The impact of land use and built environment characteristics on transport-related energy footprints in California

Research report for the Marshall Plan Foundation

About the research stay at the University of California, Davis

October 2017 – September 2018

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30.12.2018

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Summary

Most of the trips (80%) in California are carried out by car that is primarily fossil-fueled. In addition to ambient air pollution, passenger travel also contributes to greenhouse gas emissions that jeopardize goals to reduce climate change. Previous research has found evidence that land use and built environment characteristics affect travel outcomes to various extent. Though their impact on energy consumption for transport was studied to a lesser extent. This study targets this gap by providing additional insights how land use and built environment (LU and BU) characteristics affect energy consumption for different destinations and trip purposes.

We calculate energy footprints based on the California Household Travel Survey (CHTS) conducted in 2010-12. We use data from the US Environmental Protection Agency and the National Transit Database to calculate fuel economy for transit modes and private vehicles owned by households in the CHTS. We set up indicators to measure different dimensions of land use and built environment including population, employment, bike infrastructure, land use mix and availability of green areas. We use mixed-effect regression models to assess the impact of LU and BE variables on energy consumption for different trip chains. In addition, we use a seemingly unrelated equations model to analyze the interaction of energy footprints between two partners of a household.

Our results support the general finding for travel outcomes as well for transport-related energy consumption. Land use and built environment factors affect energy footprints for travel, particularly employment-related indicators showed the largest effect. In addition, LU and BE characteristics seem to affect energy footprints differently depending on the location. Employment density has a negative effect at the residence but positive effect at the workplace. This may indicate that travelling to a central business district or urban core requires on average more energy while high employment density at the residence may correlate with a shorter commute distance. For non-work or -school related trip chains other LU and BE variables such as availability of parks and greenfield become significant. In a sensitivity analysis, we test the impact of different scales at which we define LU and BE variables (0.25, 0.5 and 1-mile radius). The results highlight that LU and BE variables show the highest effect on energy consumption if defined at a one-mile radius. This study supports research findings that advocate the general importance of LU and BE characteristics for transport-related energy consumption.

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I. Introduction

Ambient air pollution in urban areas and climate change policies increase pressure on city governments to take more stringent measures to improve air quality and reduce greenhouse gas emissions. It is particularly interesting to discuss transport-related energy consumption in California since California's economic power is considerable: California's gross domestic product (GDP) amounted to 73% of Germany's GDP in 2017. In addition, this state has ambitious fuel and vehicle emission standards, but its urban areas are sprawled challenging accessibility and the provision of public transport. The last California Household Travel Survey (CHTS) 2010-12 showed that 80% of the trips are carried out by car – most of them fossil-fueled. Fossil-fueled transportation exacerbate ambient air and noise pollution and generates greenhouse gas emissions. Policies have been put in place to mitigate these negative externalities targeting fuel economy of vehicles, the use of alternative fuels and modes such as public transport. Long-term measures target change of land use and built environment in urban areas since they affect trip distances, accessibility of destinations and the quality of transit provision. Previous studies highlighted the impact of built environment on travel behavior (e.g. Cervero and Ewing 2010, 2001). For example, street design and population density are two of several factors that affect vehicle miles traveled by car and the likelihood to use transit. Single indicators seem to have a small effect on travel outcomes though the combined effect of several built environment and land use factors is considerable (Cervero and Ewing 2010).

However, little is known about the effect of built environment and neighborhood characteristics on energy consumption for travel. This study targets this gap by providing additional insights how land use and built environment (LU and BU) characteristics affect energy consumption for different destinations and trip purposes. Energy footprint for travel is an outcome of several preceding decisions, short-term such as transport mode choice or long-term such as vehicle type ownership or residential location. Instead of investigating all these decisions, we directly analyses energy consumption for travel.

Our results highlight the importance of employment-related LU and BE characteristics for transport-related energy consumption though their effect, positive or negative, changes depending on the location, i.e. workplace or residence. A sensitivity analysis shows that a one-mile radius around the block census tract leads to the highest impact of LU and BE variables on energy consumption. Moreover, the findings of this study show that energy footprints between partners living in the same household are correlated and rather compliments than substitutes. Partners seem to be differently affected by LU and BE characteristics. The findings of this study support efforts to improve land use and built environment and indicate that land use and built environment factors may be more or less effective depending on the trip purpose and pattern.

II. Literature review

1. Built environment and travel outcomes

Several studies in transportation research examined the effect of built environment and accessibility on travel outcomes, namely transport mode choice and vehicle miles traveled (VMT). Ewing and Cervero (2010) evaluated the effect of built environment on travel outcomes based on a meta-analysis and found a small effect, an elasticity often smaller than 0.39. Though the accumulated effect of different built environment variables is large and relevant (Ewing and Cervero 2010). Based on the review of studies, VMT are most strongly affected by accessibility measures at destination and the street network design (Ewing and Cervero 2010). Land use and street design also impact walkability (Ewing and Cervero 2010). The use of public transport seems to be related to the proximity to public transport stations and the street network design (Ewing and Cervero 2010). Nearby access to transit stations increases the likelihood of transit trips, also land-use mix is important for transit usage (Ewing and Cervero 2010). Though population and job density seem to be more weakly related to transit use.

Salon et al. (2012) investigated the impact of local policies on vehicle miles traveled (VMT) by reviewing the effect size found in previous studies. They looked at land use planning that may change residential density, the mix of land uses, regional accessibility, network connectivity and the distribution of jobs and housing in an area (Salon et al. 2012). They found evidence for the impact of these factors on VMT to a various extent. Land use mix seems to have a smaller effect than regional accessibility and job-housing balance on VMT. Street connectivity also affects VMT with a wider range. With respect to accessibility to public transportation, decreases in the distance to a transit station reduced VMT per mile from a station (Salon et al. 2012).

In another study, Salon (2015) clustered households in California first into neighborhood types and assessed then the effect of built environment characteristics on VMT for each neighborhood type. VMT and car ownership increase along neighborhood types (from central city, urban, suburban, rural-in-urban to rural). The impact of built environment characteristics on VMT varies between neighborhood types and is more prominent for commute than non-commute trips (Salon 2015). Job density in rural neighborhood types are stronger correlated to VMT than other neighborhoods (Salon 2015). Access to transit at the residence has a negative effect on commute VMT (Salon 2015). Transit access at the work location is negatively correlated to commute VMT in urban and central city neighborhoods and positively to other neighborhoods since residents of rural and rural-in-urban neighborhoods commute over longer distances to urban areas with better transit access.

2. Built environment and transport-related fuel consumption

Previous research findings have suggested a negative relationship between population density and transport-related fuel consumption (Frost et al. 1998, Muniz and Galindo 2005, Su 2011). Several studies highlighted the importance of the job-housing balance for energy consumption (Zhao et al. 2011, Marique and Reiter 2012, Morikawa 2012, Marique et al. 2013).

Already Newman and Kenworthy (1989) pointed out significant differences in gasoline consumption between urban areas of a city and between US cities due to differences in population densities. They showed that transit use for commute trips is negatively correlated with gasoline consumption. They calculated that average fuel consumption amounts to 335 gallons per person for the whole metropolitan area New York in 1980 while a person living in the central city consumed only 90 gallons per year (Newman and Kenworthy 1989). The same pattern can be observed when they compared US, Australian, European cities and Toronto. Interestingly Toronto differs from some US cities due to high transit access in suburban centers which points to the importance of including other built environment and accessibility indicators into the analysis beside population and job density. Contrary to some other studies, traffic speed is positively correlated to gasoline consumption per capita in their results, for example for New York. However, some authors criticized the study for being too aggregate and for ignoring other influences, such as residential self-selection, gasoline price or household income (Mindali et al. 2004, Su 2012).

On a vehicle level, Cook et al. (2015) examined VMT and fuel consumption using vehicle odometer data in California. They found that vehicles in dense urban areas consumed less fuel than the Californian average while vehicles in suburban areas had the highest level of fuel consumption. They discuss the drivers for higher fuel consumption and its geographical variation: Areas located north and east of Los Angeles consumed more fuel due to high VMT while areas in northern California used more fuel due to poor fuel economy (Cook et al. 2015). For desert and mountain regions, both VMT and poor fuel economy contributed to higher fuel consumption. Though the results of this study with respect to regional difference are interesting the study does not provide any insights on energy consumption in relation to socioeconomic information, vehicle occupancy or trip purpose. The dataset is based on two odometer measurements and relates to vehicles only.

Brownstone and Golob (2009) analyzed energy consumption for vehicle use by Californian households based on the National Household Travel Survey from 2001. They found the strongest relationship between land use variables and fuel consumption for dwelling units per square mile – an indicator for residential housing density. They point out that fuel usage declined with increasing dwelling density (for urban areas with more than 50 housing units per square mile). They specified that fuel economy was more sensitive to density than vehicle mileage with a low of 19.7 miles per gallon (mpg) for households located in areas with less than 50 housing units per square mile compared to 22.4 mpg in areas with more than 5000 housing units per square mile. Households in denser neighborhoods had fewer drivers and lower income (Brownstone and Golob 2009). They estimated that households in denser areas consumed 64.7 fewer gallons fuel as a composed effect of reduced mileage (70%) and better fuel economy (30%). Residential self-selection may also play a role for vehicle type ownership since it might be more difficult to drive and park in dense areas and people may prefer smaller, fuel-efficient cars (Brownstone and Golob 2009). For instance, Brownstone and Golob (2009) considered residential self-selection by modeling residential location choice simultaneously with vehicle mileage and fuel consumption.

The authors also explained their results in relation to socioeconomic factors. They point out that fuel consumption was more sensitive to the number of drivers in a household than annual mileage and decreases with the number of drivers in a household. One worker in a two-workers household had a shorter commute than the other. They also found that income was negatively correlated to residential density, fuel economy and positively to mileage traveled. Households with more children lived in lower-density areas, drive more and own cars with lower fuel economy. Like other studies (e.g. Cook et al. 2015, Garikapati et al. 2017, Lindsey et al. 2011), Brownstone and Golob focused on vehicle miles traveled only and did not include public transport although it may be of interest to investigate the differences in energy consumption for passengers who traveled with transit or in a private vehicle.

3. Geographic differences: case studies of cities

Several studies pointed out that population and employment densities are negatively correlated to fuel consumption for transportation. However, explanations for this relationship may differ between regions, cities and countries because densities and socioeconomic features such as household income are differently distributed between cities. For example, lower income households in Melbourne (Australia) tend to drive more, use less public transport because they live at larger distances from the Central Business District (CBD) (Newman and Kenworthy 2006). Whereas in Los Angeles, foreign born and minority populations are more likely to live in dense areas and use more transit (Modarres 2013). Differences in the housing market, population densities and sociodemographic characteristics between cities will likely affect the geographical distribution of transport-related fuel consumption.

Los Angeles Metropolitan Area: Modarres (2013) calculated energy consumption for transportation in the Los Angeles and Orange Counties, California, US for 2010. He found that passengers consumed on average 66,895 BTUs for a one-direction commute trip. According to his results, access to employment centers and transit decreased the level of energy consumption. Though race, ethnicity and income played a stronger role for the spatial distribution of energy consumption and both, densities and socioeconomic factors, are interlinked. For example, low-income minorities tend to live in densely populated neighborhoods in Los Angeles and experienced higher vehicle occupancy on their trips because they carpooled or used transit more often. He also pointed out that the relationship between migration status and travel behavior were not stable over time: The longer an immigrant stayed in the US the less he or she was likely to use transit. Modarres (2013) assumed an average fuel economy for all private vehicles which may simplify spatial heterogeneity in the fuel economy that other studies have assessed (e.g. Brownstone and Golob 2009).

