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The impact of urban form on daily mobility demand and energy use: evidence from the United States

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Abstract

The causal relationship between urban form, in particular density, and travel demand is subject to debate. Here, we investigate this relationship using a structured regression approach applied to a large-scale layered dataset of travel patterns and urban form. We find that residents of dense urban areas use 80% less energy for transportation than residents of rural areas and explore the causal factors influencing this relationship. We find that a primary driver of the density/energy use relationship is the larger number of nearby destinations available to urban dwellers, followed by reduced road network capacity for cars and higher public transit availability. An increase in destinations available further away due to urban sprawl can reduce these benefits. While these properties are correlated with density, we find that the independent effect of density is small—instead, we identify several measures of urban form that substantially affect travel energy use even within a given density bracket. We also show that urban form predominantly influences how and where people travel, rather than how often and how long. These results outline pathways for cities and communities to reduce the environmental impact of travel while increasing access to relevant destinations.

Keywords: Urban form, density, travel demand, transportation energy

Main

Personal mobility accounts for a substantial fraction of urban greenhouse gas and air pollutant emissions [1], including in the United States [2]. Travel patterns and energy demand of travel have been found to correlate with certain aspects of the built environment, in particular density [3, 4]. As a result, land use and urban design policies may contribute to energy consumption reduction and emissions mitigation strategies [5].

The built environment influences travel behavior differently at different distance scales. At the macro scale, residents of larger cities have been found to travel further each day than those of smaller cities [6, 7]. At the intermediate or meso scale, the strongest effects are commonly found [8–10], including influential factors such as most aspects of density and land use diversity (land use entropy). At the micro scale, local urban design can affect modal choice, in particular the likelihood of someone to walk [8, 11]. Effects at the meso- and micro-scale have been dubbed the "3 Ds" of travel demand: density, (land use) diversity, and design [8]. This is what we define to be 'urban form' here: the physical characteristics of the built environment that can affect travel behavior, including the density, size, and configuration of settlements and their transport network.

The observed magnitude of the causal relationship between urban form and travel demand at different scales is contested (e.g. [12, 13]) and can vary substantially based on study design [4, 14]. Differences among existing studies include how urban form and travel behavior are measured. For example, most existing studies focus on vehicle miles traveled (VMT), often per household and year [5, 15]. Such analysis does not explicitly reflect travel on non-automotive modes, limiting insights on aggregate travel demand and substitutions between modes. Studies also differ in whether they measure urban form through density as a proxy, or explicitly through concepts such as access (e.g., the typical distance or travel time to key destinations). Some consider both, thus potentially confounding the two (e.g. [3, 15, 16]). Further differences exist in whether and how residential self-selection and other forms of endogeneity are treated (e.g. [4, 17, 18]). Finally, most existing studies focus on a specific city or set of neighborhoods within a city [4], thus not capturing the full set and magnitude of differences that can exist between different areas. We include a tabularized comparison between key existing studies and this work in Supplementary Note 1.

As a result of these limitations, existing studies on X have been limited in geographical scope or comprehensiveness in representing urban form. Often looked at one metric, such as annual vehicle vehicles traveled, and rarely considered multiple or including total travel energy use.

Here, we evaluate the impact of urban form on travel demand across the entire United States. We measure travel demand as the behavior of individual people in terms of cumulative daily travel distance, cumulative daily travel energy use, cumulative daily travel time, and daily number of trips. To address the correlation between different aspects of urban form, such as density and access, we construct a layered model that allows us to investigate what specific features of urban form affect travel demand the most and how they are related to density. We include a large number of demographic characteristics and other control variables to address residential self-selection and other potential biases. We model these relationships using a path analysis—a special case of a structural equation model without latent variables.

We combine the coverage of nation-wide studies with the regional detail found in region-specific studies by merging data from the 2017 United States National Household Travel Survey [19] (NHTS) with data containing a diverse set of characteristics on urban form for each of the 220,000 census block groups in the United States, which we gathered from the U.S. Environmental Protection Agency's Smart Location database [20] and from OpenStreetMap [21].

The NHTS... While the NHTS data has previously been used to study the relationship between the built environment and travel (e.g. [10, 15, 22, 23]), the lack of detailed contextual data on urban form has been limiting its use. Our combined dataset allows us to investigate this relationship using a large, weighted sample that representatively spans the entire United States while considering detailed information on urban form at the local level.

Our work reveals the quantitative relationship between different aspects of urban form and daily travel demand. It also contributes meaningfully to the discussion of how urban form can effectively be measured and quantified in the context of mobility, and how various features of urban form relate to each other. Therefore, this work supports the fundamental understanding of the role that urban planning and design can play in the decarbonization of our cities. In doing so it uncovers specific, actionable policy measures that can contribute to decarbonization goals, as well as quantifying some of the potential benefits and risks of urban form interventions.

Observations from cross-sectional travel survey data

We begin by using the NHTS data to evaluate travel demand, measured in person travel days, in relationship to the density around the traveler's household (specifically, its census tract). Measuring travel using cumulative daily statistics, as opposed to per-trip statistics, allows us to consider shifts between modes (e.g., is a reduction in the number of trips made by car per person and day directly correlated with a corresponding increase in walking trips?) and evaluate patterns in terms of total time spent traveling and total number of trips made per day (e.g., if higher density causes trips to be shorter, do people make more trips instead?). We also use an 'effective' measure of density that is based on the number of housing units and jobs per area, capturing areas with high commercial or industrial activity more accurately while being similar in scale to the more commonly used residential population density. More details regarding our approach are provided in the Methods section.

The data indicate that density, spanning rural environments to dense urban areas, is strongly correlated with travel demand (Figure 1). People living in the densest urban areas (with a density of 13,000 household units and jobs per km^2, approximately equivalent to a residential population density of 13,000 people per km^2) travel 50% less far per day and spend 70% less energy doing so than people living in rural areas. Daily travel energy use decreases linearly with the natural logarithm of increasing density. People in urban areas also spend more time traveling each day, on average, than people living in rural to suburban areas. The average number of trips made per person and day is relatively constant, with a 15% increase in the densest areas. These observations are slightly dependent on metropolitan area population: people living in large metropolitan areas travel further and longer each day, but with fewer trips, than people living outside of metropolitan areas but in a similarly dense environment.

In rural to mid-density suburban areas (up to 2,000 housing and job units per km^2, approximately equivalent to 2,000 people/km^2), 90-95% of all trips are car trips (Figure 1d), and the number of trips per day is roughly uniform. Therefore, the decrease in daily travel distance and daily travel energy use from 0 to 2,000 units/km^2 is predominantly the result of a decrease in typical travel distances made by car (Figure 2a). This decrease is correlated with a simultaneous decrease in average car travel speeds (Figure 2a,b).

As density increases further, the average distance of trips made by car no longer decreases. Instead, more trips are made with other modes, in particular walking (Figure 1d). The travel speeds of trips made with a car, however, keep decreasing. Car trips between 5 and 10 km are almost half as fast ($\ln(0.5) = -0.69$), on average, in dense urban areas as in rural areas. This indicates that car travel speeds are strongly correlated with daily travel energy demand.

