per person-kilometer than an economy-class seat, depending on aircraft type.

Although built environment (BE) attributes, referring to the physical parts of where we live and work, such as buildings, parks, and transportation systems, influence travel choices, self-selection (SS) is key in reflecting pre-existing travel preferences: people choose where to live partly based on how and how much they want to travel (Mokhtarian and Cao, 2008). Persons and households that prefer walking and transit may seek out dense, mixed-use neighborhoods, and fly less often because they value nearby activities over distant ones. Cao et al. (2009) reviewed 38 empirical studies on BE and SS. Almost all studies still found significant BE effects after controlling for SS, but the effects were usually smaller than results without SS controls. For studies that quantified both effects, the BE contribution ranged from about 52% to 90% across different contexts. Using the 2000 San Francisco Bay Area Travel Survey (with roughly 3,500 households), Bhat and Guo (2007) built a joint mixed-logit-ordered-probit model of residential choice and vehicle count. After controlling for demographics, they found that BE factors (street-block density and transit access time) had relatively small effects on vehicle ownership, suggesting that demographic variables explain much of the self-selection effect. Using the 1998–1999 Austin Area Travel Survey of 1,903 households and Heckman's treatment-effects model, Zhou and Kockelman (2008) that BE explained over half of household VMT gaps, while residential self-selection explained up to about 40%.

Prior studies show three main findings. First, compact urban form often reduces driving and vehicle travel. Second, air travel emissions are mostly caused by a small group of high-income households and frequent flyers, which can offset ground-travel emission savings. In a study of the United Kingdom using 2013-2018 National Travel Survey data and econometric modeling, Wadud and Huda (2024) f found that the top 10% of households by income are responsible for 43% of all aviation emissions, while the bottom half of the population contributes only 9%. Third, SS matters because people choose neighborhoods based on how they like to travel and estimated BE effects usually become smaller after accounting for SS. However, much of the existing BE and SS literature focuses on discrete travel outcomes or residential categories, while fewer studies examine continuous BE measures and total emissions from both ground and air travel.

In reality, land use attributes are complex, with most BE variables continuous in nature. Using Petrin and Train's (2010) continuous approach to self-selection, the present study investigates the effect of BE on daily GHG emissions from both ground and air travel by applying a two-stage hurdle model for air travel on the survey day (using a weighted logistic), and weighted log-linear model for CO2e emissions (with a control-function residual to distinguish BE effects from residential SS). This approach reflects the zero-inflation of air travel data on a single survey day while quantifying emission differences attributable to neighborhood design versus residents' location preferences.

DATA DESCRIPTION

This paper relies on three U.S. data sets: the NHTS (FHWA, 2017) for travel behavior and household characteristics, the EPA Smart Location Database (EPA, 2021) for BE attributes at CBG level, and the crowd-sourced OurAirports data set (for distances to nearest airports).

The NHTS includes 923,572 person-trips from 129,696 households over a 12.5-month survey period (April 2016 to April 2017). We use the 2017 NHTS rather than the 2022 version to avoid the large structural changes in travel behavior caused by the COVID-19 Pandemic. According to FHWA (2024), average daily trips per person fell from 3.37 in 2017 to 2.83 in 2022, and the share of weeks with some remote work rose from 13.5% to 24.2%. Considering the NHTS uses a single-day travel diary, which often underrepresents infrequent but high-impact events like long-distance air travel. This study applies the person-level sampling weights provided in the NHTS and doubles the weight (King & Zeng, 2001) for person-days on which a flight was recorded (USDOT, 2021), yielding 219,194 weighted person-day records.