Atlanta Metropolitan Area : Garikapati et al. (2017) analyzed transport-related energy consumption for traffic analysis zones (TAZ) using a travel demand model of Atlanta (Georgia, US). Their results showed that households in suburban and rural areas had higher energy consumption then households in urban areas. This might be related to vehicle ownership, population and employment density. Households owned larger vehicles in suburban areas with lower population and employment density. In this study however, the authors distinguished only between six different vehicle types and did not include any other built environment characteristics beside population and employment densities. Their unit of analysis is the TAZ though the impact of land use and built environment characteristics may vary depending on the spatial scale of analysis. Some household types may be more sensitive to LU and BE than others. In addition, an analysis based on real vehicle occupancy may provide more useful insights since vehicle occupancy significantly alter the fuel economy of private vehicles.

Chicago: Lindsey et al. (2011) analyzed VMT of private vehicles and related energy consumption using a travel survey conducted in the Chicago region. They aggregated household data on 2.6 by 4 miles grid cell. According to their results, average daily energy consumption per household varied between 92 MJ and 472 MJ in the Chicago region, increased with distance from the central business district (CBD) and decreased with residential density. They ascertained that the fuel economy in the city center was better than compared to the urban fringe.

Baltimore: Liu and Shen (2012) studied VMT and energy consumption in Baltimore using the 2001 US National Household Travel Survey. Their results of a structural equation model highlighted that accessibility variables provided more explanatory power than density measures. In addition, the direct effect of urban form on VMT and energy consumption was small but the indirect effect through socioeconomic factors of households have been shown to be more relevant.

III. Research gap and questions

Previous findings in the literature ascertained a significant relationship between built environment characteristics and fuel consumption for transportation. Though the size of the effect varied between built environment indicators and cities. Some studies explored this relationship in greater detail and found that socioeconomic and demographic factors are correlated to energy consumption as well as to certain built environment characteristics. This study aims to provide a general analysis for California extending the perspective of case studies. It includes socioeconomic characteristics to account for the fact that transport-related energy consumption may be differently distributed across space according to socioeconomic factors as revealed in the literature review.

Most of the studies presented in the literature review concentrated on density-related characteristics of land use and built environment (LU and BE) and do not include measures for accessibility (i.e. to transit stations, walkability, distance to shopping centers or educational facilities). These studies often do not differentiate between trip purposes, but report results for VMT in general. An extensive body of literature concentrates on vehicle miles traveled and does not consider vehicle occupancy or only assumes averages. However higher vehicle occupancy may significantly ameliorate the energy footprint per passenger mile and is an important target for transportation policies. In the reviewed studies, researchers often classify neighborhoods at the household's residence although studies have shown that accessibility at the destination may be even more important (Ewing and Cervero 2010).

This study aims to fill the research gap by

- Analyzing the relationship between transport-related energy consumption and built environment for a more diverse set of indicators evaluated so far,
- Comparing the impact of built environment on transport-related energy consumption at origin and trip destination
- Assessing intra-household differences in the energy consumption for transportation

Research questions

The main research question investigates the relationship between built environment and transport-related energy consumption in California. How does this relationship change when indicators are measured at the destination and not at a trip's origin? How does this relationship change among different trip purposes? Second-order research questions aim to clarify to which extent energy footprints vary between household members and if some household members may react differently to built environment and land use characteristics. Finally, we are interested to which extent the scale matters at which land use and built environment indicators are defined.

IV. Methods

This section summarizes the data and methods used to analyze the impact of land use and built environment (LU and BE) on transport-related energy consumption in California. First, we explain primary and secondary data used in this analysis. Assumptions on fuel economy for private and public transport are presented in detail since they are one of two relevant inputs for the calculation of energy footprints. Second, we discuss the statistical methods, particularly econometric models, used in this analysis.

1. Data

California Household Travel Survey

The California Department of Transportation conducts every ten years the California Household Travel Survey (CHTS) – the data basis for this analysis. We use the last CHTS conducted between 2010 and 2012 (California Department of Transportation 2017). The sampling frame for this survey included all residential addresses that receive US Mail delivery in California and cell phone numbers. The California Department of Transportation used computer assisted telephone interviewing (CATI) and online websites to recruit participants, retrieval was done via CATI, online or mail. The sampling strategy aimed at a stratified probability sample of households meaning that the whole population is divided into groups from which households are randomly selected. This sampling strategy assures that each group is well represented, particularly hard-to-reach households, for instance low-income or non-English speaking households. The recruit response rate was 4.9%. The sample is representative for households living in the 58 counties in California according to the 2010 US Census data. The CHTS 2010-12 includes 42,431 households with 109,113 participants and pools information on travel behavior for one day for all household members, vehicle ownership, transit passes and socio-demographic data. For each trip, individuals indicated which mode they used, the zip code of the destination, activity at the destination, trip distance and persons who accompanied them. If they drove by their own vehicle, they also indicated which of their vehicles they used. Participants provided a 24h travel diary and an overview over long-distance travel for the last eight weeks.

Data for the fuel economy of private vehicles

The US Environmental Protection Agency (EPA) provides detailed information on fuel economy for private vehicles for model years 1984 to 2019 (US Department of Energy 2018a). We use the combined factor (for cities and highways) to assess the fuel economy (miles per gallon) of each vehicle type reported in the CHTS. The EPA also provides a factor that indicates the usage rate of each fuel if several fuels are used in a car. We matched vehicles from the CHTS to the EPA data set based on the vehicle model, construction year, fuel type and transmission. We distinguish between seven fuel types: gasoline, diesel, compressed natural gas, biofuel, natural gas, gasoline and electricity. The vehicles types that did not match with any model in the EPA database, have been matched without transmission information. For those households who did not report a construction year of the vehicle, we imputed the mean mpg for this model, transmission and fuel type from the survey. For vehicles older than 1984, we used historic data from the US Energy Information Administration (2012). For vehicles older than 1949, we used the average mpg from 1949. For households who only report the model we calculated the mean of the model across transmissions and fuel types. We used the average fuel economy of the light duty vehicles for the specific year provided by the US Department of Transportation (2018c) for household who specified other vehicle models than provided in the database of the EPA. For motorcycle models with more than 20 counts in the CHTS, we used the fuel economy specific to the model and construction year (Total Motorcycle 2018). For all other motorcycles, we considered the average fuel economy for motorcycles based on the construction year (US Department of Transportation 2018a). Since participants provided information on the number of persons traveled with them, we include vehicle occupancy for the use of private vehicles.

Data for the fuel economy of transit modes

The National Transit Database provides detailed information on energy consumption and passenger miles traveled per mode and transit agency (Federal Transit Administration 2018a, b, c). The Californian transit agencies supplied information on the following transit modes in 2011: commuter buses, cable car, commuter rail, demand response (service provided in response to calls from passengers on non-fixed routes and schedules), ferryboat, heavy rail, light rail, bus, bus rapid transit, trolleybus, vanpool, hybrid rail. We used annual fuel consumption and passenger miles to calculate the fuel economy for every mode and transit agency. Energy consumption for different fuel types were converted into British thermal units and later into gallons of gasoline equivalent. We calculated fuel economy by dividing passenger miles traveled by energy consumption for each transit agency and mode (cf. Table 5). Due to deviations for some transit agencies from the literature, we decided to use California averages for each mode instead of the specific value of each transit agency. We calculated a weighted mean of the fuel economies over transit agencies in California per mode, weighted by passenger miles traveled with each transit agency.

In addition, participants provided information on public-private transport modes (i.e. taxis, airplane, shuttle services). For air travel, we assumed a fuel economy for domestic flights since most of the trips by plane in the CHTS were domestic flights (US Department of Transportation 2018b). For taxis, rental cars and other private transit operators (such as UBER or Lyft), we assume average miles per gallon (mpg) for cars in 2011 (US Environmental Protection Agencies 2018a). For shuttles, we assume fuel economy of minivans and vans (US Environmental Protection Agencies 2018b) and vehicle occupancy of 10 persons per shuttle (Chester 2008).

Figure 1 shows the process to calculate energy footprints measured in gallon gasoline equivalents for private, public-private and public transport modes.

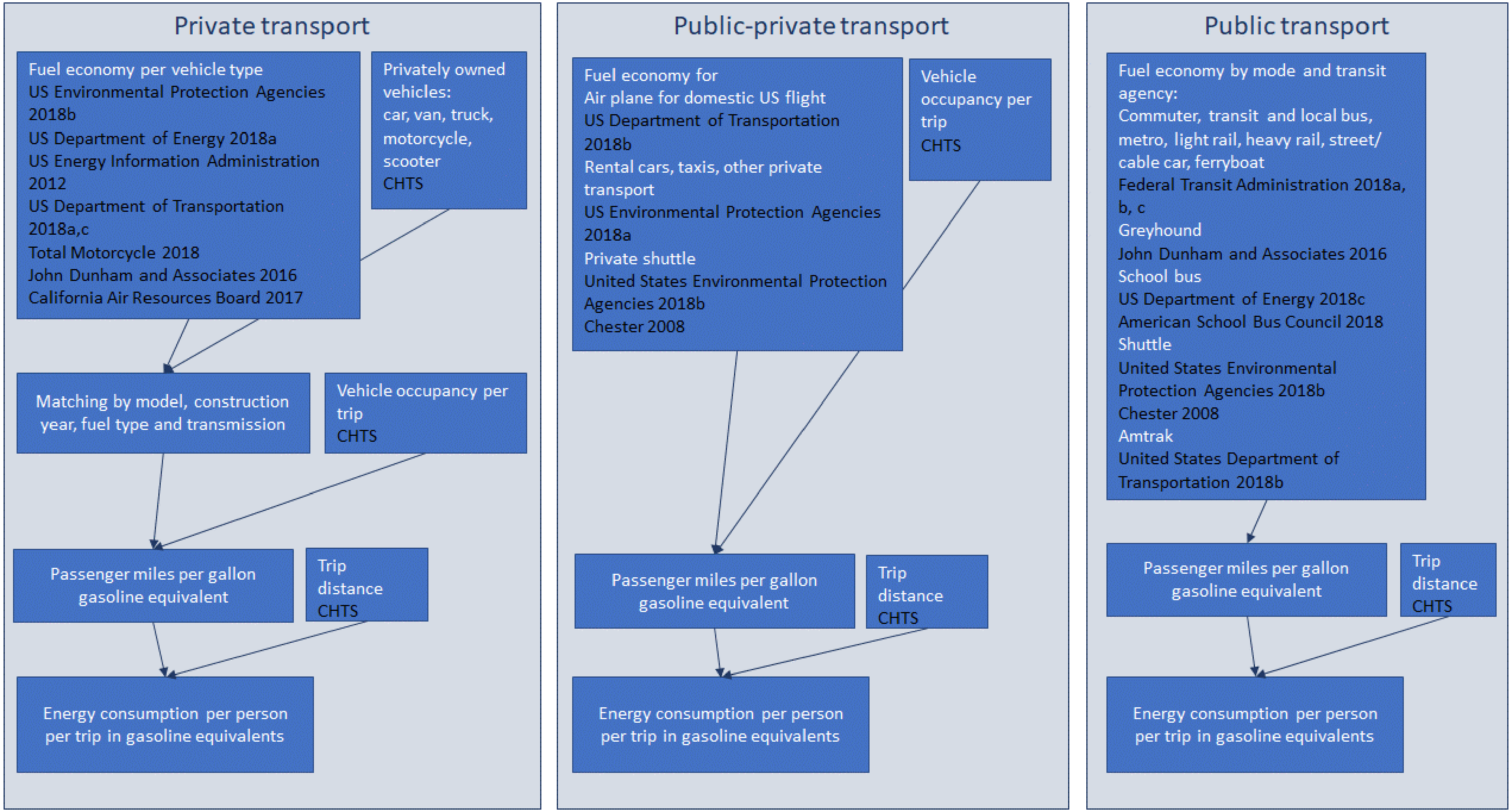

Figure 1 Calculation of energy footprints per trip, person and mode (Data source in black color, CHTS: California Household Travel Survey 2011-12)

2. Results on fuel economy for different modes

Table 1 shows the average fuel economy (passenger miles per gallon gasoline equivalent - pmpg) for 2011 for Californian transit agencies. For unreasonable outliers, we imputed 2011 national averages, specifying a lower bound of pmpg per mode (American Public Transportation Association 2018, US Department of Transportation 2018d) and upper bound of pmpg based on calculated Californian average fuel economy for each transit mode. For the following analysis, we used Californian averages for each mode weighted by passenger miles of each transit agency (cf. Table 1).