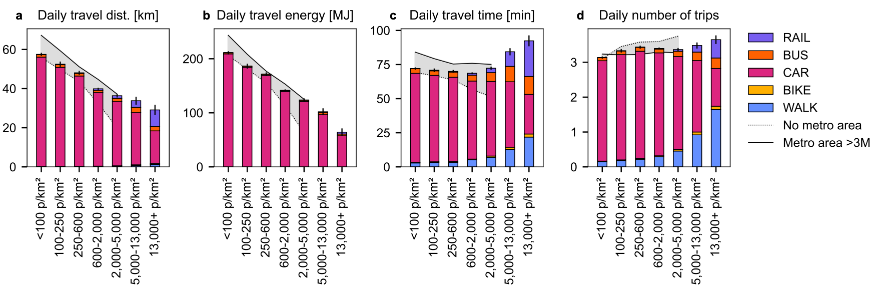

Fig. 1 The four travel behavior indicators as a function of density and metropolitan area size. Density is based on household units and jobs per land area and is comparable to residential population density in terms of magnitude (see Methods). The bars show average values for all people living in an area with the corresponding density, and the bootstrapped 95% confidence interval of the daily total. Shaded areas reflect the range between people living within large (population >3M) metropolitan areas and people living outside of any metropolitan area. For the highest two population density brackets, the sample size for 'No metro area' is too small. People who did not travel on the sampled travel day (0 for all indicators) are included. n=246,072.

Modeling effect pathways and controlling for demographics

The preceding section provides insight into the correlation between travel demand and density across the United States. However, it still leaves many questions unanswered. Where does the strong effect of density on travel behavior come from? How much is it confounded by demographic characteristics and residential self-selection (i.e., people with an inherent preference toward certain travel characteristics choosing to live in an environment that enables those preferences)? Is the increase in average daily travel time in higher density areas the result of decreased car travel speeds (and correspondingly longer typical travel times for trips made by car), or the result of an increase in public transit and walk mode share? And is there evidence that higher car travel speeds *cause* higher daily travel energy demand, or is the observed correlation fully explained by confounding factors?

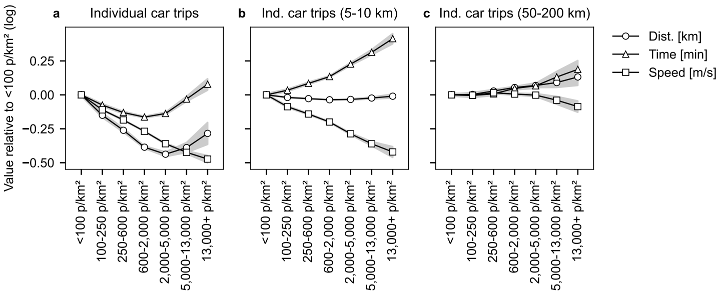

Fig. 2 Trip distance, duration, and average speed for individual car trips (not travel days) across different effective density (household units and jobs per area) brackets, for all trips made by car (left; n=749,110), for trips with a distance between 5 and 10 km (center; n=161,863) and for trips with a distance between 50 and 200 km (right; n=33,501).

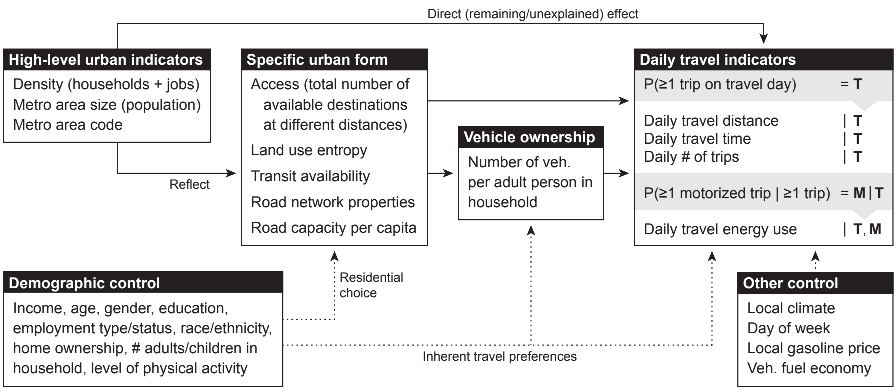

Fig. 3 Schematic of the path analysis. A detailed description of each group and the specific features representing a given indicator is available in the Methods section. Solid arrows reflect links related to urban form; dotted arrows reflect controls.

To address these questions, we extend a restricted (i.e., non-public) version of the 2017 NHTS data that contains the approximate location (the census tract) of each traveler's household by matching that household location with additional information from the Smart Location database [20], OpenStreetMap (accessed using OSMnx [21]), and the Typical Meteorological Year (TMY, [24]). We then apply a path analysis to this comprehensive dataset that enables us to explain which aspects of urban form affect travel behavior and how they are correlated with density while controlling for residential self-selection and other characteristics (Figure 3). A more extensive discussion of residential self-selection is available in the Methods and Discussion sections.

Explaining the impact of density on travel through urban form

We confirm that population density has a substantial impact on daily travel behavior and energy consumption, even when controlling for demographics and other factors (Figure 4a,b). Compared to the least-dense areas, dense urban areas show a reduction of 72%[1] in daily average travel distance and a reduction of 78% in daily travel energy use. While a larger fraction of the population travels on a given day in dense urban areas (+8.1%), Figure 4e), fewer travelers make any motorized trips (−16.8%, Figure 4f). Combining these probabilities with the reduction in energy consumption of people who do make at least one motorized trip (Figure 4b), the densest urban areas cause a reduction in daily travel energy use of 80% as compared to the least dense rural areas.

Supplementary Note 8 adds further insight into why demographic factors do not substantially affect the previously identified relationship between density and travel demand: while demographic factors explain a large fraction of daily travel demand, they are barely correlated with specific characteristics of urban form such as access, road network properties, and public transit infrastructure.

Of the total effect of density on travel demand, a large portion (46% in terms of daily travel distance, 40% in terms of daily travel energy use) can be attributed to the correlation between increased density and increased access to locations no more than 10 km away (beeline distance). The rest of the effect on daily travel energy use can be explained by road network properties (such as block size and network structure), road capacity per capita, public transit infrastructure, and land use entropy, in this order of importance.

We also confirm that the size of a metropolitan area has a considerable effect on daily travel distance, energy use, and travel time Figure 4a-c). People living in large cities (with a metropolitan area population of 3 million or more) travel 28% further each day, for 17% more time, than people living outside of a metropolitan area, all else being equal. This is predominantly the result of an increased number of possible destinations at least 10 km away (an effect that,

[1] $e^{-1.39+0.12} - 1 = -0.72$; see section on coefficient interpretation in Methods