To count ground trips made before boarding a flight (first-mile, FM) and after landing a flight (Last-mile, LM), all trips are sorted within each person-day by daily sequence number (TDTRPNUM) and flight segments (TRPTRANS = 19). Then the ground trips that connect to flight segments were found in two ways: 1) flagging any trip where the destination and origin purpose is a mode change via the NHTS trip-purpose codes (WHYFROM = 07), yielding 1,259 FM legs and 1,241 LM legs; 2) locate first flight segment and following the last flight segment as the FM and LM respectively, yielding 1,270 FM and 1,287 LM legs. After removing 229 misclassified flight segments from the combined union of both methods (1,520 FM and 1,538 LM legs), the final counts are 1,291 FM legs and 1,309 LM legs. This study doubles the emission for 56,377 Household drop-off (WHYTO = 06) trips and 56,615 pickup trips (WHYFROM = 06) so the driver's escort trip is counted (FHWA, 2018). Among the airport access trips, 462 taxi and rideshare trips were scaled up by a factor of 1.45 to account for the empty return trip that the driver makes after dropping off or picking up a passenger. Because taxi and rideshare drivers must drive back without a paying customer after each trip, also known as deadheading, the actual VMT and emissions generated are about 45% higher than the passenger's reported trip distance alone (Schaller, 2018). Airport proximity is measured based on the 2024 OurAirports open database, which covers 16,174 U.S. airports classified as 15,275 small, 737 medium, or 162 large. For each trip endpoint, the nearest airport was identified using the haversine distance. Where airport distance information was missing for a given traveler, it was filled in using the CBG median. Table 1 reports the person-day-level summary statistics.

Table 1 Person-day Summary Statistics, 2017 NHTS (n = 219,194 person-days)

Variable	Mean	Median	Std Dev	Min	Max
AirTrip (1=flew on survey day)	0.0067	0	0.259	0	1
Age	47.93	52	21.39	5	92
Household size	2.7	2	1.39	1	13
Male (1=yes, 0=no)	0.479	0	0.5	0	1
No high school or college degree (1=yes, 0=no)	0.256	0	0.436	0	1
Some college or associate (1=yes, 0=no)	0.284	0	0.451	0	1
Bachelor's degree (1=yes, 0=no)	0.243	0	0.429	0	1
Graduate degree (1=yes, 0=no)	0.217	0	0.412	0	1
No household vehicle (1=yes, 0=no)	0.028	0	0.166	0	1
One household vehicle (1=yes, 0=no)	0.218	0	0.413	0	1
Two or more household vehicles (1=yes, 0=no)	0.753	1	0.431	0	1
Income < $50k (1=yes, 0=no)	0.22	0	0.414	0	1
Income $50k–$100k (1=yes, 0=no)	0.29	0	0.454	0	1
Income $100k–$200k (1=yes, 0=no)	0.412	0	0.492	0	1

Income > $200k (1=yes, 0=no)	0.077	0	0.267	0	1
Non-metro	0.147	0	0.354	0	1
Metro < 1M (msasize_3 = 2; MSA3_2 in Stage 1)	0.407	0	0.491	0	1
Metro ≥ 1M (msasize_3 = 3; MSA3_3 in Stage 1)	0.446	0	0.497	0	1
Daily total CO_2e (lb/person-day; weighted mean)	37.66	10.97	276.8	0	17,420
Daily air CO_2e (lb/person-day; zero-inflated weighted mean)	13.19	0	264.8	0	17,370
Daily ground CO_2e (lb/person-day; weighted mean)	19.42	9.71	47.1	0	6,470
Daily FM+LM CO_2e (lb/person-day; zero-inflated weighted mean)	5.05	0	35.9	0	6,370

Table 2 shows how home locations fall into 5 density categories (based on US population density percentiles, and whether the home falls inside urban area boundaries). These five range from "CBD" to "Rural" settings (using the NHTS variable HBHUR) which is based on the Claritas Urbanicity model. Unlike the Census, which mainly uses administrative boundaries, Claritas classifies each U.S. neighborhood into one of five non-overlapping categories using a combined method based on local population density, the density of nearby areas, and whether it functions as its own center or depends on a larger nearby city. Urban (U) areas are the highest-density neighborhoods (75th+ percentile [%ile]) and include downtowns and nearby inner-city areas, such as Manhattan in New York City or central Chicago. Suburban (S) areas have medium density (40 to 90th %ile), but they depend on a larger nearby city rather than serving as their own center. Examples include Plano near Dallas or Chevy Chase near Washington, D.C. Second City (C) areas are also the medium-density neighborhoods (40 to 90th %ile), but they function as their own local population centers like Austin, Texas, Madison, Wisconsin, or Gaithersburg, Maryland. Small Town (T) areas are lower-density places (under 40th %ile), and include towns, villages, exurban communities, and outer fringe settlements, such as Georgetown or Brenham. Rural (R) areas also have the lowest-density (under 40th %ile), including farming communities and sparsely settled locations with limited connection to urban centers, such as rural counties in West Texas or eastern Kansas.