Table 1 Average fuel economy (passenger miles per gallon gasoline equivalent) for modes for California in 2011

Transit mode	PM/GGe
Commuter bus	32.83
Cable car	32.22
Commuter rail	60.34
Demand response	50.40
Ferryboat	14.55
Heavy rail	54.69
Light rail	40.32
Bus	58.90
Bus rapid transit	40.54

Figure 2 shows average vehicle occupancy measured in persons per vehicle per mode. The vehicle occupancy for automobile driver, automobile passenger, carpooler, user of motorcycle and rental car is based on the actual vehicle occupancy on the trip reported by participants in the CHTS. For school buses, we assume a vehicle occupancy rate of 54 persons per vehicle (American School Bus Council 2018) and for private and public transit shuttles 10 persons per vehicle (Chester 2008). Another assumption was that only one person takes a taxi or other private transit vehicle. For buses and rail modes, we assumed a fuel economy (vehicle miles per gallon) only for this graph to show average vehicle occupancy in Figure 2 although we did not use these assumptions to calculate passenger miles per gallon gasoline equivalent for the later analysis. We only used these assumptions to show differences in the vehicle occupancy in Figure 2. For buses, we assumed a fuel economy of 3.30 vehicle miles per gallon gasoline equivalent, for Amtrak (intercity rail) 2.68, for other rail services (commuter rail) 1.41 (US Department of Energy, 2018b).

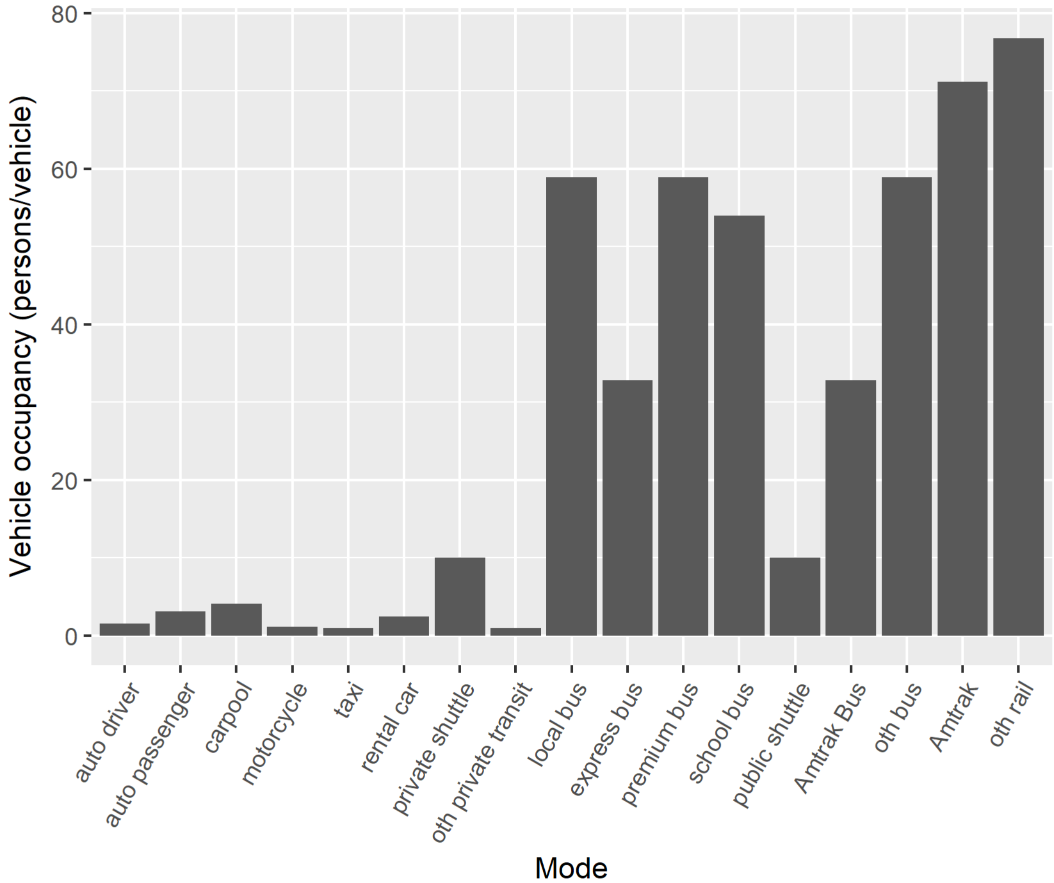

Figure 2 Mean vehicle occupancy (persons/vehicle) per mode

Average vehicle occupancy is considerably higher for transit modes compared to private modes (Figure 2). Rail has the highest vehicle occupancy rate. Vehicle occupancy varies between the types of buses.

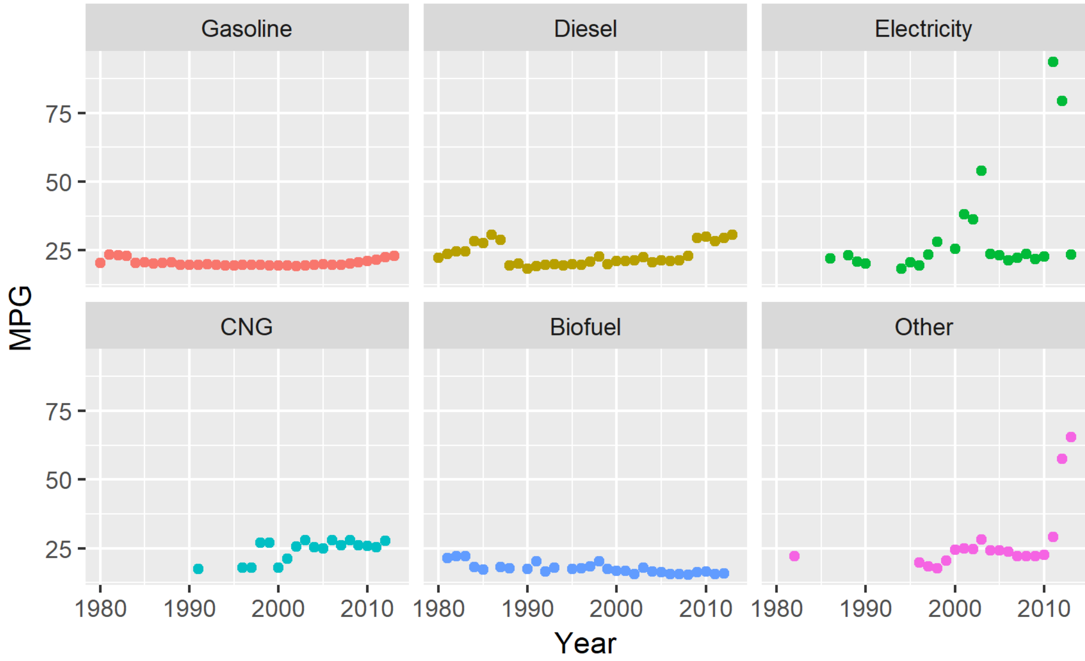

Figure 3 Average fuel economy (miles per gallon) per fuel type and year for vehicles owned by participants in the CHTS (miles per gallon gasoline equivalent for electric propulsion and CNG)

Figure 3 shows the average fuel economy for private vehicles in miles per gallon (mpg). The figure shows vehicle miles but not passenger miles per gallon. Mpg for vehicles with electric propulsion varies considerably over the years and models. Mpg for vehicles powered by gasoline and biofuel show lower mpg than vehicles fueled by gasoline only due to the lower heat of combustion values that affect fuel efficiency.

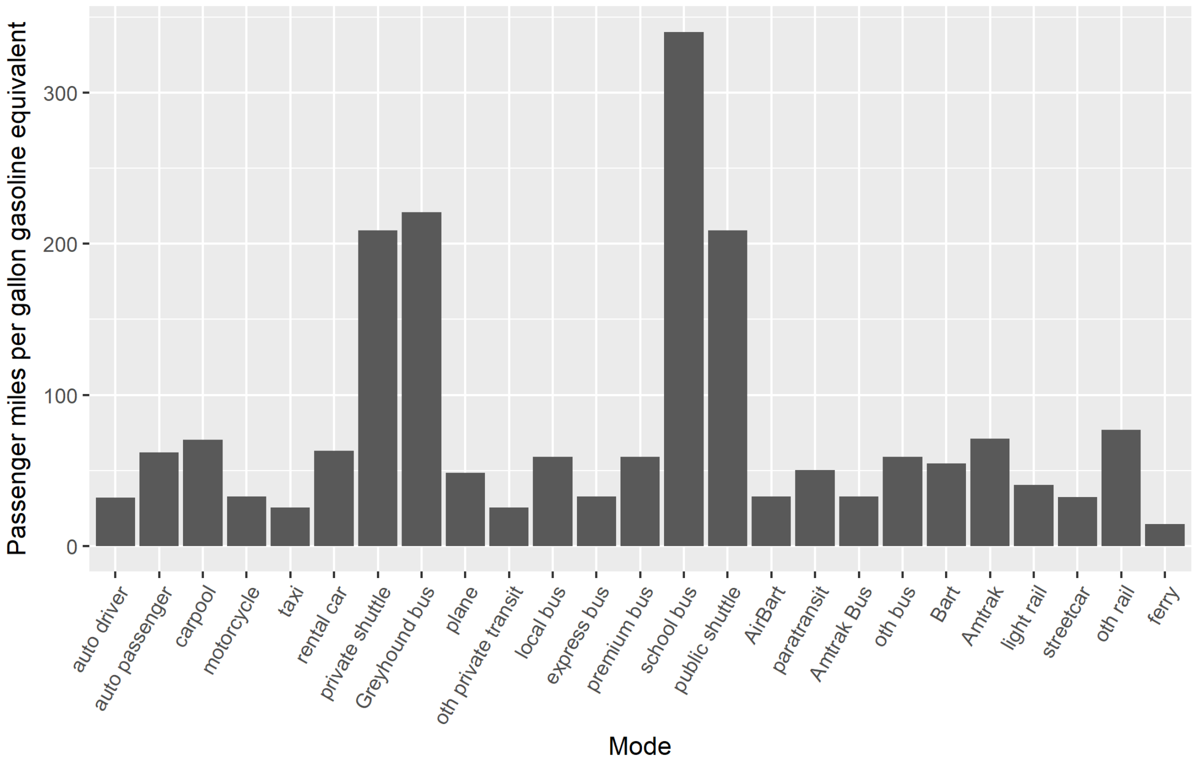

Figure 4 Fuel economy for transport modes in the CHTS in passenger miles per gallon gasoline equivalent per transport mode

Figure 4 provides an overview over the fuel economy measured in passenger miles per gallon gasoline equivalent (pmpg) across transport modes. School buses and carpoolers show higher pmpg due to on average higher vehicle occupancy compared to auto drivers or other buses. Likewise, private shuttles and greyhound buses optimize their utilization with a high vehicle occupancy rate. In general, public transport can be considered more energy-efficient than private transport (International Energy Agency 2011). Interestingly, some private modes of transportation (carpool) become competitive in terms of fuel economy with transit modes in California because of the low vehicle occupancy rate of some Californian transit modes.