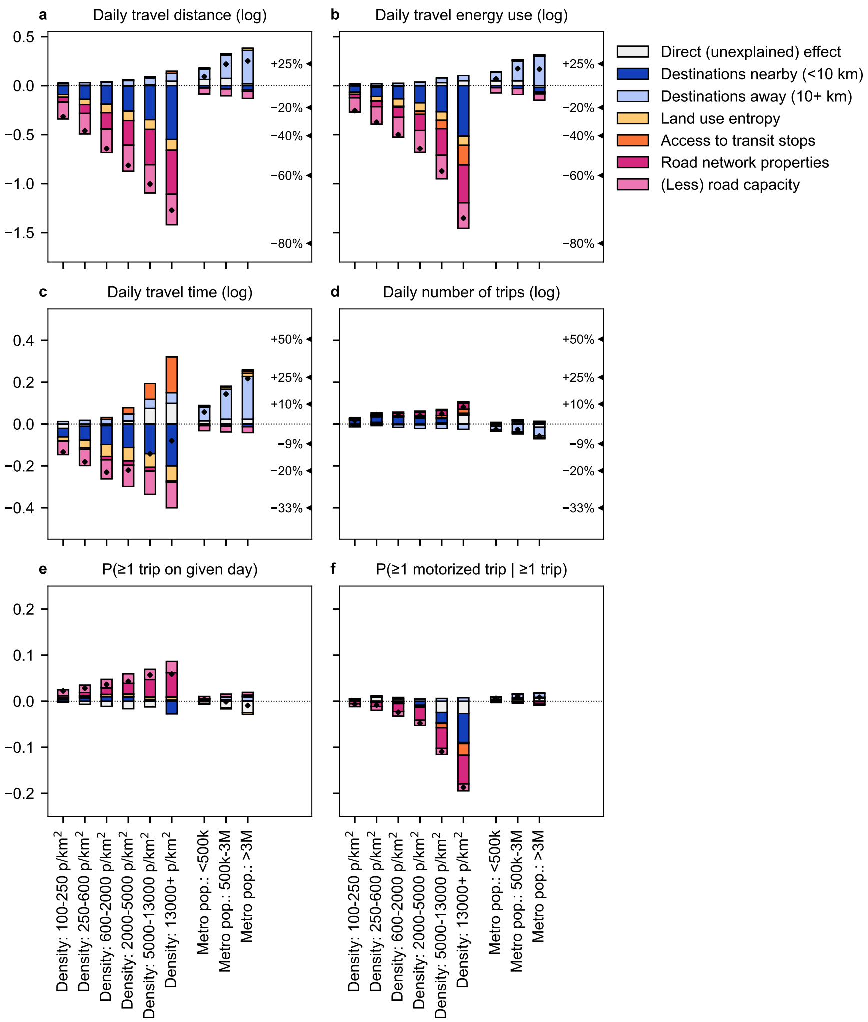

Fig. 4 Effect of adjusted population density and metropolitan area size on travel demand, explained by 6 groups of features of urban form and direct (unexplained) effects. The baseline is <100 p/km^2 and not part of any metropolitan area. The percentage values on the right reflect the impact in percent ($p = \exp(-v) - 1$, where v is the original y-axis value). The black diamond markers show the net effect size. Results for the fixed effects of each of the 10 metropolitan area codes with largest sample size (see Figure 3, top left) are shown in Supplementary Note 5.

as we will show later, can be mitigated by having access to more destinations nearby).

Daily average travel time and in particular the number of trips per day are affected less by density than daily travel distance and travel energy use, even when controlling for demographics (Figure 4c-d). The net effect is also partially negated by the fact that dense areas are mostly located inside large metropolitan areas in the United States, and larger cities exhibit higher daily travel times and number of trips. The increased access to public transit in dense urban areas also leads to an increase in typical daily travel times, acting in opposition to the correlation between density and accessibility to nearby destinations. Increased access to public transit (typically slower than car), in combination with the increase in far-away destinations associated with large metropolitan areas, causes the observed increase in average daily travel time in dense areas in Figure 1.

Notably, the direct or unexplained effect of density and metropolitan area size is small for all travel metrics, in particular for daily travel distance and energy use (Figure 4a-f). This implies that the measures of urban form that we did include comprehensively cover the mechanisms through which density reduces daily travel distance and energy use. It also indicates that the identified relationships in their sum are unlikely to be strongly under- or overestimated. If they were, the free coefficients for the unexplained effect would need to correct an overestimated effect for some, but not all, density or metropolitan area size brackets.

Investigating specific aspects of urban form

Next, we explore individual measures of urban form and their impact on daily travel energy use, daily travel time, and the probability of making at least one motorized trip during a given day (results for the other three indicators are available in the Supplementary information). Contrary to the results in the previous section, where aspects of urban form were evaluated in the context of density and metropolitan area population size, the results of this section are independent of the extent to which individual aspect of urban form are correlated with density and size.

Access to destinations nearby, particularly to destinations closer than 2 km, is one of the key causes for a reduction in average daily travel energy use (Figure 5b). This effect is amplified considerably when many destinations 10-100 km away are present, which lead to an increase in daily travel energy demand. This interaction illustrates a ‘tension’ between nearby and further-away destinations.

In our formulation, urban form can impact travel demand directly, or it can impact vehicle ownership, which in turn impacts travel demand. We find that most of the effect of urban form on travel demand is direct, but that vehicle ownership still plays a substantial role. This suggests that the choice to walk or take public transit is less tied to the lack of availability of a car than it is to the availability of destinations that are accessible by these alternative modes. Similarly, it suggests that policies leading to marginal changes to car ownership, when isolated from other impacts on urban form, are unlikely to effectively reduce (or increase) travel energy demand.

Changes in observed daily travel time can result from changes to daily travel distance, from passengers switching from one mode to a faster or slower one, or from changes to the travel speed associated with a given mode (in

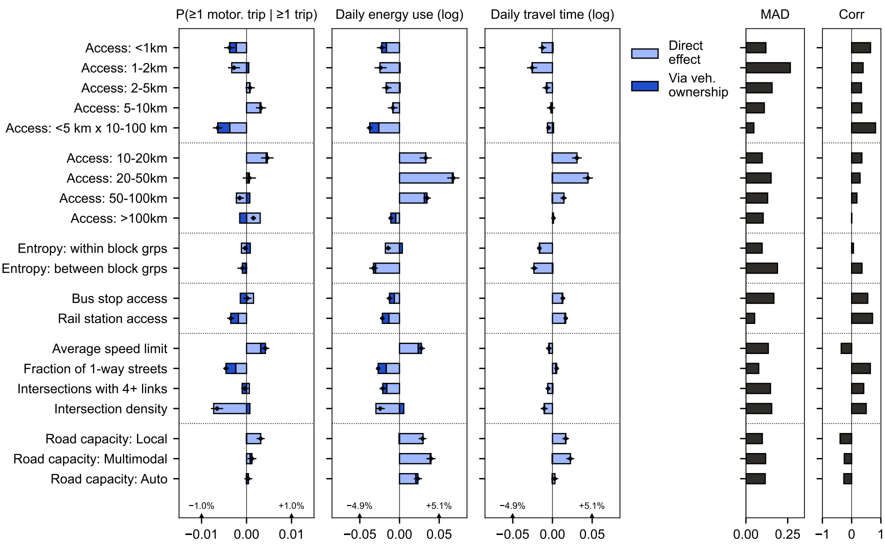

Fig. 5 Effect of individual aspects of urban form on the probability of making at least one motorized trip, daily travel energy use of those motorized trips, and daily travel time. Equivalent results for the other three indicators (see Figure 3) are shown in Figure 6 in Supplementary Note 6. All features are normalized to a range between 0 and 1, and all coefficients have been multiplied by the mean average deviation of the corresponding predictor (column 'MAD') to indicate the average contribution of variation in daily travel patterns of each aspect across the United States. Equivalent figures with unadjusted coefficients (showing the maximum impact rather than the average contribution) are shown in Figures 7-8 in Supplementary Note 7. Column 'Corr' indicates the correlation coefficient between each aspect and the natural logarithm of density. A detailed description of how each feature is defined is available in the Methods section.

particular, from roadway congestion). Access entropy (land use diversity) and access to destinations less than about 2 km away are both associated with decreases in typical average daily travel time, implying that they allow travelers to take shorter-distance trips and spend less time traveling overall. On the other hand, increased bus and rail station access is associated with increased daily travel time through changes in mode split, and an increase in access to destination 10-100 km away and increased road capacity is associated with an increase in daily travel time through longer trips.