Table 2 Sample Distribution by NHTS Urban Category (n = 219,011)

Urban Category (HBHUR)	**# Person-Days**	**Share**
Urban (U): High-density neighborhoods (75th+ percentile [%ile]), including downtown areas and nearby inner-city neighborhoods that form the main center of large metropolitan regions.	25,728	11.7%
Suburban (S): Medium density neighborhoods (40 to 90th %ile) connected to a larger nearby city, but not functioning as their own main population center.	51,161	23.4%
Second City (C): Medium density neighborhoods (40 to 90th %ile) that serve as an independent local population center, such as smaller cities or satellite cities within a broader region.	42,819	19.5%

Small Town (T): Lower-density neighborhoods (under 40th %ile) located in small towns, outer fringe communities, villages, or exurban areas outside major city centers.	50,284	23.0%
Rural (R): Low-density tracts (under 40th %ile) located in farming communities or sparsely settled areas with limited connection to larger urban centers.	49,019	22.4%

Because CBG boundaries in US follow administrative lines rather than physical or social ones, two households living right next to each other can fall into different census block groups with very different recorded density values. This study replaces each block group's raw BE values from SLD with inverse-distance-weighted (IDW) averages over the ten nearest block-group centroids. IDW means that nearby CBGs receive more weight than farther CBGs. For each target neighborhood, the calculation includes its own original value plus the values of the 10 closest neighboring CBGs. All distances are straight-line measurements between the centroids of the neighborhoods. A one-mile buffer is added to each distance so that one very close neighboring CBG does not dominate the average.

$$x^{\mathrm{IDW}} = \frac{x_0 + \sum_{i=1}^{10} \frac{x_i}{d_{0i} + c}}{1 + \sum_{i=1}^{10} \frac{1}{d_{0i} + c}},$$

where x_0 is the attribute value at the target CBG, x_i is its value at the i-th nearest neighbor CBG, d_{0i} is the Euclidean centroid distance in miles, and buffer distance c = 1 mile (after sensitivity check with c = 0.1 and c = 10 miles), so inverse-distance weights do not explode when a neighbor centroid is very close.

Table 3 presents distributions before and after IDW for the above BE attributes. Population density (PopDen) is residents per acre. Employment density is the number of jobs per acre. Land-use (LU) balance measures how well housing and jobs are mixed on a scale of 0 to 1. A score of 0 means a neighborhood is only housing or only offices, while 1 means they are perfectly mixed. Intersection density counts how many street intersections with three or more roads exist per square mile; more intersections usually mean a more walkable area. Transit distance is the shortest distance along the actual street network from the center of the neighborhood to the nearest transit stop, such as a bus stop or rail station. Destination accessibility is the total number of jobs a person can reach from that neighborhood within a 45-minute drive. Regional centrality is a score from 0 to 1 that shows how close a neighborhood is to the main hubs of the larger metropolitan area. All these values are linked to respondents by their home CBG, not by exact home address, to protect household privacy.

Table 3 BE Variable Distributions (CBG level)

Variable	Mean	Median	Std Dev	Min	Max
Population density (persons/acre, raw)	6.65	3.18	16.39	0.00	809.67
Population density (persons/acre, smoothed)	7.40	4.56	14.79	0.01	711.63
Employment density (jobs/acre, raw)	2.63	0.41	19.20	0.00	1460.13

Variable	Mean	Median	Std Dev	Min	Max
Employment density (jobs/acre, smoothed)	2.85	1.16	13.89	0.00	1323.96
LU Balance (0–1 entropy)	0.511	0.516	0.212	0.000	1.000
Intersection Density (/sq mi, raw)	62.9	45.0	68.0	0.0	1452.2
Intersection Density (ints./sq mi)	71.5	63.5	53.8	0.0	626.9
Transit Distance (network-miles)	0.317	0.290	0.182	0.000	0.750
Destination Accessibility (jobs within 45 min drive)	27,054	18,355	25,334	3	98,983
Regional Centrality Index (0–1)	0.435	0.427	0.265	0.000	1.000

METHODOLOGY

This study uses a two-stage hurdle model for daily GHG emissions on person-days because flying is rare on a given survey day (about 0.67% of person-days: 1,460 flyer-days out of the NHTS' 219,194 person-days). But the average carbon footprint of those who fly on the survey day is 2,334 lb CO2e - and thus more than 100 times the average ground CO2e (~19.4 lb) on a typical person-day. The hurdle model includes a (population-weighted) logistic that explains whether the respondent flew on the survey day, and a log-linear model for CO2e, where Y = ln(1 + $CO2e_i$ [in kilograms]), with the same set of covariates.