In reviewing the literature, we find that our fuel economies are somewhat lower. For European countries in the OECD, light duty vehicles (LDV) reach a fuel economy of about 43 pmpg (passenger miles per gallon gasoline) compared to buses with 102 pmpg and rail 273 pmpg (International Energy Agency 2011). For the US, fuel economy is on average lower with 26 pmpg for LDV, 68 pmpg for buses, 136 pmpg for rail (International Energy Agency 2010, p. 364). Chester (2008) calculated the fuel economy for different modes in California. For fuel combustion, automobile consumed on average 30 pmpg, urban buses 42 pmpg, BART – a rail service connecting San Francisco to the bay area- 115 pmpg, Caltrain – an inter-city rail service in California – 124 pmpg, San Francisco tramway (Muni) 108 pmpg (Chester 2008). Chester (2008) found higher fuel economies for public transit compared to our values based on data provided by the National Transit Database (Federal Transit Administration 2018a, b, c).

Differences may occur since we use annual data for passenger miles and energy consumption provided by each transit agency for a specific mode. This may differ from Chester's (2008) results since he calculated fuel economy based on fuel efficiency and vehicle occupancy assumptions whereas we use aggregate annual data.

3. Statistical analysis

A central goal of this analysis is to assess the influence of built environment and land use characteristics on transport-related energy consumption. Ewing and Cervero (2010) define five dimensions in their meta-analysis that summarize pathways through which built environment and land use influence travel behavior: density, diversity, destination accessibility, design and distance to transit – the so called "5 Ds" (Ewing and Cervero 2010). Density relates to a variable of interest such as population or employment measured per unit area. Diversity describes the number of different land uses in an area and is often operationalized by entropy measures (Ewing and Cervero 2010). Street network characteristics form the design of an area. Potential measures are average block size, sidewalk coverage, street widths or interconnectedness of streets. Gravity models measure destination accessibility that describe the ease to access a trip destination (Ibid.). Last, distance to transit describes one angle of accessibility to transit. Some authors argue for a broader understanding of accessibility that also includes access to basic services and interdisciplinary approach to accessibility (Sola, Vilhelmson and Larsson 2018). Though the five beforementioned dimensions reflect well the discussion on the impact of built environment on travel in general.

Our methodological approach aimed to consider each of Ewing and Cervero's (2010) five dimensions of built environment by including at least one indicator for each dimension. We set up a range of built environment and land use indicators listed in Table 4 and based on the work of Salon et al. (2019). These indicators cover four of the outlined dimensions (not the fifth one: accessibility to transit which will be included in the analysis at a later point). These indicators assess land use (LU) and built environment (BE) characteristics at residence, work and school location (or educational facility) of participants. It was possible to assess these locations on census block level instead of at the officially provided census tract level. Therefore, it was possible to set up indicators at different spatial granularity: locations were buffered by a quarter mile, half mile and full mile radii to create circular areas for each indicator. In the sensitivity analysis, we analyze the impact on spatial granularity of LU and BE variables on energy footprints. Bicycle routes and bike friendly street design probably show the lowest data quality in this data set due to the lack of data in some parts of the study area.

We selected LU and BE variables for our statistical models based on four analytical steps: correlation analysis between energy consumption and LU and BE variables to extract the most relevant variables, correlation analysis between LU and BE variables to avoid redundancy, principal component analysis to assess different meaning of accessibility measured by LU and BE variables.

First, a section on descriptive statistics provide insights into variations in energy footprints with respect to travel purpose. In the following, we investigate the influence of LU and BE variables on energy consumption for specific trip chains per person and household. Our data has a hierarchical structure since participants are grouped into households and pursue different trips over the day. Observations are not independent and standard errors will be biased if the model does not account for this correlation. Linear mixed models (LMM), also called multilevel models, permit to integrate the hierarchical structure of our dataset in the model. LMM include fixed and random effects at the same time. We are primarily interested in the mean effect of LU and BE characteristics on energy consumption which are modeled as fixed effects. Fixed effects provide insights into the shifts in the mean of energy consumption due to variation in LU and BE variables. Besides, we want to control for the fact that different persons belong to the same household and include a random intercept for household membership to account for within household variance. In addition, LMM allow unevenly spaced measurements (i.e. number of persons per household).

Moreover, we are interested in the variation of energy footprints between partners of the same household. We model total energy consumption for a day for each partner separately. Though to account for the interdependence between partners, we use a seemingly unrelated equations model (Zellner 1962) and assume that the error terms are correlated and follow a multivariate normal distribution. We used female-male partner couples to assess gender differences in energy consumption at the same time.

Table 6 provides an overview about the covariates included in the regression models with their mean and standard deviation. One of our research questions focusses on the impact of the spatial granularity of land use variables on energy consumption which we also explore in a sensitivity analysis.

V. Results

1. Overview over energy footprints

We calculated energy footprints for one day of travel and compared them across modes. Figure 5 compares energy footprints per trip between different modes. Energy footprints are a composite of fuel economy and actual traveled distance. Although carpool has a higher fuel economy its average energy footprint is slightly higher than for auto drivers. Carpoolers hence tend to drive longer distances than individuals who drive alone in a car (auto drivers). Individuals who are passengers not drivers in a car have a low mean energy footprints. Individuals who use modes designed for long trip distances such as rail or air transport also consume more energy. Persons who take Amtrak buses consume most energy about 1.45 gallons gasoline equivalent (GGe). This figure excludes travel by plane to improve readability. On average, persons traveling by plane consume 31.98 GGe. Energy footprints for school bus trips are low since school buses have a high vehicle occupancy and school bus trips are on average shorter than trips by other modes.

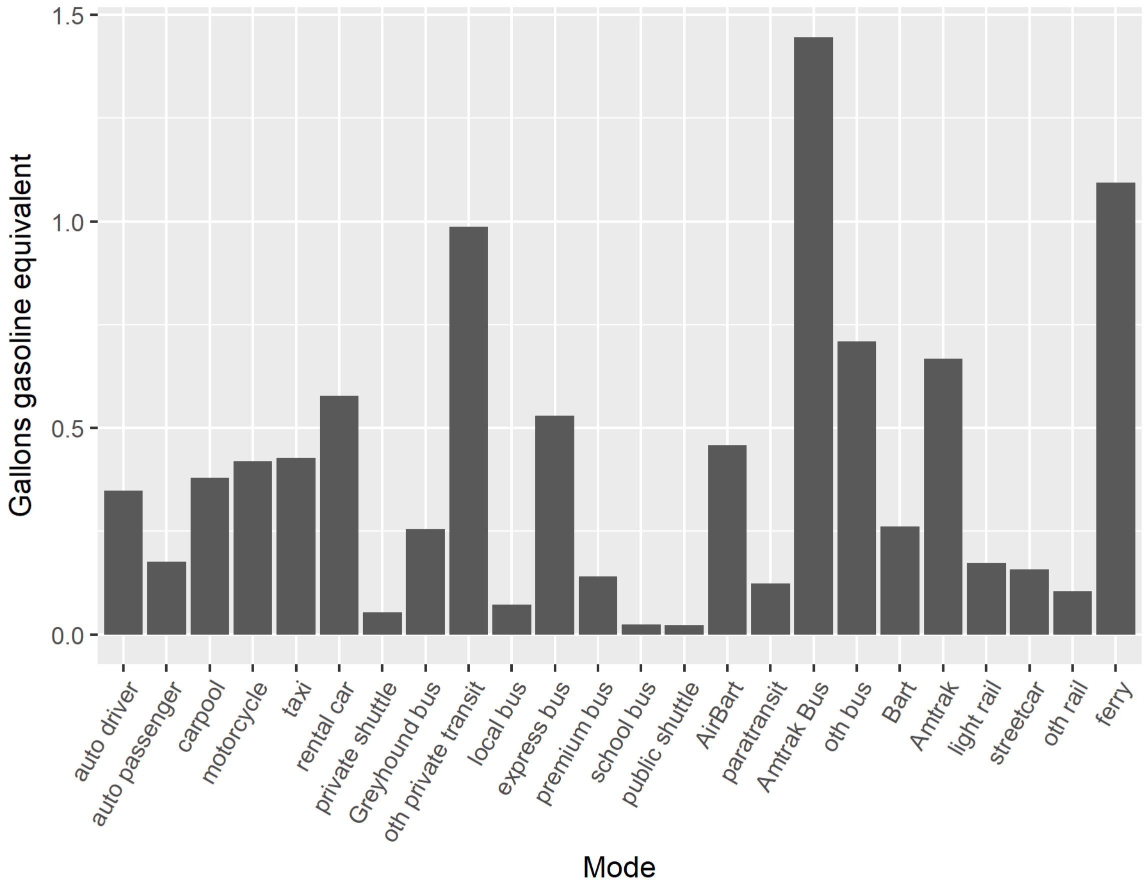

Figure 5 Mean energy footprint per trip and mode in gallons gasoline equivalent

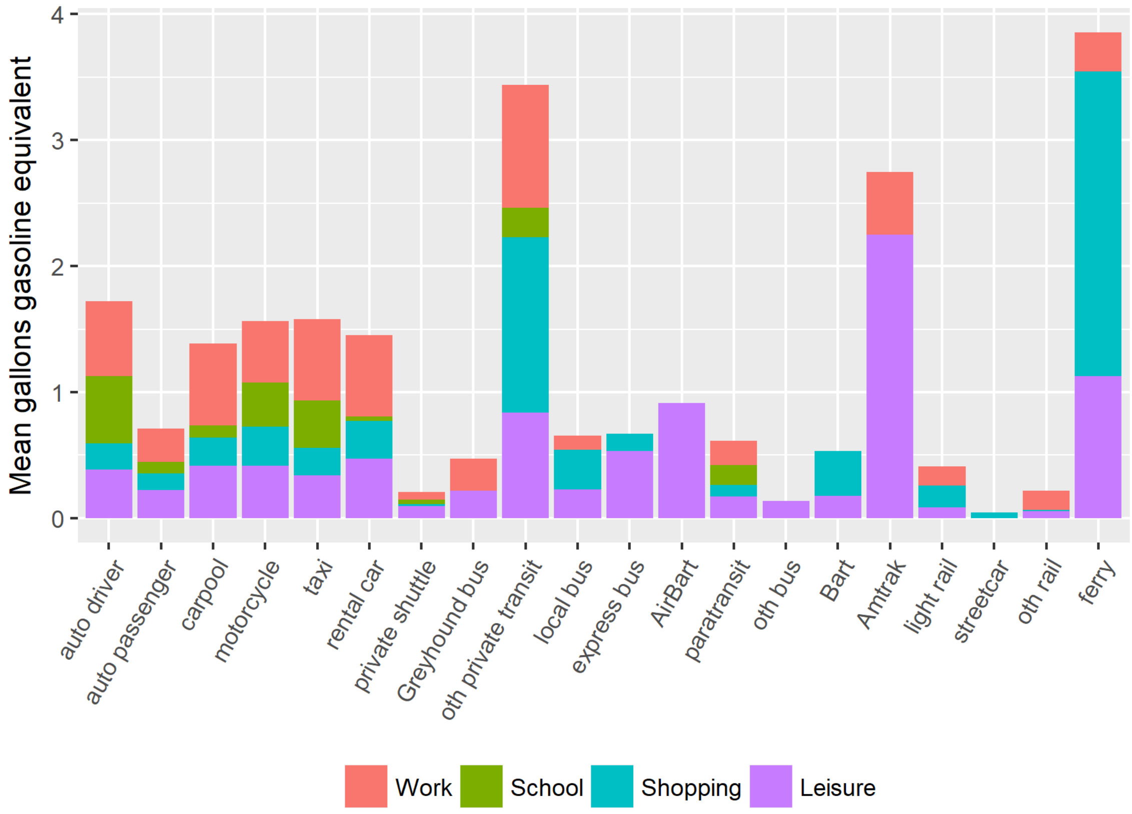

Figure 6 Mean energy footprints per trip purpose and mode

Figure 6 shows mean energy footprints for trip purpose and mode. Different activities can be pursued after one trip. School trips also include trips to higher educational institutions such as universities. In our sample, individuals use Amtrak, a company providing rail services, mostly for leisure activities and not to commute. Trips done by rental car for work also have a relatively high mean energy footprint. Interestingly, the mean energy footprint for work and school trips converge (0.57 GGe for work and 0.50 GGe for school trips) for individuals who drive alone in a car. This result point to the high vehicle usage among young adults to commute to school once they receive their driver's license.