Notably, these results have been adjusted by the extent to which each aspect varies across the United States (column 'MAD' in Figure 5). Unadjusted results are shown in Supplementary Note 7. They highlight, for example, that access to rail can reduce daily energy use substantially, but that the average effect across the country is mitigated by the fact that most households currently do not have access to rail service.

If you build it, they will come

Another factor that is strongly correlated with an increase in daily travel energy use and time is road capacity (Figure 5a-c). In particular, increased road capacity may enable access to destinations 10-100 km away (which increases overall travel distance), and appears to disincentivise travelers from using non-motorized modes (Figure 5a). This finding is consistent with the expected impacts of induced demand—a phenomenon that takes place when roadway congestion is acting as a binding constraint on demand for car travel, and by which increasing roadway capacity leads to more car travel. Were induced demand to be unimportant, one would expect increases in roadway capacity to be associated with *decreases* in travel time owing to reduced congestion, suggesting that the travel-inducing impacts of increases in roadway capacity outweigh the congestion-mitigating ones.

Evidence for induced demand, particularly in urban areas, can also be found elsewhere. In particular, urban form characteristics associated with faster or easier driving do not tend to lead to overall reductions in travel time. For instance, an increase in the average speed limit can be expected to be associated with an increase in typical travel speeds for car trips, but higher speed limits lead to no net decrease in travel time, suggesting that travel speed increases due to higher speed limits (and the associated higher-speed roadway design) are entirely counteracted by increases in congestion and/or longer distance trips. A smaller share of one-way streets and a lower intersection density (e.g. longer blocks) increase the likelihood of taking at least one car trip, appearing to make car travel more, and non-motorized travel potentially less convenient. Fewer four way intersections (associated with a suburban rather than a typical urban street layout) are not associated with the same increase in car trips, but these factors all lead to an increase in daily travel energy use while hardly affecting daily travel time suggesting that car-friendly urban form leads to either more or longer car trips.

Similarly, increases in roadway capacity are associated with more car trips, more energy use, and more travel time. The observed effect of automotive road capacity (where pedestrians are not allowed) is smaller than that of pedestrian-accessible roads. This is likely because we only measure road capacity around the traveler's household in a radius of 5 km, not around each trip origin or destination, thus only partially capturing the effect of automobile road capacity on the prevalence of longer car trips. We discuss this modeling choice more extensively in the Methods section.

Discussion

Our results suggest that higher density does indeed lead to substantially less travel energy use, in a large part due to increased access to nearby destinations less than 10 km away, and in particular destinations less than 2 km away. Part of the benefit of denser areas, however, is offset by the fact that most dense areas are located in large metropolitan areas. Combining these observations,

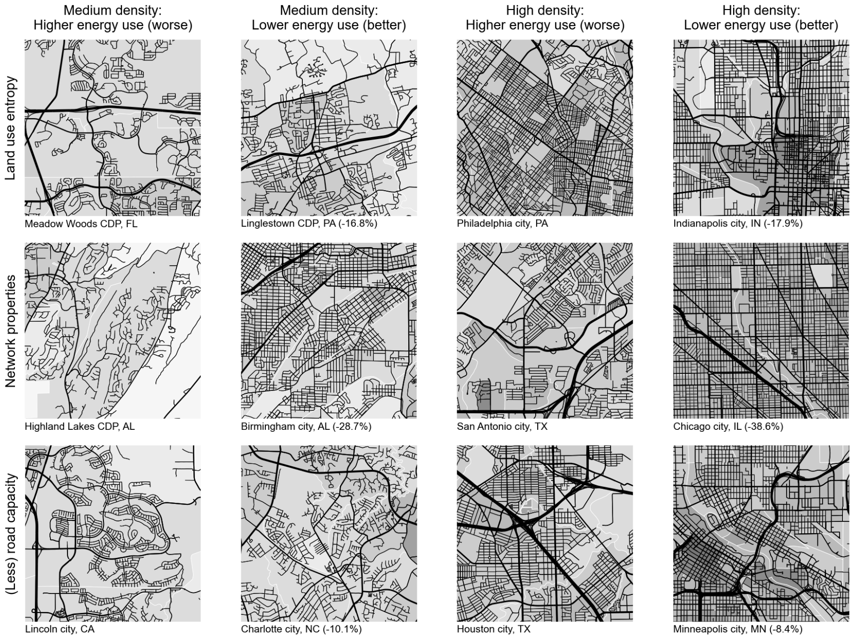

Fig. 6 Examples of areas with higher and lower predicted energy use while controlling for density and access to nearby destinations, for medium density (left two columns) and high density (right two columns). The percentages indicate the estimated difference in per-capita mobility energy use compared to the corresponding urban area to the left due to differences in the category of the corresponding row. This illustrates that population density is a reasonable but not definitive predictor of travel energy use, and that there are measures that can be taken to reduce travel energy use without having to increase density. Each map shows an area of 3x3 km. Public transit access, which also was found to have an impact on travel energy demand (see Figures 4 and 5 and Supplementary Note 7), is not shown. Plotted using network data from OpenStreetMap (accessed through OSMnx [21]).

our work suggests that promoting many urban centers no more than about 3-5 km apart from each other, to build 'cities within a city', may mitigate the demand-increasing effect of large cities while maximizing the demand-decreasing effect of local access.

While density is a good overall predictor of travel demand, properties of the local street network contribute as well. And while density and access to nearby destinations are correlated, they are not identical: an area with a given density can still have better or worse overall access to a variety of destinations closeby. For a given population density, lowest private vehicle travel energy use is therefore found in areas with strong local access, a highly connected street network, and low road capacity per capita (Figure 6). These examples also illustrate that there are measures that can be taken to reduce travel energy use without having to increase density, accommodating people who prefer to live in lower-density areas.

Efforts to reduce travel energy use should not come at a cost of reduced access to opportunities for the population. Lowering road capacity for cars, for example, should be complemented by increasing walking access to nearby and public transit and cycling access to destinations further away (conversely, any increases to road capacity should be complemented by policies aimed at discouraging new, long-distance trips). Critically, our work indicates that providing access to a variety of destinations for all communities throughout a city is symbiotic with lowering energy consumption if all key measures are implemented simultaneously.

While in line with existing literature overall, our results indicate a stronger relationship between urban form and travel demand than some existing work [4] and appear to contradict certain previous findings that the impact of the built environment on travel is strongly confounded by demographic characteristics and attitude (e.g. [18, 25]). While we observe that demographic factors indeed explain a large fraction of the variance in daily travel demand, they are weakly correlated with specific characteristics of urban form (see Table 3 in the Supplementary information).

Instead, we postulate that there are two major drivers that distinguish our findings and those previous observations. First, we consider the most rural all the way to the densest urban areas, while incorporating detailed information on urban form for each location. Studies that attribute a strong confounding effect to attitude have predominantly compared individual, nearby neighborhoods (e.g. [25, 26]). This design makes it more likely that differences in travel behavior are attributed to attitude, especially when those neighborhoods are relatively similar in terms of urban form, but distinct in terms of demographic characteristics. Second, attitudes themselves may be affected by the built environment over time [18, 26–28]—in fact, attitudes may exemplify a key mechanism through which urban form can affect travel demand: by modifying the perceived attractiveness of certain modes and destinations compared to other options.