To calculate carbon emissions, each trip is converted into a CO2e value based on how far the person traveled and what mode of transportation they used. For flights, each passenger-mile generates 0.819 kg of CO2-equivalent emissions, after combining the direct exhaust emissions from burning jet fuel (0.30 kg CO2 per passenger-mile, from the International Council on Clean Transportation), a multiplier of 2.1 to account for the additional warming caused by contrails and other high-altitude atmospheric effects (Lee et al., 2021), and a adjustment of 1.3 to reflect the greater fuel use per seat in first-class and business-class because they take up more space on the plane. For private motorized ground trips (covering Car, SUV, Van, Pickup, Golf Cart, Motorcycle, and Rental Vehicles), the emission factor is 0.267 kg CO2e per passenger-mile, equal to 404 g CO2 per vehicle-mile from the EPA divided by 1.5 occupants per vehicle-trip. Taxi and rideshare trips to or from airports doubled to account for the empty return trip the driver makes after dropping off or picking up a passenger. The person-day CO2e total from 105,935 ground trip segments is the sum of emissions from ground travel and air travel (including travel to and from airports, bus stops, train stations, and rental cars).

To partially explain the effect of neighborhood design on travel emissions from the fact that people partly choose where they live based on how much they like to travel, this study uses a two-step statistical correction known as the control-function approach (Petrin and Train, 2010). Given a household's observed characteristics, MSA size tier, and Census region within the NHTS and SLD datasets, this method estimates the neighborhood density a household would be expected to live at the CBG level using survey-weighted least squares (WLS) regression. The difference between the predicted density and the actual density the household chose, called the residual v_i, which indicates unobserved personal preferences that led someone to choose a denser or less dense neighborhood than the direct statistical prediction would suggest. The density prediction equation is:

$$\ln(PopDen\_IDW + 1)_i = \beta_0 + \beta_1 MSA_{Med,i} + \beta_2 MSA_{Large,i} + \beta_3 Demographics_i + \beta_4 \ln(TractPopDen{+}1)_i + \beta 5 UrbanType_i + \beta_6 Region_i + v_i$$

Where $\ln(PopDen\_IDW + 1)_i$ is block-group residential density (D1B from SLD) smoothed by IDW; $Demographics_i$ is a vector of household and individual charactertics, including household size, number of workers, income level, vehicle ownership, gender, age, and education level; $\ln(TractPopDen{+}1)_i$ is the tract-level population density control (HTPPOPDN from NHTS, persons per square mile); the residual v_i from the first stage of control-function is then included in the two part hurdle model—the participation stage (Logit) and the intensity stage (WLS)—as a SS control for unobserved factors about a person's neighborhood density choice that are not explained by observed variables at the first stage.

$$Demographics_i{=}(HHSize_i,\ HHWorkers_i,\ Income_i,\ Vehicles_i,\ Male_i,\ Age_i,\ Educ_i)$$

Table 4 shows these variables with metropolitan size indicators (MSA_{Med} and MSA_{Large}).

Table 4 Summary Statistics and Variable Definitions (n = 219,194)

Varible	Weighted Mean	Counts
ln(PopDen$_{\mathbf{IDW}}$ + 1) = Natural Log of Smoothed Population Density (persons per square mile).	1.8933	219,011
PopDen = Population Density (# of residents per square mile).	4,733.6	219,011
MSA$_{\mathbf{Med}}$ = Medium Metropolitan Area Indicator (1 = in an MSA with 1,000,000–2,999,999 population, 0 = otherwise).	0.2085	219,194
MSA$_{\mathbf{Large}}$ = Large Metropolitan Area Indicator (1 = in an MSA with 3,000,000+ population; 0 = otherwise).	0.3557	219,194
HHSize = Household Size (# of persons per household).	3.1610	219,194
HHWorkers = Workers in Household (# of employed persons per household).	1.5201	219,194
Income = Household Income Level (11 categories mapped to midpoints: $5,000, $12,500, $20,000, $30,000, $42,500, $62,500, $87,500, $112,500, $137,500, $175,000, and $225,000).	6.1961	213,145
Vehicles = Household Vehicle Ownership (# of vehicles available).	2.2081	219,194
Male = Gender Indicator (1 = male, 2 = female).	1.5028	219,009
Age = Respondent Age (years).	40.2475	218,835
Educ = Education Level (1 = Less than Bachelor's degree (BA); 2 = BA; 4 = Graduate degree).	1.5882	200,038
Workers = Worker Status Indicator (1 = employed, 0 = not employed).	1.3355	195,856