2. The impact of land use and built environment on energy footprints for specific trip chains

This section explores the role of land use and built environment on transport-related energy consumption for specific trip chains. Table 2 shows the results for the mixed effect model for home-work-home, home-school-home and home-else-home trip chains. Energy consumption as well as all land use and built environment (LU and BE) variables are logged.

Table 2 Impact of land use and built environment variables on energy footprints for work, school and other trip chains

	Home-work-home		Home-school-home		Home-else-home	
	coefficient	std.errors	coefficient	std.errors	coefficient	std.errors
Gender (female = 1, male= 0)	-0.253***	-0.02	0.028	-0.03	-0.071***	-0.01
Age (16-35 compared to <16)	0.857***	-0.21	0.140*	-0.06	0.069*	-0.03
Age (36-65 compared to <16)	0.788***	-0.21	0.290*	-0.13	-0.005	-0.04
Age (>65 compared to <16)	0.509*	-0.22	-0.618	-0.37	-0.215***	-0.06
Age (NA)	0.826***	-0.22	0.035	-0.15	-0.06	-0.06
Educational degree (high school compared < high school)	0.047	-0.04	1.408***	-0.07	0.198***	-0.03
Educational degree (Bachelor or similar compared < high school)	-0.001	-0.05	1.610***	-0.12	0.227***	-0.03
Educational degree (Graduate or higher compared < high school)	-0.04	-0.05	0.862***	-0.24	0.214***	-0.04
Educational degree (NA)	-0.02	-0.09	0.993**	-0.33	0.106	-0.09
Race (Black or African American compared to White, Native Hawaiian, others)	0.126*	-0.06	0.095	-0.11	0.213***	-0.05
Race (American Indian or Alaska Native compared to White, Native Hawaiian, others)	-0.043	-0.05	-0.116	-0.08	0.052	-0.04
Race (Asian compared to White, Native Hawaiian, others)	0.008	-0.04	-0.192**	-0.07	-0.049	-0.03
Race (not specified compared to White, Native Hawaiian, others)	0.138	-0.09	0.049	-0.16	0.072	-0.07
Driver's license (**no=1, yes=0**)	-0.956***	-0.07	-1.043***	-0.07	-0.816***	-0.04
Transit pass (yes=1, no=0)	0.05	-0.05	0.005	-0.12	-0.075**	-0.03
Household size	-0.018	-0.01	-0.172***	-0.02	-0.123***	-0.01
Number of household workers	-0.046**	-0.02	0.080**	-0.03	0.063***	-0.01
Income	0.063***	-0.02	0.102***	-0.03	0.032*	-0.01
Rent (yes=1, no=0)	-0.053	-0.03	-0.144**	-0.06	-0.015	-0.03
Number of household vehicles	0.086***	-0.01	0.123***	-0.03	0.100***	-0.01
Number of household bicycles	0.002	0.00	-0.001	-0.01	-0.001	0.00
Weekend day (yes=1,no=0)	-0.075*	-0.03	0.101	-0.13	-0.206***	-0.02
Trip outside of California	1.088**	-0.35	2.935***	-0.43	1.607***	-0.14
Land use and built environment at residence in 1-mile radius						
The sum of acres in the grid cells considered greenfield.	0.001	0.00	0.001	0.00	0.002**	0.00
The sum of acres in the grid cells parcels considered mixed use.	0.002	0.00	0.002	0.00	-0.001	0.00
The sum of employees.	0.159***	-0.02	0.116**	-0.04	0.130***	-0.02
The sum of medical and social services employees.	0	0.00	-0.005	0.00	-0.002	0.00
The sum meters of bike hostile roads.	0.001	0.00	0.002	0.00	0	0.00
The sum bike routes in meters.	0.001	0.00	-0.002	0.00	-0.001	0.00
The number of bike/pedestrian friendly intersections	-0.030*	-0.01	-0.053*	-0.02	-0.060***	-0.02
Population density	0.042***	-0.01	-0.012	-0.02	-0.008	-0.01
Employment density	-0.289***	-0.03	-0.216***	-0.06	-0.227***	-0.03
Park area within the buffer in square meters	-0.001	0.00	0.004	0.00	0.003**	0.00
The area of overlap between bike routes and radius area (in m²)	0	0.00	0.001	0.00	0.002*	0.00
The distance to the closest job center with a minimum gross density of 10 emp/acre.	0.005***	0.00	-0.004	0.00	0.003*	0.00
Land use and built environment at workplace/school in 1-mile radius						
The sum of acres in the grid cells considered greenfield.	-0.001	0.00	-0.003	0.00		
The sum of acres in the grid cells parcels considered mixed use.	0.003*	0.00	0.003	0.00		
The sum of employees.	-0.094***	-0.02	-0.005	-0.05		
The sum of medical and social services employees.	-0.009***	0.00	0	0.00		
The sum meters of bike hostile roads.	0.001	0.00	0.001	0.00		
The sum bike routes in meters.	0.002	0.00	0.002	0.00		
The number of bike/pedestrian friendly intersections	-0.035***	-0.01	-0.044**	-0.02		
Population density	-0.026***	0.00	-0.033*	-0.01		
Employment density	0.183***	-0.03	0.068	-0.06		
Park area within the buffer in square meters	-0.002*	0.00	-0.001	0.00		
The area of overlap between bike routes and radius area (in m²)	0.002	0.00	0.003	0.00		
The distance to the closest job center with a minimum gross density of 10 emp/acre.	0	0.00	-0.002	0.00		
Constant	-2.415***	-0.66	-4.070***	-1.13	-3.214***	-0.43
Standard deviation within households	0.632***	-0.02	0.903***	-0.02	0.790***	-0.01
General standard deviation	0.798***	-0.01	0.752***	-0.01	0.777***	-0.01
Observations	9862		4784		20281	

The focus of this study lies on the impact of LU and BE characteristics on energy consumption. We differentiate between characteristics at the residence and workplace or educational facility (e.g. school location). In general, employment-related variables seem to have the largest effects on energy consumption. For LU and BE at the residence, a one percent increase in the employment density leads to a 0.3 percent increase in energy consumption. Likewise, population density significantly affects energy footprints. Surprisingly, employment density has a negative effect on energy consumption at the residence but a positive effect at workplace. This is a remarkable outcome. A workplace or school located nearby a lot of jobs and medical and social services reduces energy consumption for travel. Likewise, bike and walking friendly street design and population density decreases energy footprints. Table 2 highlights differences in the coefficients of LU and BE variables between the trip chains. The same LU and BE variables at the residence are significant across different trip purposes. The highest coefficients can be found for work trips for both locations: residence and workplace. For trips that include other destinations than workplace or school, other LU and BE characteristics at residence become significant too though only at a low level of significance. Greenfield area, parks and bike paths at residence positively contribute to energy consumption while bike and pedestrian friendly street design reduce energy consumption. The standard deviation between households is significant which highlights that after controlling for fixed effects (first part of the table), a considerable amount of variance can be explained by intra-household variation. The likelihood ratio test that compares the mixed effect model results to an ordinary linear regression is significant indicating that intra-household variations should be accounted for to estimate unbiased standard errors.

Although it is not the focus of this study, it is worth to point out several results of the sociodemographic characteristics. Women consume less energy than man. The difference for non-work trips is small, though considerable for work trips (25% lower energy footprints than men). Educational attainment seems to be only important for trips including educational facilities as destination. The effects seem non-linear: after high school, transport-related energy footprints increase up to an educational level of a Bachelor degree but decrease for graduates. The possession of a driver's license has one of the biggest impacts on energy footprints. For instance, individuals without driver's license use on average 104% less energy on their trip to school and back home compared to holders of a driver's license.

3. The impact of land use and built environment on different household members

The next model attempts to answer whether household members are differently affected by land use and built environment (LU and BE) characteristics. Table 3 presents the results for the seemingly unrelated equations model that compares the logged energy consumption of a female partner to her male partner. Energy footprints between partners living in the same household are likely to be dependent since they may travel together, share mobility resources or use other transport modes depending on the partner's travel behavior.

Table 3 Comparison of daily energy consumption for transport between partners of the same household

	Women		Men	
	coefficient	std.errors	coefficient	std.errors
Age (16-35 compared to <16)			-0.239	(0.73)
Age (36-65 compared to <16)	-0.012	(0.05)	-0.156	(0.73)
Age (>65 compared to <16)	-0.122	(0.11)	-0.221	(0.74)
Educational degree (high school compared < high school)	-0.053	(0.09)	0.020	(0.08)
Educational degree (Bachelor or similar compared < high school)	-0.029	(0.10)	-0.038	(0.09)
Educational degree (Graduate or higher compared < high school)	-0.042	(0.10)	-0.108	(0.09)
Race (Black or African American compared to White, Native Hawaiian, others)	0.125	(0.10)	0.163*	(0.10)
Race (American Indian or Alaska Native compared to White, Native Hawaiian, others)	-0.111	(0.07)	0.021	(0.08)
Race (Asian compared to White, Native Hawaiian, others)	0.035	(0.05)	-0.029	(0.06)
Race (not specified compared to White, Native Hawaiian, others)	0.004	(0.13)	0.271*	(0.14)
Driver's license **(no=1, yes=0)**	-0.644***	(0.11)	-0.748***	(0.17)
Transit pass (yes=1, no=0)	-0.219***	(0.06)	-0.297***	(0.06)
Employment status (student compared to employed)	0.020	(0.15)	-0.174	(0.26)
Employment status (homemaker compared to employed)	-0.157	(0.11)		
Employment status (other compared to employed)	0.306*	(0.17)	-0.455***	(0.17)
Household size	-0.122***	(0.01)	-0.067***	(0.01)
Number of household workers	0.070**	(0.04)	-0.018	(0.03)
Income	0.023**	(0.01)	0.034***	(0.01)
Rent (yes=1, no=0)	-0.007	(0.05)	-0.101*	(0.05)
Number of household vehicles	0.085***	(0.02)	0.110***	(0.02)
Number of household bicycles	0.001	(0.00)	0.003	(0.00)
Trip outside of California	1.860***	(0.14)	2.012***	(0.14)
Weekend day (yes=1,no=0)	-0.160***	(0.04)	-0.255***	(0.04)
Number of shared trips	-0.239***	(0.04)	-0.438***	(0.04)
Number of trips	0.082***	(0.01)	0.103***	(0.01)
Commute distance differential (Men-Women)	0.003	(0.03)	-0.157***	(0.03)
Commute distance of partner	-0.006***	(0.00)	-0.010***	(0.00)
Land use and built environment at residence in 1-mile radius				
The sum of acres in the grid cells considered greenfield.	0.004***	(0.00)	0.004***	(0.00)
The sum of acres in the grid cells parcels considered mixed use.	-0.001	(0.00)	0.000	(0.00)
The sum of employees.	0.111***	(0.03)	0.093***	(0.03)
The sum of medical and social services employees.	0.006*	(0.00)	0.003	(0.00)
The sum meters of bike hostile roads.	-0.001	(0.00)	0.000	(0.00)
The sum bike routes in meters.	-0.001	(0.00)	-0.003*	(0.00)
The number of bike/pedestrian friendly intersections	-0.028*	(0.02)	-0.024	(0.02)
Population density	-0.027*	(0.01)	0.023	(0.02)
Employment density	-0.223***	(0.04)	-0.190***	(0.04)
Park area within the buffer in square meters	-0.000	(0.00)	0.003	(0.00)
The area of overlap between bike routes and radius area (in m²)	0.002	(0.00)	0.001	(0.00)
The distance to the closest job center with a minimum gross density of 10 emp/acre.	0.002	(0.00)	0.001	(0.00)
Land use and built environment at workplace/school in 1-mile radius				
The sum of acres in the grid cells considered greenfield.	-0.000	(0.00)	0.000	(0.00)
The sum of acres in the grid cells parcels considered mixed use.	0.001	(0.00)	0.004**	(0.00)
The sum of employees.	0.036	(0.04)	-0.009	(0.03)
The sum of medical and social services employees.	0.002	(0.00)	-0.002	(0.00)
The sum meters of bike hostile roads.	0.002**	(0.00)	-0.000	(0.00)
The sum bike routes in meters.	-0.001	(0.00)	0.001	(0.00)
The number of bike/pedestrian friendly intersections	-0.055***	(0.02)	-0.006	(0.01)
Population density	-0.046***	(0.01)	-0.030***	(0.01)
Employment density	0.037	(0.05)	0.033	(0.04)
Park area within the buffer in square meters	0.000	(0.00)	-0.004***	(0.00)
The area of overlap between bike routes and radius area (in m²)	0.004	(0.00)	0.004**	(0.00)
The distance to the closest job center with a minimum gross density of 10 emp/acre.	-0.000	(0.00)	-0.002*	(0.00)
Constant	-3.369***	(0.84)	-1.656	(1.08)
Observations	4,679		4,679	
R-squared	0.161		0.176	
Correlation of residuals between women and men	0.35***			