Our work also reaffirms that the daily travel time budget is relatively constant across very different urban environments [29, 30], although we observe an even higher regularity for the average number of trips made per day. As such, our findings add to current literature on the underlying regularity of human travel patterns (e.g. [31]). These observations are closely related to induced demand: if the time spent traveling per day is constant for a given individual, then an increase in travel speed will lead to higher daily travel distance and energy use through longer trips and/or modal shifts. This indicates that the urban environment can influence how people travel and where, but not how often and for how long. Therefore, the former should be the focus of future policy and planning decisions aimed at decarbonization. Similarly, since travel patterns are largely derived from the built environment, we should plan for the patterns we want there to be, not for those that we project based on historical data.

A limitation of our study is the resolution and accuracy of certain measures of urban form. Since all data is collected at the census block group level, we are not able to investigate micro-scale effects of urban form on travel behavior. In addition, while we do identify an impact of land use entropy on travel demand, our measure of entropy is relatively coarse (see Methods). Finally, for street network properties, certain data had to be imputed, possibly mitigating the resulting effect size. Improvements in these measures would be unlikely to alter any of our key conclusions, but could improve our understanding of the relative importance of specific aspects of urban form in different contexts, especially for walking trips.

Future work could therefore improve how urban form is measured and find ways to integrate information on urban form measured at the origins and destinations of each trip, rather than just around the location of each traveler's household, and information on travel speed and congestion, without introducing simultaneity or other forms of endogeneity. Another key avenue for future work will be to achieve an increase in the spatial resolution of the analysis. Analyses based on travel survey data, such as ours, could be combined with crowd-sourced mobility pattern data to verify and further investigate the observations made here [32]. This increase in spatial resolution could be accompanied by additional measures of urban form. Image processing of satellite and street view images may assist in these measures, similarly to recent efforts for building energy modeling [33]. More sophisticated methods could also be used to include the impacts of climate, including urban microclimates, on travel.

Our work provides evidence for a strong causal link between properties of urban form and daily travel demand and energy use. Distributed urban centers that provide local access to a variety of destinations to a large part of the population, connected streets with low capacity for motorized vehicles, and public transit infrastructure should be prioritized in order to lower the energy consumption of travel. This outlines a pathway for cities and communities to reduce the energy demand and traffic of personal mobility while maximizing access to destinations for all communities.

Method

Summary

We evaluate the relationship between urban form and daily travel demand per capita while controlling for demographic and other properties. We implement the model structure shown in Figure 3 using a path analysis, a subtype of structural equation models (SEMs) without latent variables. Similar techniques have previously been used in the context of travel demand modeling [15, 23, 34].

The model is applied to the weighted National Household Travel Survey (NHTS) data, consisting of randomly sampled travel days made by 245,072 people after filtering. This travel survey data is complemented with data from other sources at the census block group (CBG) level, aggregated to the census tract (CT). The average CBG has a population of about 1,500 people, meaning that there are about 220,000 CBGs in the United States. There are about 3 CBGs per CT. A summary of properties of all variables used in the analysis is available in Supplementary Note 9. The estimated coefficients, along with their significance levels, are shown in Supplementary Note 10.

Measuring mobility demand

Existing analyses of mobility demand can be grouped along three axes: the modes they consider (usually either car trips only, or all urban trips), their geographic scale of analysis (individual person, household, or neighborhood/city), and the unit of time over which they measure mobility (annual, daily, or individual trips). The most common metric to gauge travel demand in the context of energy use and sustainability is daily or annual household vehicle miles traveled (VMT; see Table 1 in the Supplementary information for a list of examples). However, VMT do not include trips made with other travel modes, making it difficult to determine whether and how trips are substituted when they are not made by car. Household VMT are also confounded by household size and structure. Finally, in many travel surveys, VMT are self-reported, making the metric prone to noise and potentially response biases.

Modal choice studies, on the other hand, often focus on individual trips. While this mitigates some of the issues associated with measurements of annual household VMT, analysis of individual trips does not capture unobserved aspects of travel behavior that may be correlated with the characteristics of individual trips. For example, if higher density means trips become shorter, do people make more trips instead?

Here, we measure travel behavior in terms travel days. Each travel day represents the cumulative sum of travel activity (such as travel distance) made by a given person on a single day. This approach can allow us to combine the benefits of annual travel miles with the benefits of measuring individual trips. Specifically, we consider four indicators of travel behavior: daily total (cumulative) travel distance per person, daily travel energy use per person, daily travel time per person, and number of individual trips made per person and day. These four indicators provide a comprehensive picture of the different ways in which urban form might affect travel behavior.

Measuring urban form

Early efforts to quantify the impact of urban form on travel demand often focused on population density. In the late 90's, the notion of the "3 D's" of travel demand (density, land use diversity, and design) was popularized, based on evidence from travel surveys [8]. The list of D's kept expanding, often including measures of access (access to relevant destinations and/or infrastructure, including public transit infrastructure). Access as well as street network properties are closely related to density, however, and may reflect one of the key mechanisms through which density affects travel behavior rather than being separate factor [4, 35].

To preserve the intuitive concept of density but also understand the relevance of specific aspects of urban form, such as access, land use diversity, and road network properties, we measure urban form in two layers. Initially, we consider three urban indicators: (1) population density; (2) metropolitan area population of the core statistical area (CSA); and (3) fixed effects for individual metropolitan areas with sufficient sample sizes. These indicators are readily available in most travel surveys and are intuitive to understand.

In a second step, we tie these indicators to specific measures of urban form, including access to destinations, land use diversity or entropy, access to public transit network, and various street network and road design properties.

Notably, removing this second layer from the model would not change the total measured effect of the first-layer urban indicators on daily travel demand. The purpose of the second layer is to explain where the total effect of density, metropolitan area population, and metropolitan area code on travel comes from, and which aspects of urban form and urban design could be leveraged most effectively to reduce daily travel energy use.

Through the structure in Figure 3, we also assume that there are no strong causal links between the individual aspects of urban form measured here that would need to be included explicitly. We believe this assumption to be justified, since the different properties can be planned, designed, and adjusted simultaneously and largely independently. Correlations, however, are likely to exist, and need to be evaluated carefully to avoid over- or underestimation of coefficients due to strongly correlated predictors. We discuss this further in the section describing endogenous variables reflecting urban form.

Finally, instead of measuring density as residential population density, we consider the combined household and job density (the sum of the number of households and jobs per area) as indicated by the smart location database [20]. This approach alleviates issues with residential population density where dense but predominantly commercial or industrial areas would be considered low-density due to the lack of residents in the area. Conveniently, the sum of the total number of housing units and jobs across the United States. (324,600,000) is almost identical to the sum of the total number of residents (322,900,000; -0.53%), meaning that the combined housing and job density is comparable in scale to residential population density, whose figures may be more intuitively familiar.

Addressing residential self-selection and other forms of simultaneity

The relationship between urban form and travel behavior can be obfuscated by residential self-selection: people with specific attitudes (e.g., preference to walk) may choose to live in specific areas (e.g., dense urban areas), meaning that the built environment does not necessarily cause the choice to walk [36]. This represents simultaneity, where multiple variables (travel behavior, urban form as a residential choice) are co-determined and affect each other. Simultaneity is a case of endogeneity and can therefore lead to biased coefficient estimates [23].

Self-selection preferences are often measured by some form of attitude. Prior evidence suggests that urban form does affect travel behavior even when attitude is controlled for [11, 26, 27, 36]. While these previous studies include a measure of attitude towards travel to account for self-selection, the NHTS data used here does not contain sufficient data to evaluate inherent attitude towards travel. In addition, attitude itself can be shaped by the built environment [18, 26–28], implying that including attitude explicitly may lead to underestimations of the effect of urban form on travel. Here, we control for residential self-selection by incorporating a wide variety of demographic characteristics, and allowing those characteristics to moderate the link between the urban indicators and travel demand through the included endogenous variables, as well as the final travel demand itself (see Figure 3).