The first stage estimates whether the respondent flew on the survey day, using a weighted logistic regression. Only variables that are known before the travel decision are included in this model, so that the results are not affected by travel outcomes such as distance or miles traveled:

$$P(AirTrip_i = 1 \mid X_i) = \Lambda(\alpha_0 + \alpha_1 \ln(PopDen_{IDW,i} + 1) + \alpha_2 v_i + \gamma Demographics_i + \delta BE_i)$$

where $\Lambda(\cdot)$ is the standard logistic function that converts a linear prediction into a probability between zero and one; The BE_i vector includes the built-environment attributes listed in Table 4, including employment density, land-use mix, intersection density, transit proximity, regional job accessibility, and regional centrality.

$$BE_i = (EmpDen_i, LandUse_i, Intersections_i, Transit_i, Access_i, Centrality_i, VehicleMix_i)$$

The second stage estimates how large the total daily emissions are for all travel combined, using WLS regression on the log-transformed total CO2e:

$$\ln(1 + CO2e_i) = \theta_0 + \theta_1 ln(PopDen_{IDW,i} + 1) + \theta_2 v_i + \varphi Demographics_i + \psi BE_i + \varepsilon_i$$

Both equations include the same neighborhood density measure, the density residual from the first step, a set of personal and household characteristics, and additional BE variables. To keep the model from becoming unnecessarily complicated, a stepwise selection process is used to simplify the model by removing variables with limited statistical contribution while keeping the stable model. In each round, any variable whose p-value is above 0.05, meaning its estimated effect could reasonably be zero by chance, is removed. The remaining variables are then checked to make sure that no two of them are so closely correlated with each other that they make the estimates unreliable, using a variance inflation factor (VIF) threshold of 10. Starting from 66 candidate variables, this process retains 29 terms in the final emissions-intensity model.

This study uses three measurements to show how neighborhood density changes travel behavior and how much of the emission difference between the five urban categories comes from BE versus from SS in home location. The five categories are used for descriptive comparisons, while the main models use continuous density and BE variables.

The first measurement estimates the marginal effect on daily VMT when a neighborhood's gross residential population density (EPA SLD D1B, IDW-smoothed) increases by 1,000 persons per square mile while holding household demographics and other BE measures, and the density sorting residual v_i constant. Becasue density (PopDen) is measured in persons per acre, the addition of 1,000 people per square mile is first converted into a change in the log-scale regressor (Δln) evaluated at a baseline density $\bar{D}$ (in persons per acre):

$$\Delta \ln = \ln(1 + \bar{D} + 1000) - \ln(1 + \bar{D})]$$

The marginal change ΔVMT is then obtained by multiplying this log-scale shift by the corresponding coefficient β from the model:

$$\Delta VMT = \beta_{VMT} \times \Delta \ln$$

where β_{VMT} is the estimated coefficient on ln(*PopDen_IDW* + 1) obtained from WLS regression, reflecting the expected change in daily VMT (miles per person-day) with a one-unit increase in ln(*PopDen_IDW* +1), holding all other variables fixed.

The second measurement compares predicted daily emissions across the five neighborhood types for a reference person, defined as a 40-year-old female worker with a bachelor's degree, household income falls into \$50,000–\$74,999 while fixing other demographic variables. Two versions of the prediction are computed to separate different sources of the emission difference.

Prediction A isolates the BE effect for the reference person. The density residual, which captures unobserved factors associated with SS, is set to zero. All other BE variables are set to the weighted average for that neighborhood category c. Predicted daily emissions are calculated as:

$$E[CO2e_i|\text{c, Prediction } A] = \exp\{\theta_0 + \theta_1 \overline{ln(PopDen_{IDW} + 1)_c} + \phi Profile + \psi \overline{BE_c}\} - 1$$

where $\overline{x}$c refers to the weighted mean of variable x within category c.