*p<0.05, **p<0.01, *** p<0.001

Women are more affected by LU and BE characteristics at the residence than men whereas men are more affected by these variables at the workplace or at school. The quality of bike infrastructure and street design at the residence seem to affect women's energy footprint but not those of their male partners. For instance, bike- and pedestrian-friendly street design as well as bike-hostile roads at the work or school significantly affect women but not men. On the other side, the quantity of bike infrastructure seems to affect men more than women at the workplace. The provision of medical and social services seems to affect women more than man at their residence though only at a weak significance level. The number of employees positively affects energy footprints at residence but employment density negatively. Employment density may indicate a general high economic activity whereas a high number of employees may only refer to a concentrated job center in an area that does not necessarily provide other urban functions. Mixed land use at work has a positive effect on men's energy footprint which may hint to the effect of a longer commute to an urban center. The correlation coefficient between energy footprints of partners indicate that they are significantly correlated and rather complements than substitutes.

Relating to sociodemographic factors, household size affects women more than men, an additional household member decreases the daily energy footprint of women by 12% and of men by 7%. Interestingly, an additional shared trip reduces men's energy footprint by 44% but women's "only" by 24%. Another remarkable outcome refers to the commute distance differential that indicates the difference in commute distance (home-workplace) between men and women. Increases in the difference between commute distances decreases the total daily energy consumption of men by 16% but does not affect daily energy consumption of women. Equally, men are more affected by the commute distance of their female partners than vice versa.

VI. Sensitivity analysis: The relevance of spatial scale

In this section, we compare the coefficients of LU and BE variables in the mixed-effect model if defined at different radii around the residence and workplace or school. A quarter of a mile, half a mile, one-mile radii have been chosen to assess the impact of spatial scale on the effect of LU and BE variables on energy consumption. Figure 7 gives an overview over the size of LU and BE coefficients in the mixed-effect model for home-work-home trip chains. Since both variables, energy consumption and LU and BE, are logged the coefficients can be interpreted as elasticities. Employment-related indicators exhibit the highest elasticities with respect to energy consumption. Most coefficients increase with the radius chosen around the specific location (i.e. residence, workplace, school). This may indicate that transport-related energy consumption is more sensitive to LU and BE variables at a higher spatial scale, i.e. than at block or near neighborhood level. All indicators show higher coefficients for the one-mile radius compared to half- or a quarter-mile radii. The only exception is the sum of greenfield acres whose impact gains in importance (though still very small) the lower the radius around the location. The coefficient triples from one-mile to a quarter-mile radius.

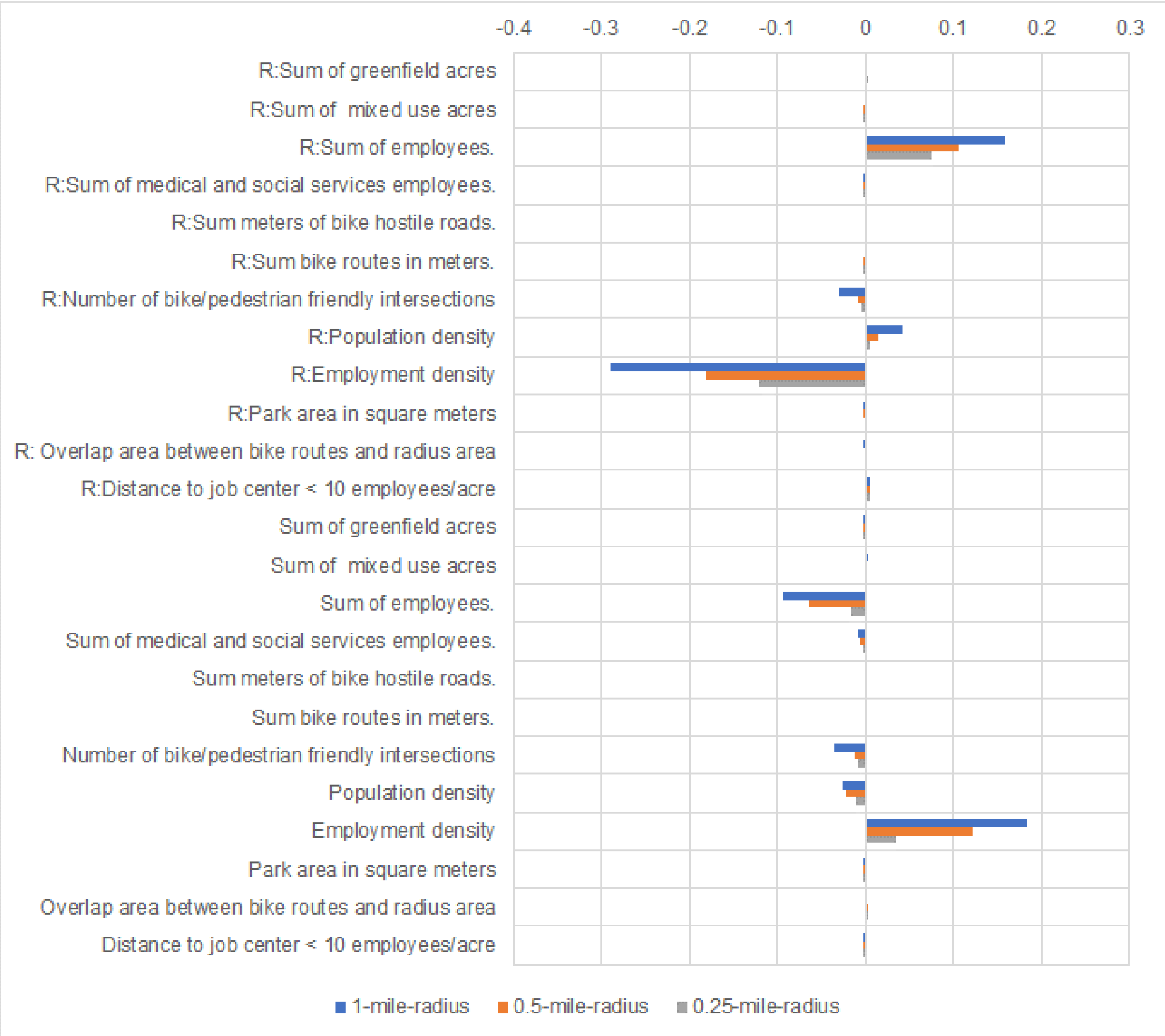

Figure 7 Comparison of elasticities between land use and built environment variables and energy consumption for Home-Work-Home trip chains for different radii (based on the mixed-effect model, land use indicators relate to residence (R) or to workplace/school)

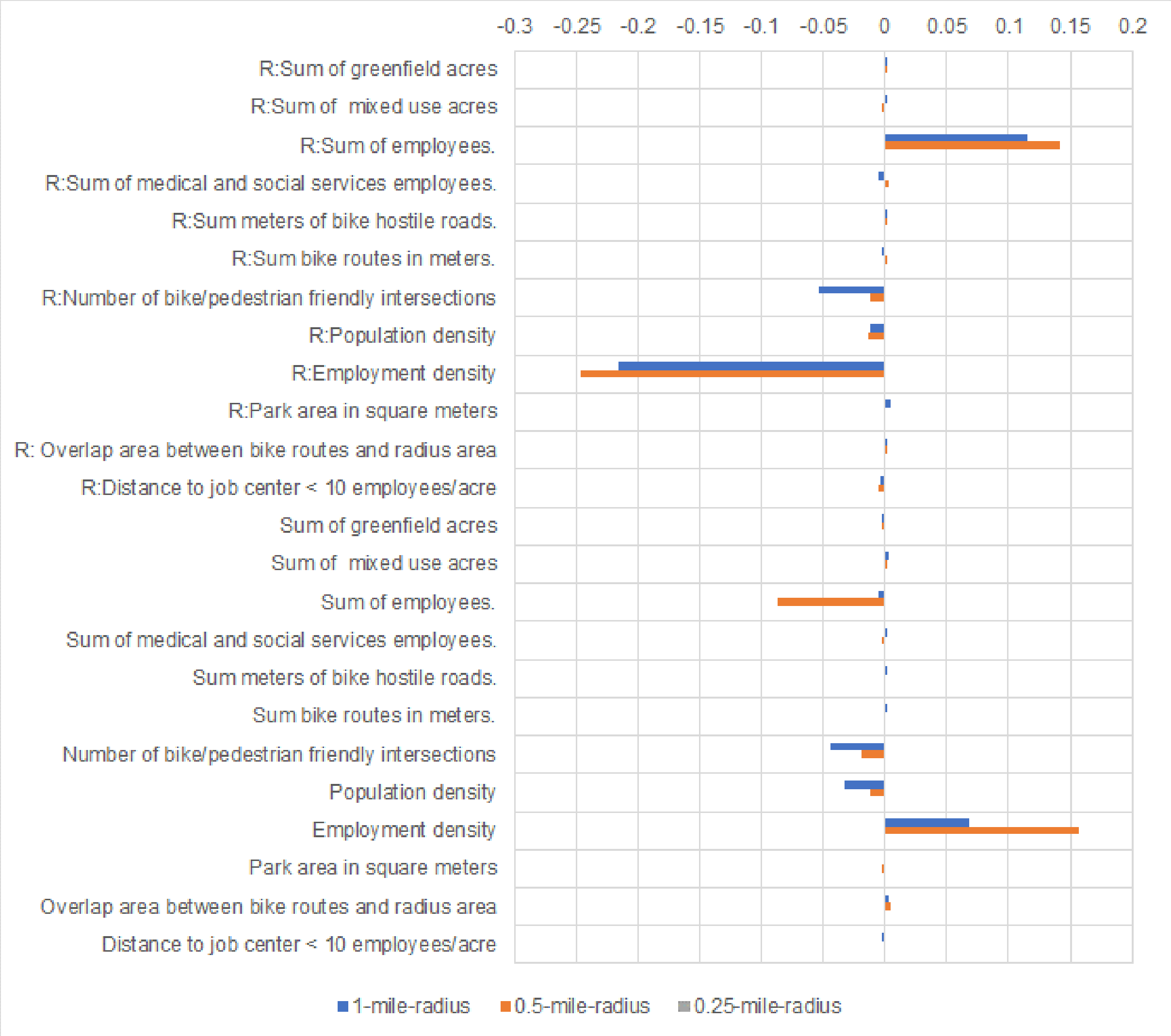

Figure 8 Comparison of coefficients of land use and built environment variables in mixed-effect model for Home-School-Home trip chains for different radii

However, the coefficients of LU and BE variables are higher at a half-mile radius for home-school-home trip chains (Figure 8). Particularly primary education institutions are more equally distributed and at shorter distances from residence. Therefore, direct surroundings of the residence and school location plays a more important role than for work trips. Population density and bike- and pedestrian-friendly street design play a more important role at a 1-mile radius.