Notably, residential self-selection is not the only aspect of simultaneity that can occur in the context of this analysis. In particular, it might seem tempting to measure the population density at the origin and destination of each trip instead of at the traveler's household location, yielding a more accurate picture of the urban environment in which the trips took place. However, relating urban form to individual trips can introduce bias. For example, we may find that if both trip origin and trip destination are located in a high-density area, trips are shorter than if only the origin is located in a high-density area. However, this could simply be the result of the fact that two high-density areas are inherently more likely to be close to each other than a randomly chosen high-density and a randomly chosen low-density area.

Similarly, we may find that a high road capacity at all trip origins throughout a travel day is related to a high modal share of car trips. However, someone who is going to drive can be more likely to choose destinations with high road capacity; this does not mean that a higher capacity leads to more travel. For similar reasons, average travel speeds and congestion levels are difficult to include as an explanatory variable for travel demand as measured here: shorter trips may have inherently lower travel speeds and higher levels of congestion because they take place in denser areas, but that does not mean that low travel speeds or congestion caused a trip to be shorter. For these reasons, we measure all properties of urban form at and around the traveler's household, rather than the origin or destination of each trip.

Model setup

We specify a system of simultaneous equations where all causal effects are directed at four different measures of travel behavior (see Figure 3). For each of the four measures of travel behavior, y, our model can be written as follows:

$$
\begin{cases}
\boldsymbol{y} = \boldsymbol{U}\boldsymbol{\beta}_{y1} + \boldsymbol{e}\beta_{y2} + \boldsymbol{X}\boldsymbol{\beta}_{y3} + \boldsymbol{C}\boldsymbol{\beta}_{y4} + \boldsymbol{L}\boldsymbol{\beta}_{y5} + \boldsymbol{\epsilon}_1 \\
\boldsymbol{e} = \boldsymbol{U}\boldsymbol{\beta}_{e1} + \boldsymbol{X}\boldsymbol{\beta}_{e3} + \boldsymbol{C}\boldsymbol{\beta}_{e4} + \boldsymbol{\epsilon}_2 \\
\boldsymbol{U} = \boldsymbol{X}\boldsymbol{\beta}_{u3} + \boldsymbol{C}\boldsymbol{\beta}_{u4} + \boldsymbol{\epsilon}_3
\end{cases}
\tag{1}
$$

where:

- $\boldsymbol{y}$ is a $(n) \times 1$ vector of the mobility / travel behavior variable in question;
- $\boldsymbol{U}$ is a $(n) \times 20$ matrix reflecting endogenous measures of urban form;
- $\boldsymbol{e}$ is a $(n) \times 1$ vector of the number of vehicles per adult person in the household of the traveler;
- $\boldsymbol{X}$ is a $(n) \times 20$ matrix reflecting exogenous urban indicators, including density (1 of 8 brackets, with the lowest density being the default/withheld), metropolitan area size (1 of 4 brackets, with no metro area being the default/withheld), and metropolitan area CBSA code (1 of 10 codes, with none/others being the default);
- $\boldsymbol{C}$ is a $(n) \times 33$ matrix reflecting all demographic properties;
- $\boldsymbol{L}$ is a $(n) \times 11$ matrix reflecting other exogenous control properties, including climate variables (heat-index temperature, solar irradiation, and precipitation), day of the week (with Monday being the default/withheld), the local gasoline price, and vehicle fuel economy (which is imputed where missing);
- $\boldsymbol{\beta}_{...}$ are coefficient vectors; and
- $\boldsymbol{\epsilon}_i$ are $n \times 1$ error vectors.

$\boldsymbol{y}$, $\boldsymbol{e}$, $\boldsymbol{C}$, and part of $\boldsymbol{L}$ (day of week, gasoline price, and vehicle fuel economy) are taken or inferred from the National Household Travel Survey (NHTS) data. The properties of $\boldsymbol{U}$ are obtained from other data sources and merged with NHTS data using a restricted version of NHTS that contains the census tract of each household, trip origin, and trip destination. The same is true for the climate variables in $\boldsymbol{L}$. A more detailed descriptions of all variables follows and is summarized in Supplementary Note 9.

The four travel behavior indicators can be 0 if the traveler did not make any trips during the sampled travel day. Daily energy consumption is also 0 if the traveler made only non-motorized trips during the sampled traveled day, since we define the energy use of non-motorized trips to be 0. Therefore, we employ a censored (Tobit-type) model. The four travel behavior indicators $\boldsymbol{y}$ are modeled conditional on $y > 0$. For daily number of trips, daily travel distance, and daily travel time, this means that the person made at least one trip during that day (event $\boldsymbol{T}$ in Figure 3). For daily energy consumption, this also means that the person made at least one trip with energy consumption > 0 (at least one motorized trip), given that the person made at least one trip (event $\boldsymbol{E}$ in Figure 3).

$$\begin{aligned}
\boldsymbol{T} &= \boldsymbol{y}_{\text{trips}} > 0 \\
\boldsymbol{E} \mid \boldsymbol{T} &= \boldsymbol{y}_{\text{energy}} > 0 \mid \boldsymbol{T} \\
\boldsymbol{y}_{\text{distance}} &= \boldsymbol{y} \mid \boldsymbol{T} \\
\boldsymbol{y}_{\text{energy}} &= \boldsymbol{y} \mid \boldsymbol{T}, \boldsymbol{E} \\
\boldsymbol{y}_{\text{time}} &= \boldsymbol{y} \mid \boldsymbol{T} \\
\boldsymbol{y}_{\text{trips}} &= \boldsymbol{y} \mid \boldsymbol{T}
\end{aligned} \tag{2}$$

Events $\boldsymbol{T}$ and $\boldsymbol{E}$ are estimated using the set of equations 1. For $\boldsymbol{T}$, vehicle fuel economy is removed from control variables $\boldsymbol{C}$, since this value cannot be determined for the corresponding travelers.

Contrary to common implementations of a type I Tobit model [37], we consider the two cases ($y = 0$; $y > 0$) separately, and use a linear model for the first submodel (whether y is 0 or not), even though the outcome is binary. In cases where the fitted coefficients are only interpreted for causal inference, but not used for predicting individual choices, the sample size is large, and where most predicted values would fall into $[0, 1]$, the use of linear models with binary dependent variables can be justified [38]. Specifically, it allows for better interpretability of the magnitude of the fitted coefficients [38]. In our case, it also allows for direct comparison between the first submodel with a binary outcome and the second submodel with a continuous outcome.

To further verify the feasibility of a linear model of the binary outcomes $\boldsymbol{T}$ and $\boldsymbol{E}$, we also fit a Probit model to the same set of predictors and compare the predicted values between the linear and the Probit models (using unweighted samples for each case). Compared to the Probit model, the linear implementation yields a mean absolute error (MAE) of 0.020 and a root mean squared error (RMSE) of 0.027 ($\boldsymbol{T}$) and a MAE of 0.012 and RMSE of 0.022 ($\boldsymbol{E} \mid \boldsymbol{T}$). The mean error of the linear model compared to the Probit model is therefore around 1 to 2 false predictions per 100 travel days. There is almost no bias (mean difference between linear and Probit predictions of < 0.0002 for both $\boldsymbol{T}$ and $\boldsymbol{E}$).