Prediction B reflects both BE and SS. The reference person's age and education are fixed, but other characteristics such as income and vehicle ownership are adjusted to match the average resident of each neighborhood type. The predicted daily emissions are:

$$E[CO2e_i|\text{c, Prediction B}] = \exp\{\theta_0 + \theta_1 \overline{ln(PopDen_{IDW} + 1)_c} + \theta_2 v_c + \phi Profile_c + \psi \overline{BE_c}\} - 1$$

A counterfactual approach is then applied to all individuals (86,226 person-day observations obtained from the original 219,194 weighted NHTS person-day records after excluding observations with incomplete information for one or more retained model variables) to estimate how the same group of people with fixed demographics would travel under different BE conditions.

The third measurement compares observed emissions with counterfactual predictions to evaluate how much of the differences between Rural areas, and the other four Urban Categories (HBHUR) is influenced by resident demographics, aviation behavior (including both probability of flying and air-travel distance), and remaining SS effects not captured by the observed variables.

The observed emissions difference between neighborhood category c and Rural areas is calculated as:

$$\Delta_{obs,c} = \overline{Y}_c - \overline{Y}_{Rural}$$

Where $c \in \{Urban, Second\ City, Suburban, Small\ Town\}$. The difference caused by BE alone is calculated using the counterfactual prediction:

$$\Delta_{BE,c} = \overline{Y}(BE_c) - \overline{Y}(BE_{Rural})$$

where BE_c and BE_{Rural} represent the weighted average continuous BE conditions observed among respondents classified in neighborhood category c and Rural areas, respectively.

The remaining difference is then calculated as:

$$\Delta_{Comp,c} = \Delta_{obs,c} - \Delta_{BE,c}$$

where $\Delta_{Comp,c}$ reflects the combined influence of demographics, aviation behavior, and remaining SS that offset the emissions reductions predicted under denser BE settings.

RESULTS

This section uses three steps to explain why residents in the highest-density urban areas often have higher observed transport emissions. First, observed emissions are shown for each neighborhood type. Then, CO2e emissions are predicted ignoring SS effects. Finally, emissions are predicted using both BE and SS effects (along with demographics, of course).

Table 5 shows the observed daily emissions across the five neighborhood settings. The results suggest that Urban residents emit the most total emissions, which come from higher air travel. Rural residents produce the most emissions from driving (27.39 lb/day) because they rely more heavily on cars for longer trips. Urban residents, by contrast, have the lowest driving emissions (13.27 lb/day) but by far the highest flying emissions (45.77 lb/day). Urban residents are also much more likely to fly on any given survey day (1.89%) compared to rural residents (0.57%). When all travel modes are combined, Second City and Small Town residents have the lowest total daily emissions, while Urban and Suburban residents have the highest.

Table 5 Average Daily Emissions by Neighborhood Category (lb CO_2e per person-day)

Urban Category	# Person-Days	Prob (Flew Today)	Air CO_2e	Ground CO_2e	FM+LM CO_2e	Total CO_2e
Urban	25,728	1.89%	45.77	13.27	4.76	63.80
Second City	42,819	0.85%	18.02	17.24	4.78	40.03
Suburban	51,161	1.40%	33.37	18.63	6.96	58.97
Small Town	50,284	0.80%	17.53	22.28	5.06	44.87
Rural	49,019	0.57%	13.81	27.39	6.25	47.45

The first measurement asks what would happen to travel if add 1,000 more residents per square mile to a neighborhood. As shown in Table 5, higher density reduces both driving and flying distances. For the average resident, this density increase reduces daily driving by about 0.57 miles and daily flying distance by about 0.72 miles. Although the probability of flying increases slightly, the reduction in driving distance and total VMT outweigh this effect, leading to a net reduction of about 1.07 lb CO2e per day.

Table 6 Estimated Change from a +1,000 Persons/sq mi Density Increase

Outcome	Baseline Mean	Δ at National Mean Density	Percent Change
Individual vehicle miles/day	33.27 mi	−0.57 mi	−1.71%
Air miles/day	25.00 mi	−1.23 mi	−4.92%
Total CO_2e (lb/day)	51.40 lb	−1.07 lb	−2.09%
P(flew today)	0.67%	+0.028 ppt	+4.2%

The second measurement explores how a representative person (a 40-year-old female worker with a bachelor's degree and a household income around \$50,000–\$74,999) would generate emissions across five neighborhood settings if everything else about her were held constant.