Relating to leisure and shopping trips (home-else-home), employment-related indicators mostly affect energy consumption if specified at a 1-mile radius around the residence (Figure 9). Population density and greenfield area seem to be more relevant at a lower scale.

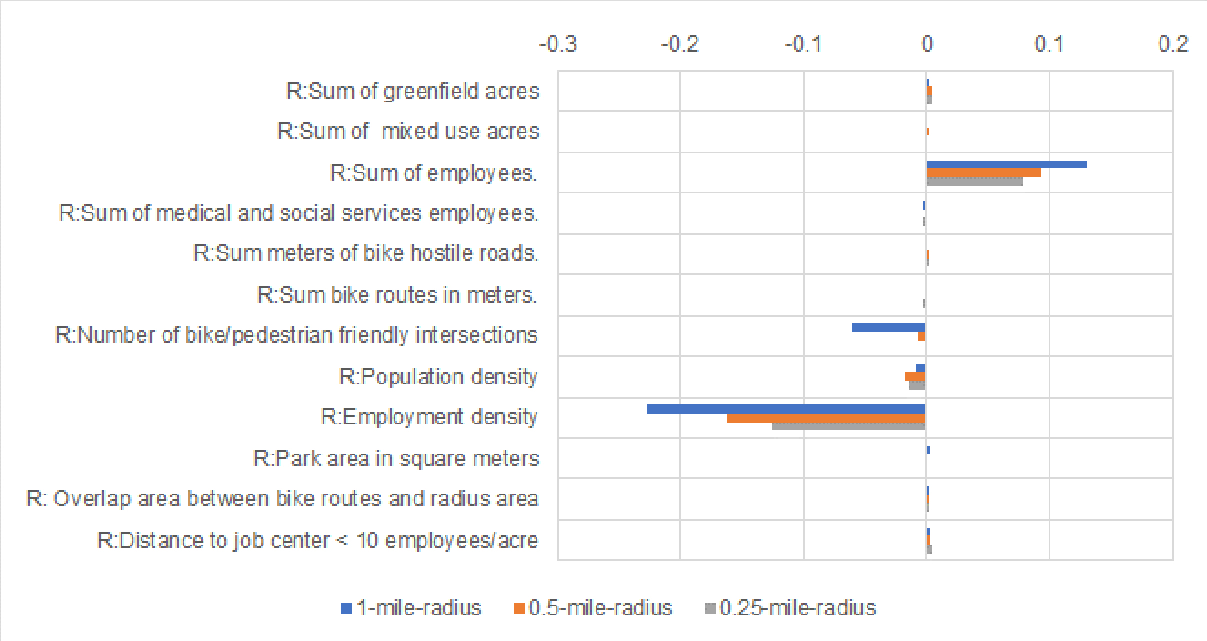

Figure 9 Comparison of coefficients of land use and built environment variables at the residence in the mixed-effect model for Home-Else-Home trip chains for different radii

VII. Discussion and conclusion

In this study, we assess the influence of land use and built environment (LU and BE) characteristics on transport-related energy consumption. Previous research has demonstrated the impact of these variables on different travel outcomes such as vehicle miles traveled. Though their impact on energy consumption for transport has been studied less. We contribute to this literature by including other than LU and BE variables related to density and compare their influence at different locations (residence, workplace, school) and for different trip purposes.

The results show that in general LU and BE factors have a significant though small effect on energy consumption. Employment-related variables seem to have the biggest effect on energy consumption. Interestingly the sign of employment-related variables changes depending on whether they relate to home residence or workplace. High employment density at the residence has a negative effect on energy consumption potentially pointing towards employment opportunities nearby and shorter commute distance. At the workplace, high employment density contributes to energy consumption which may indicate that the workplace is located in a central business district or urban core. Individuals may have to travel larger distances to reach these centers. Other LU and BE variables become relevant for non-work or non-school trips such as greenfield sites, bike paths and street design.

One interesting finding reveals that household members show different sensitivity to LU and BE variables. Women seem to be more affected by LU and BE characteristics at the residence while men are more sensitive to these factors at the workplace. The quality of bike infrastructure plays a role for energy footprints of women whereas for their male partners the quantity of bike infrastructure is more relevant. The correlation coefficient between energy footprints of partners indicates that they are significantly correlated and rather complements than substitutes. Another finding shows that men tend to reduce their energy footprint to a larger extent then women if partners share trips. Likewise, men seem to be more affected by the commute distance of their female partner than vice versa.

The current study indicates that the scale at which LU and BE factors are defined matters. Most coefficients of LU and BE variables for home-work-home trip chains increase if the scale of the variables increase, i.e. from a quarter-mile to one-mile radius. Considering that employment-related variables have the biggest coefficients, characteristic pattern of employment and economic activity may only effectively impact travel at a larger spatial scale. For home-school-home trips however, half-a-mile radius leads to the highest coefficients. One explanation may relate to the fact that distance to schools is generally lower than trip distance to work.

Some general insights from the descriptive statistics of energy footprints showed that mean energy footprints for work and school trips converge indicating the high vehicle use even among young adults. A considerable number of students travel to school by car. It seems that transit is not often used for work trips but rather for leisure or shopping purposes. In addition, men have higher mean energy footprints for private transport mode whereas gender differences are less pronounced for public transport.

The findings of this study broadly support the work of previous research that found that population- and employment related factors affect energy consumption for transport. Though this study contributes to the body of literature by differentiating between locations. LU and BE have different effects depending whether the relate to the residence, workplace or educational facility. Our results show that particularly employment-related indicators are relevant. This points to the relevance of the distribution of economic activity for travel outcomes and related energy consumption. Other indicators such as bike infrastructure and green areas seem to have smaller effects. This result may be explained by the fact that only a small percentage of trips are carried out by transit and we did not include non-motorized trips. Both transit and non-motorized trips are differently affected by land use and built environment than private motorized transport.

These findings are particularly relevant for transport demand models and urban planning since they suggest that household members may react differently to land use and built environment characteristics. Transport demand models are based on household surveys and calibrated to household characteristics and often do not consider differences within households potentially leading to biased estimates.

Further research should be undertaken to investigate the impact of land use and built environment characteristics at larger spatial scale, for instance at the regional level. The results also showed differences in the effect of job centers and general employment density. Concentration of work can have different impacts depending on its actual distribution.

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IX. Appendix

Table 4 Built environment and land use variables

	Mile-radius		
	0.25	0.5	1
Acres in the grid cells.	x	x	x
The sum of acres in the grid cells considered urban.	x	x	x
The sum of acres in the grid cells considered greenfield.	x	x	x
The sum of acres in the grid cells considered constrained.	x	x	x
The sum of acres in the grid cells parcels considered residential.	x	x	x
The sum of acres in the grid cells parcels considered employment.	x	x	x
The sum of acres in the grid cells parcels considered mixed use.	x	x	x
The sum of population.	x	x	x
The sum of employees.	x	x	x
The sum of retail employees.	x	x	x
The sum of restaurant and accommodations employees.	x	x	x
The sum of entertainment and recreation employees.	x	x	x
The sum of office employees.	x	x	x
The sum of education employees.	x	x	x
The sum of medical and social services employees.	x	x	x
The sum of public employees.	x	x	x
The sum of manufacturing employees.	x	x	x
The sum of transportation and warehousing employees.	x	x	x
The sum of utilities employees.	x	x	x
The sum of wholesaling employees.	x	x	x
The sum of construction employees.	x	x	x
The sum of other employees.	x	x	x
The sum of agricultural employees.	x	x	x
The sum of extraction industry employees.	x	x	x
The sum meters of bike friendly roads.	x	x	x
The sum meters of bike hostile roads.	x	x	x
The sum bike routes in meters.	x	x	x
The number of bike/pedestrian friendly intersections.	x	x	x
The land area (square mile) that is not included in parks or waterbodies	x	x	x
Population density (100,000 persons per square mile)	x	x	x
Employment density (100,000 employees per square mile)	x	x	x
Land area (square meters)	x	x	x
Park area (square meters)	x	x	x
Number of parks with different names intersecting	x	x	x
The overlapping area between the bike routes convex hull and the radius area measured in square meters	x	x	x
The distance to the closest job center with a minimum gross density of 10, 25, 50, 75, 100 employees/acre.			

Table 5 Fuel economy (passenger miles per gallon gasoline equivalent) per mode and transit agency in California for 2011

Name of transit agency	NTDID	Mode	PM/GGe

San Joaquin Regional Transit District(RTD)	9012	CB	28.7
City of Los Angeles Department of Transportation(LADOT)	9147	CB	22.9
San Diego Metropolitan Transit System(MTS)	9026	CB	31.9
Placer County Department of Public Works(PCDPW)	9196	CB	48.7
Santa Barbara Metropolitan Transit District(SBMTD)	9020	CB	58.3
Yuba-Sutter Transit Authority(YSTA)	9061	CB	73.5
City of Elk Grove(etran)	9205	CB	32.8
San Francisco Municipal Railway(MUNI)	9015	CC	32.2
North County Transit District(NCTD)	9030	CR	43.8
Southern California Regional Rail Authority dba: Metrolink(Metrolink)	9151	CR	61.0
Peninsula Corridor Joint Powers Board dba: Caltrain(PCJPB)	9134	CR	61.3
Altamont Commuter Express(ACE)	9182	CR	74.1
San Joaquin Regional Transit District(RTD)	9012	DR	7.2
Redding Area Bus Authority(RABA)	9093	DR	7.2
City of Elk Grove(etran)	9205	DR	7.2
Norwalk Transit System(NTS)	9022	DR	7.2
Yuba-Sutter Transit Authority(YSTA)	9061	DR	7.2
Livermore / Amador Valley Transit Authority(LAVTA)	9144	DR	7.7
Yolo County Transportation District(YCTD)	9090	DR	7.8
Napa County Transportation Planning Agency(NCTPA)	9088	DR	8.8
The Eastern Contra Costa Transit Authority(Tri Delta Transit)	9162	DR	9.2
City of Fairfield - Fairfield and Suisun Transit(FAST)	9092	DR	9.4
Santa Maria Area Transit(SMAT)	9087	DR	13.9
City of Redondo Beach - Beach Cities Transit(BCT)	9214	DR	15.3
City of Lodi - Transit Division(Grapeline)	9175	DR	15.4
City of Santa Rosa(Santa Rosa CityBus)	9017	DR	16.1
City of Visalia - Visalia City Coach(Visalia Transit)	9091	DR	16.4
Imperial County Transportation Commission(ICTC)	9226	DR	16.7
Alameda-Contra Costa Transit District(AC Transit)	9014	DR	18.6
San Mateo County Transit District(SamTrans)	9009	DR	19.1
Ventura Intercity Service Transit Authority(VISTA)	9164	DR	20.8
LACMTA - Small Operators(LACMTA)	9166	DR	23.7
San Luis Obispo Regional Transit Authority(SLORTA)	9206	DR	25.4
Golden Empire Transit District(GET)	9004	DR	26.8
City of Commerce Municipal Buslines(CBL)	9043	DR	32.1
Butte County Association of Governments(BCAG)	9208	DR	32.5
San Francisco Municipal Railway(MUNI)	9015	DR	34.9
Culver City Municipal Bus Lines(Culver CityBus)	9039	DR	39.7
Gold Coast Transit(GCT)	9035	DR	40.1
City of Riverside Special Transportation(City of Riverside)	9086	DR	42.1
Merced County Transit(The Bus)	9173	DR	44.9
Placer County Department of Public Works(PCDPW)	9196	DR	45.6
Kings County Area Public Transit Agency(KART)	9200	DR	50.4
SunLine Transit Agency(SunLine)	9079	DR	50.4
Santa Clarita Transit(SCT)	9171	DR	50.4
Fresno Area Express(FAX)	9027	DR	50.4