Coefficient estimation

We estimate the coefficients in Equations 1 and 2 using the Lavaan package in R using maximum likelihood estimation with robust standard errors (MLM) as well as sampling weights for each row equal to the default NHTS weight set. Incorporating the sampling weights is critical for correcting sampling and response biases in the survey and required when working with NHTS data.

Coefficient interpretation

All continuous travel indicators y (daily travel distance, daily travel energy use, daily travel time, and daily number of trips) are transformed using the natural logarithm. This transformation yields distributions for y that are close to normal (see Figure 11 in Supplementary Note 9). The transformation reduces the heteroscedasticity in our model, therefore improving accuracy.

Therefore, the first line of Equation 1 can be rewritten as:

$$\log(\boldsymbol{y}) = \boldsymbol{U}\boldsymbol{\beta}_{y1} + \cdots + \boldsymbol{\epsilon}_1 \tag{3}$$

The relative change in y, $\Delta_{y,\%}$, (e.g., the relative change in daily average travel distance) as a result of a unit increase (+1) in a specific predictor u_i can then be expressed as [39]:

$$\Delta_{y,\%} = \frac{y - y_0}{y_0} = e^{\beta_{u_i}} - 1 \tag{4}$$

Since the range of all predictors has been normalized to $[0, 1]$, this means that the difference between the smallest and largest value of each predictor is associated with a relative change of $\Delta_{y,\%}$ in travel indicator y. Furthermore, the simultaneous effect of a unit increase in multiple predictors can be assessed similarly:

$$\Delta_{y,\%} = e^{\beta_{u_1} + \beta_{u_2} + \beta_{u_3} + \cdots} - 1 \tag{5}$$

Data filtering

The NHTS contains 923,572 trips made by 264,234 people. Those people recorded their travel activities during a randomly assigned travel day. We filter the sampled individuals by: (1) unknown population density of the census tract of the traveler's household; (2) traveler was out of town that day; (3) any demographic characteristic except income is unknown. In total, 11,610 of 264,234 people were filtered out that way (4.4%).

In addition, we filter individual trips according to the following characteristics: (1) unknown trip distance or time as well as any trips faster than 100 m/s on average and walking trips faster than 10 m/s (5,103 trips); (2) travel mode is unknown or airplane (9,208 trips). We then remove all people from the dataset for which at least one trip was among those trips filtered as per the rules above (since their remaining travel days would be incomplete), which corresponds to an additional 6,158 people being removed from the dataset.

After joining the NHTS data with urban form features $\boldsymbol{U}$, a final 394 people are removed from the data because one or several features could not be determined for the corresponding household's census tract.

The final sample sizes are 245,072 people and 882,846 individual trips (made by 203,600 people; the remaining individuals did not travel during the sampled travel day).

Endogenous travel behavior variables ($\boldsymbol{y}$)

We use four measures of travel behavior: energy use, distance, time, and number of trips. Each of them is considered on a per-travel-day basis, that is, reflects the cumulative sum of the corresponding quantity across all trips made by a given person on a given day. For trips past midnight, the start of the trip is considered. To do so, we aggregate the 882,846 individual trips to 245,072 travel days (or 'day trips'), where each travel day reflects all trips made by the corresponding person on their assigned date.

Travel energy use is not available directly in NHTS. Instead, we estimated the energy use of each trip based on travel distance, mode, and in the case of car trips, travel speed. For walking and biking, 0 J/m is used. For public transit, we apply a fixed consumption of 500 J/m (rail) and 1000 J/m (bus). For car trips, we estimate the energy consumption per distance based on [40]:

$$F_v = \begin{cases} (15 - v)/15, & \text{if } v \leq 15 \\ 0, & \text{otherwise} \end{cases}$$

$$F_d = \begin{cases} (d - 50)/100, & \text{if } d \geq 50 \\ 0, & \text{otherwise} \end{cases}$$

$$F = F_0 + 1.2 - F_v + F_d \tag{6}$$

where F is the trip fuel economy in miles per gallon (MPG), F_0 is the official combined fuel economy rating of the vehicle used for this trip, v is speed in m/s, and d is the distance in km. Adding a constant values of 1.2 ensures that across all trips captured by the travel survey, a car's average fuel economy is approximately equal to F_0. This approximation serves the purpose of capturing the impact of urban form on average daily travel energy consumption through changes in typical travel distances and trip speeds; in reality, the trip-specific fuel economy would depend on weather [41], driving style [42], and particular characteristics of the corresponding powertrain.

Exogenous variables reflecting urban area ($\boldsymbol{X}$)

We measure (1) density of the census tract that the traveler's household is located in; (2) metropolitan area population of the core statistical area (CSA) that the traveler's household is located in; and (3) metropolitan area code of that household if it is located within one of the 10 metropolitan areas with the largest sample size in NHTS that are part one of the so-called 'Add-on areas.' The first two sets (population density and metropolitan area population) represent meso- and macro-scale aspects of urban form, respectively. The fixed effects for metropolitan areas can account for differences between individual cities that are not captured by the other two variables.

We use dummy variables for both population density and metropolitan area size. This allows us to capture non-linear effects between those variables and mobility demand. It also lets use evaluate whether the specific aspects of urban form, $\boldsymbol{U}$, fully explain the relationship between $\boldsymbol{X}$ and $\boldsymbol{y}$, since any remaining (or unexplained effect) would be allocated to the dummy variables in $\boldsymbol{X}$.

Endogenous variables reflecting urban form ($\boldsymbol{U}$)

While the urban indicators in $\boldsymbol{X}$ are intuitive and available directly in NHTS, they do not allow us to answer *why* density, metropolitan area size, or the specific metro area may affect travel behavior, and what other aspects of urban form may matter in the context of travel demand. Therefore, we add a comprehensive set of features reflecting specific, detailed measures of urban form to the data.

Each of these metrics is estimated at the level of the CBG. Those values are then aggregated to the census tract (CT) level, where each CT consists of 2-4 CBGs. This is done because geographical locations in NHTS are available specifically at the CT level. Finally, the CT values are joined with the CT of the traveler's household location.

Since CBGs and CTs are defined such that they contain a relatively constant residential population, they are smaller in dense areas than in low-density areas. As a consequence, any analysis based on census tracts themselves could therefore be confounded by density. Instead, we measure all properties of urban form $\boldsymbol{U}$ in a given, constant radius around each CBG (see Figure 7). Nonetheless, the spatial resolution of our analysis is higher in dense areas as well as in areas with a higher residential population density compared to lower-density areas and/or areas with commercial or industrial activity but fewer residents.

As noted previously, we only rely on information about the urban environment in the area of the traveler's household, not the specific origins and destinations of trips that the traveler makes. This is because the later can easily lead to biased coefficient estimates. We discuss this extensively in section 'Addressing residential self-selection and other forms of simultaneity'.

Strong correlation between two or more indicators should be avoided as well. Such correlation could lead to unstable coefficient estimates. We have carefully chosen the final set of indicators $\boldsymbol{U}$ by testing the effect of removing one or more indicators from the model and observing the stability of the estimated coefficients of the indicators that remain in the model. This is a key reason for why we do not measure most aspects of urban form in different distance intervals around each traveler's household, but selected one specific radius instead.