Table 7 Predicted Daily CO_2e (lb per person-day) for a Reference Person (40-Year-Old female worker, Bachelor's Degree and Mid-Range Income)

Neighborhood Category	Prediction A (BE Only)	Prediction B (BE+ SS)	Observed
Urban	42.0	38.5	58.7
Second City	50.3	46.8	44.0
Suburban	56.7	53.9	53.7
Small Town	61.2	58.6	43.8

Rural	66.1	63.4	54.0

As shown in Table 7, prediction A suggests that if the exact same person moves from a Rural BE setting to an Urban BE setting, her predicted emissions would fall from 66.1 lb to 42.0 lb CO_2e per day. This pattern indicates that the BE conditions, including shorter travel distances, higher street connectivity, and better transit access, help reduce total transport emissions. Similar but smaller reductions are also predicted for Second City (50.3 lb), Suburban (56.7 lb), and Small Town (61.2 lb) settings. Prediction B incorporates both the BE treatment and SS by adjusting demographics and unobserved SS effects (v_i) to match the average resident of each neighborhood category. Even with sorting controls included, predicted emissions remain lowest under Urban conditions (38.5 lb) compared to Rural conditions (63.4 lb). However, actual observed emissions for the full sample in Urban areas (58.7 lb per person-day) nearly double the BE effect alone. This gap reflects that rich, highly educated people tend to live in dense cities, but their frequent flying (a 1.89% daily flight probability) emits huge CO_2e that completely offset the savings from driving less.

The third measurement explains why transport emissions vary across neighborhood categories by separating the observed emission gap between each neighborhood type and rural areas into two parts: (1) the counterfactual effect of the BE alone and (2) the remaining difference capturing resident demographics, aviation behavior, and remaining SS effects.

Table 8 Daily CO_2e Differences Relative to Rural Category (lb CO_2e/person-day)

Comparison vs. Rural	Observed Difference	BE Counterfactual Effect	Remaining Difference (Composition + Aviation + SS)
Urban vs. Rural	+4.66	−15.23	+19.89
Second City vs. Rural	−10.01	−11.93	+1.92
Suburban vs. Rural	−0.36	−6.12	+5.76
Small Town vs. Rural	−10.21	−4.75	−5.46

The decomposition results in Table 8 suggests that denser BE settings consistently reduce predicted CO_2e. If the same person were hypothetically assigned to the average continuous BE conditions found in Urban neighborhoods instead of Rural ones, predicted CO_2e would decrease by 15.23 lb per person-day. The remaining demographic and SS effect are much smaller in Second City (+1.92 lb/day) and Small Town (−5.46 lb/day) areas, where residents tend to drive less than Rural residents because their neighborhoods are more compact, but they also fly less often than Urban and Suburban residents because their average incomes and air travel demands are lower. As a result, observed emissions in Second City and Small Town areas are estimated to be 10.01 lb/day and 10.21 lb/day lower than Rural areas, respectively.

Table 9 summarizes the key factors that influence total daily emissions and the likelihood of flying on any given day, based on the two-stage hurdle model.

Table 9 Key Factors Influencing Travel Emissions and Flying Choices.

Factor	Δ	Impact on Daily Emissions	Impact on Flying Odds
ln(1 + PopDen_IDW)	+1 SD	−3.18%	+19.78%
Self-selection (SS)	+1 SD	+2.35%	+14.88%
Higher Education	+1 category	+3.42%	+31.67%
Higher Income ($10,000 HH income)	+$10k	+1.12%	+9.21%
Household Size	+1 person	+6.94%	−16.85%
Workers in Home	+1 worker	−3.96%	−28.74%
Male	vs. Female	+2.61%	−20.94%
Vehicle Ownership	+1 vehicle	—	−15.63%
Individual VMT	+1 SD	+49.73%	—