Paratransit, Inc.	9223	DR	50.4
City of Gardena Transportation Department(GMBL)	9042	DR	50.4
Thousand Oaks Transit(TOT)	9165	DR	50.4
City of Vallejo Transportation Program(Vallejo Transit, Baylink)	9028	DR	50.4
Western Contra Costa Transit Authority(WestCAT)	9159	DR	50.4
San Diego Metropolitan Transit System(MTS)	9026	DR	50.4
Santa Monica's Big Blue Bus(Big Blue Bus)	9008	DR	50.4
City of Petaluma(Petaluma Transit)	9213	DR	50.4
City of La Mirada Transit(LMT)	9024	DR	50.4
Long Beach Transit(LBT)	9023	DR	50.4
Sonoma County Transit	9089	DR	50.4
City of Turlock(BLAST and DART)	9201	DR	50.4
Antelope Valley Transit Authority(AVTA)	9121	DR	50.4
Central Contra Costa Transit Authority(County Connection)	9078	DR	50.4
Santa Barbara Metropolitan Transit District(SBMTD)	9020	DR	50.4
Golden Gate Bridge, Highway and Transportation District(GGBHTD)	9016	DR	50.4
City of Los Angeles Department of Transportation(LADOT)	9147	DR	50.4
Victor Valley Transit Authority(VVTA)	9148	DR	50.4
City of Arcadia Transit(Arcadia Transit)	9044	DR	50.4
Omnitrans(OMNI)	9029	DR	50.4
Riverside Transit Agency(RTA)	9031	DR	50.4
Orange County Transportation Authority(OCTA)	9036	DR	50.4
Modesto Area Express(MAX)	9007	DR	50.4
Santa Cruz Metropolitan Transit District(SCMTD)	9006	DR	50.4
North County Transit District(NCTD)	9030	DR	50.4
Access Services (AS)	9157	DR	50.4
Santa Clara Valley Transportation Authority(VTA)	9013	DR	50.4
San Francisco Bay Area Water Emergency Transportation Authority(WETA)	9225	FB	8.7
Golden Gate Bridge, Highway and Transportation District(GGBHTD)	9016	FB	12.6
City of Vallejo Transportation Program(Vallejo Transit, Baylink)	9028	FB	25.5
Los Angeles County Metropolitan Transportation Authority dba: Metro(LACMTA)	9154	HR	33.9
San Francisco Bay Area Rapid Transit District(BART)	9003	HR	60.5
Sacramento Regional Transit District(Sacramento RT)	9019	LR	26.4
Santa Clara Valley Transportation Authority(VTA)	9013	LR	29.5
San Francisco Municipal Railway(MUNI)	9015	LR	32.6
Los Angeles County Metropolitan Transportation Authority dba: Metro(LACMTA)	9154	LR	42.6
San Diego Metropolitan Transit System(MTS)	9026	LR	64.6
Modesto Area Express(MAX)	9007	MB	28.7
Yuba-Sutter Transit Authority(YSTA)	9061	MB	28.7
City of Vallejo Transportation Program(Vallejo Transit, Baylink)	9028	MB	28.7
City of Los Angeles Department of Transportation(LADOT)	9147	MB	28.7
Merced County Transit(The Bus)	9173	MB	28.7
Napa County Transportation Planning Agency(NCTPA)	9088	MB	28.7
City of Petaluma(Petaluma Transit)	9213	MB	28.7

Livermore / Amador Valley Transit Authority(LAVTA)	9144	MB	18.1
Central Contra Costa Transit Authority(County Connection)	9078	MB	18.4
City of Fairfield - Fairfield and Suisun Transit(FAST)	9092	MB	20.3
San Joaquin Regional Transit District(RTD)	9012	MB	20.6
The Eastern Contra Costa Transit Authority(Tri Delta Transit)	9162	MB	21.8
Laguna Beach Municipal Transit(CLB)	9119	MB	23.0
San Mateo County Transit District(SamTrans)	9009	MB	23.9
City of San Luis Obispo(SLO Transit)	9156	MB	24.8
Ventura Intercity Service Transit Authority(VISTA)	9164	MB	26.1
Western Contra Costa Transit Authority(WestCAT)	9159	MB	26.2
Anaheim Transportation Network(ATN)	9211	MB	26.9
Torrance Transit System(TTS)	9010	MB	28.2
Alameda-Contra Costa Transit District(AC Transit)	9014	MB	29.5
Monterey-Salinas Transit(MST)	9062	MB	29.8
Santa Maria Area Transit(SMAT)	9087	MB	30.0
City of Santa Rosa(Santa Rosa CityBus)	9017	MB	31.2
Norwalk Transit System(NTS)	9022	MB	33.7
San Francisco Municipal Railway(MUNI)	9015	MB	34.3
Butte County Association of Governments(BCAG)	9208	MB	35.6
LACMTA - Small Operators(LACMTA)	9166	MB	36.3
Peninsula Corridor Joint Powers Board dba: Caltrain(PCJPB)	9134	MB	36.5
Santa Monica's Big Blue Bus(Big Blue Bus)	9008	MB	37.3
Santa Clara Valley Transportation Authority(VTA)	9013	MB	38.0
Kings County Area Public Transit Agency(KART)	9200	MB	43.5
Redding Area Bus Authority(RABA)	9093	MB	45.6
City of Visalia - Visalia City Coach(Visalia Transit)	9091	MB	45.7
Orange County Transportation Authority(OCTA)	9036	MB	46.0
Golden Gate Bridge, Highway and Transportation District(GGBHTD)	9016	MB	46.0
Santa Barbara Metropolitan Transit District(SBMTD)	9020	MB	46.2
Fresno Area Express(FAX)	9027	MB	46.6
Santa Clarita Transit(SCT)	9171	MB	53.2
City of Turlock(BLAST and DART)	9201	MB	55.0
Long Beach Transit(LBT)	9023	MB	57.2
North County Transit District(NCTD)	9030	MB	58.7
Montebello Bus Lines(MBL)	9041	MB	60.0
City of Lodi - Transit Division(Grapeline)	9175	MB	62.3
Antelope Valley Transit Authority(AVTA)	9121	MB	65.8
City of Redondo Beach - Beach Cities Transit(BCT)	9214	MB	69.9
Imperial County Transportation Commission(ICTC)	9226	MB	71.1
San Luis Obispo Regional Transit Authority(SLORTA)	9206	MB	71.6
Golden Empire Transit District(GET)	9004	MB	78.4
City of Commerce Municipal Buslines(CBL)	9043	MB	84.7
Victor Valley Transit Authority(VVTA)	9148	MB	87.9
Thousand Oaks Transit(TOT)	9165	MB	89.8
Santa Cruz Metropolitan Transit District(SCMTD)	9006	MB	94.3
San Diego Metropolitan Transit System(MTS)	9026	MB	96.4

Foothill Transit	9146	MB	98.4
Placer County Department of Public Works(PCDPW)	9196	MB	99.5
Yolo County Transportation District(YCTD)	9090	MB	58.9
Gold Coast Transit(GCT)	9035	MB	58.9
Sacramento Regional Transit District(Sacramento RT)	9019	MB	58.9
Chula Vista Transit(CVT)	9193	MB	58.9
City of Elk Grove(etran)	9205	MB	58.9
SunLine Transit Agency(SunLine)	9079	MB	58.9
Riverside Transit Agency(RTA)	9031	MB	58.9
Unitrans - City of Davis/ASUCD(Unitrans)	9142	MB	58.9
Culver City Municipal Bus Lines(Culver CityBus)	9039	MB	58.9
Omnitrans(OMNI)	9029	MB	58.9
Los Angeles County Metropolitan Transportation Authority dba: Metro(LACMTA)	9154	MB	58.9
City of Gardena Transportation Department(GMBL)	9042	MB	58.9
Sonoma County Transit	9089	MB	58.9
Livermore / Amador Valley Transit Authority (LAVTA)	9144	RB	28.7
San Joaquin Regional Transit District (RTD)	9012	RB	53.9

CB Commuter Bus, CC Cable car, CR Commuter Rail, DR Demand response, FB Ferryboat, HR Heavy Rail, LR Light Rail, MB Bus, RB Bus Rapid Transit

Table 6 Descriptive statistics of covariates

Variable	Percentage /mean(std.dev.)
Gender	
Female	0.48
Male	0.52
Age	
<16	0.24
16-35	0.23
36-65	0.46
>65	0.03
Not specified	0.03
Educational degree	
< high school	0.33
high school	0.24
Bachelor	0.26
Graduate	0.15
Race	
White, Native Hawaiian or Pacific Islander, other	0.81
Black or African American	0.03
American Indian or Alaska Native	0.06
Asian	0.08
Not specified	0.02
Driver's license	
Yes	0.70
No	0.30
Transit pass	
Yes	0.07
No	0.93
Household members	0.71(1.00)
Numbers of workers in household	1.49(0.93)
Income (median)	
$0 - $9,999: $5000	0.03
$10,000 - $24,999: $17,499.5	0.09
$25,000 - $34,999: $29,999.5	0.07
$35,000 - $49,999: $42,499.5	0.10
$50,000 - $74,999: $62,499.5	0.15
$75,000 - $99,999: $87,499.5	0.16
$100,000 - $149,999: $124,999.5	0.21
$150,000 - $199,999: 174,999.5	0.10
$200,000 - $249,999: 224,500	0.04
$250,000 or more: 375,000	0.05
Rent	
Yes	0.22
No	0.78
Number of vehicles in household	2.11(1.00)
Number of bicycles	2.05(3.78)
Weekend day	
Yes	0.28
No	0.72
Trip outside of California	
Yes	0.00

No	1.00
Number of trips	4.51(3.11)
Number of shared trips	0.43(0.49)
Commute distance differential (Men-Women)	2.89(0.38)
Commute distance of women	12.33(17.89)
Commute distance of men	17.22(30.49)
Land use and built environment at residence in 1-mile radius	
The sum of acres in the grid cells considered greenfield.	371(516)
The sum of acres in the grid cells parcels considered mixed use.	119(173)
The sum of employees.	7,884(14,789)
The sum of medical and social services employees.	1,178(2,071)
The sum meters of bike hostile roads.	9,840(9,869)
The sum bike routes in meters.	8,860(8,642)
The number of bike/pedestrian friendly intersections	237(142)
Population density	0.0024(0.002)
Employment density	0.001(0.002)
Park area within the buffer in square meters	497,069(752,680)
The area of overlap between the bike routes convex hull and the radius area is measured in square meters. It is possible that some areas subject to overlapping convex hulls (mostly SCAG and ABAG/MTC might have totals larger than the area of the radius)	7,195,326(2,850,588)
The distance to the closest job center with a minimum gross density of 10 emp/acre.	1,111(3,118)
Land use and built environment at workplace/school in 1-mile radius	
The sum of acres in the grid cells considered greenfield.	313(482)
The sum of acres in the grid cells parcels considered mixed use.	148(195)
The sum of employees.	16,323(32,439)
The sum of medical and social services employees.	1,983(3,513)
The sum meters of bike hostile roads.	12,623(10,919)
The sum bike routes in meters.	10,097(9,557)
The number of bike/pedestrian friendly intersections	12,623(10,919)
Population density	0.0024(0.0022)
Employment density	0.0021(0.0047)
Park area within the buffer in square meters	424,222(654,590)
The area of overlap between the bike routes convex hull and the radius area is measured in square meters. It is possible that some areas subject to overlapping convex hulls (mostly SCAG and ABAG/MTC might have totals larger than the area of the radius)	7,302,473(2,745,056)
The distance to the closest job center with a minimum gross density of 10 emp/acre.	814(3,106)