The negative relationship between neighborhood density and emissions (−3.18% per standard deviation) suggests that densification helps reduce daily emissions after controlling the demographics and BE conditions. However, the positive impact of SS residual (+2.35% for emissions and +14.88% for flying odds) suggests that people who choose denser neighborhoods often have emit higher emissions caused by traveling like frequent aviation activity, indicating SS partly offset the emission reductions from the BE. In the flying participation model, the positive density effect (+19.78%) suggests that residents in denser areas are more likely to fly on any given survey day. As expected, major airports and business hubs are in or near large cities, making air travel much more accessible and common for urban residents compared to the rural residents. Among all demographics, household income and education have the strongest positive effects on flying behavior. A $10,000 increase in household income increases flying odds by about 9.21%, while a one-category increase in education increases flying odds by about 31.67%. Conversely, daily emissions are most sensitive to individual VMT, with a 1-SD increase raising CO_2e emissions per person-day by 48.47%. Comparing the results with and without the control for SS suggests that about 43% of the daily CO_2e gap is offset by denser Urban BE conditions, while the remaining 57% is attributable to demographics, aviation behavior, and unobserved SS effects, based on the ratio between the Urban BE reduction effect (15.23 lb CO_2e/person-day) and the combined absolute decomposition (Urban vs. Rural) effect (15.23 + 19.89 lb CO_2e/person-day).

CONCLUSION

The relationship between urban form and travel-related carbon emissions is complex, and air travel is a dimension that most existing studies have not addressed. Most research to date has focused on driving distances, mode choice, vehicle ownership, or simplified land-use categories, producing varied answers about whether compact urban settings reduce total travel emissions. This study applied a two-stage hurdle model with a self-selection correction to estimate how neighborhood density affects daily carbon emissions from both ground and air travel, using a sample of 219,194 person-days drawn from the 2017 NHTS linked to the EPA Smart Location Database.

For ground travel alone, denser neighborhoods with better street connectivity and transit access shorten driving distances, even after controlling for the self-selection that people who prefer to drive less tend to choose denser areas. Adding 1,000 persons per square mile (about 1.56 persons per acre) to a neighborhood reduces private vehicle miles per day by about 0.57 miles, or 1.7%, with a corresponding reduction in ground emissions. This finding supports compact-city goals, in that physical neighborhood design lower travel emissions. However, SS also matters, about 34.6% of the emission gap between neighborhood types is explained by the types of people who choose each setting.

When air travel is included, the highest-density Urban neighborhoods (the highest-density neighborhoods in the top 75^{th}+ %ile of U.S. density, including downtowns and surrounding inner-city areas), generate the highest observed total daily emissions of any category. Urban residents are more than three times as likely to fly as rural (low-density areas below the 40^{th} percentile) residents, with participation rates of 1.89% versus 0.57% on any given survey day. On days when someone flies, their average air travel emissions reach 2,334 lb CO2e, more than 100 times what a typical non-flying person produces from driving alone. As a result, urban residents average the highest total daily emissions at 63.80 lb per person-day, while Second City residents (those living in independent satellite cities with their own downtowns, also in the 40 to 90^{th}+ %ile) emit the lowest total at 40.03 lb per day.

Despite this, increasing neighborhood density still reduces overall emissions at the margin. Adding 1,000 persons per square mile is predicted to lower daily transport emissions of CO2e by 1.07 lb per day per person, or 2.1%, as ground travel savings offset the small increase in flying probability. However, focusing only on VMT ignores the large share of air emissions for people who live in dense urban areas. For those living in urban cores and surrounding inner-city areas, air travel is the primary source of daily transport emissions. Research shows that flying is highly concentrated among higher-income, highly educated frequent flyers. Gössling and Humpe (2020) estimated that only 11% of the world's population flew in 2018, while the top 1% of global frequent flyers generated about 50% of passenger aviation CO_2 emissions. Policies aimed at frequent flyers, like corporate carbon budgets for business travel or higher taxes on premium cabin seating, could have a larger climate impact than policies focused only on driving.

There are ways to improve this research in the future. The 2017 NHTS captures only a single survey day per person, so rare but high-emission events like long flights are estimated through statistical weighting rather than direct observation. Travel diaries that follow a person across a longer period (such as a full year) would provide more accurate observed. In addition, changes in travel behavior (such as remote work) since 2017 may have changed the relationship between urban location and air travel demand, so it is worth examining whether city residents still generate more transport emissions through flying in a post-pandemic context. Finally, more detailed neighborhood categories and better measures of airport accessibility would help clarify why urban residents fly more and how much the proximity to major airports accounts for this phenomenon.

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