We measure urban form in 5 sets: access to destinations at certain distance intervals, land use entropy, access to public transit stops, road network properties, and road network capacity. These metrics are taken or derived from the U.S. Environmental Protection Agencies Smart Location (SL) database [20], complemented with information from OpenStreetMap (accessed using OSMnx [21]). In Supplementary Note 3, we provide a detailed comparison between the measured of urban form contained in the SL database and our measures, along with reasons for potential differences and additions.

The first set of variables reflect access to destinations of the same type as those used to calculate density: residential units and jobs. To calculate access for a given distance bracket (e.g., 2-5 km), we sum up the total number of residential units and jobs inside CBGs whose centroid is within the corresponding distance interval (e.g., 2-5 km) from the centroid of the original CBG. For the lowest bracket (0-1 km), the original CBG counts itself as well. The widths of the distance brackets (0-1 km, 1-2 km, 2-5 km, 5-10 km, 10-20 km, 20-50 km, 50-100 km, and 100+ km) are chosen to balance accuracy of the analyzing with limiting errors introduced due to the fact that we do not know the exact location of each possible destination. In addition, we indicate the product between the number of destinations accessible in the 0-5 km interval and the number accessible in the 10-100 km interval. This interaction term allows us to gauge whether the effect of having access to destinations nearby on travel demand is amplified in cases where there are more destinations available further away, as is the case in large cities.

The second set of properties reflect the land use entropy or diversity. This includes land use entropy within each CBG (averaged over a given radius), as well as land use entropy between CBGs. Land use entropy within each CBG is based on the combined employment and household entropy in the SL database. A more even split between residential household units and jobs, as well as a higher diversity among the types of jobs, both contribute to a higher entropy measure. Land use entropy between CBGs is based on the standard deviation of the total number of destinations (household units and jobs) across all CBGs within a given radius around the household's CBG.

The third set of properties reflect access to public transit stations. Rather than relying on information on public transit access from the SL database,

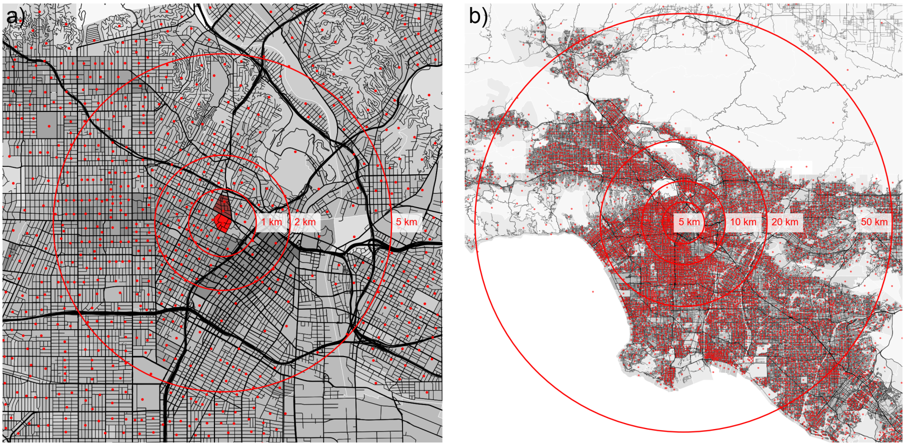

Fig. 7 Illustration of the spatial scale of urban form metrics, showing Los Angeles (CA). The red area in subfigure a) indicates a census block group (CBG), the adjacent dark red area the rest of the census tract. The red dots in both subfigures represent the centroids of other CBGs. The shade of grey reflects density. In a), the 1, 2, and 5 km radii around the centroid of the red shaded CBG are indicated; in b) the 5, 10, 20, and 50 km radii.

we use information from OpenStreetMap on the number of bus and railway stops accessible within a given radius around each CBG's centroid. To do so, we collect data from OpenStreetMap for each of about 220,000 CBGs in the United States, bounded by the corresponding polygon obtained from the Tiger Shapefile database [43].

From the SL database, we obtain the intersection density in number of intersections per land area and the fraction of intersections with at least four links (4-way intersections or higher). The street network density is indicated for pedestrian, multimodal, and automobile roads. We use the sum of pedestrian and multimodal roads to calculate street network density. These three types are pre-defined in the SL database, based on the speed limit, direction of travel, and classification of each road segment. The fraction of 4-way intersections of higher is based on pedestrian roads only.

The fifth and final set of properties reflect the road capacity per capita for the same three road types that are used for intersection density: pedestrian, multimodal, and automobile roads. The road capacity per capita for a given road type is not directly indicated in the SL database, but can be derived. We obtain it by multiplying the facility miles of corresponding road links per square mile, which is given, with the corresponding land area, and then dividing it by the total number of housing units and jobs in that CBG. Rather than calculating the sum across the three road types (as for street network density), we consider the three types separately for road capacity.

Once all missing speed limit and lane count values have been imputed, we calculate 20 different metrics for each CBG, based on the corresponding road network and public transit stop nodes:

1. The number of destinations (indicated as household units and jobs) available within a given distance interval from the CBG in question (including itself) at 8 different distance intervals; as well as the interaction term between destination nearby (0-5 km) and further away (10-100 km);
2. The average land use entropy within each CBG, averaged across all CBGs in a radius of 2 km around the CBG in question;
3. The land use entropy between CBGs in a radius of 2 km around the CBG;
4. The number of bus stops per area among all CBGs less than 2 km away from the centroid of the CBG in question (including itself);
5. The number of railway stations per area among all CBGs less than 2 km away from centroid of the CBG in question (including itself);
6. The average speed limit across non-residential/non-local road segments across inside of CBGs less than 5 km away from the CBG in question (including itself), reflecting typical road design;
7. The fraction of 1-way streets among pedestrian-accessible streets across all CBGs less than 5 km away from the CBG in question (including itself);
8. The fraction of intersections with 4 or more segments or links across all CBGs less than 5 km away from the CBG in question (including itself), reflecting the connectivity of the road network;

9. The intersection density of pedestrian-friendly roads (in intersections per square mile) across all CBGs less than 5 km away from the CBG in question (including itself); and
10. The road facility miles intensity (per capita-equivalent) of automobile, multi-modal, and pedestrian-friendly roads in miles per household units and jobs across all CBGs less than 5 km away from the CBG in question (including itself).

The distance thresholds in km for these metrics are chosen to balance specificity (a smaller radius makes results more specific to each household's location) and relevance (a larger radius will apply to and affect a larger fraction of trips). Details on how each radius was determined, along with results comparing different radii from 1 km to 50 km for each applicable metric, are available in Supplementary Note 4.

While all of these metrics are calculated at the CBG level, the household location in the restricted NHTS dataset is only available at the CT level. Therefore, CBGs are aggregated to CTs, with each metric being averaged across all CBGs inside a given tract before joining with NHTS. Finally, extreme values are trimmed from the data, setting values below the 0.1th percentile to those at the 0.1th percentile, and values above the 99.9th percentile to those at the 99.9th percentile. For bus and rail stop access (for which many values are 0), only the upper range of the distribution is trimmed, and only to the 99.99th percentile. These properties are summarized in Supplementary Note 9.

Vehicle ownership ($\boldsymbol{e}$)

Vehicle ownership is reflected by the number of vehicles per adult person owned by the household of the traveler. This number is capped at 1.5, since we found that a vehicle ownership rate of more than 1.5 vehicle per adult household member has no additional marginal effect on travel behavior. More details are provided in Supplementary Note 2.

Similarly to variables $\boldsymbol{T}$ and $\boldsymbol{E} \mid \boldsymbol{T}$, which are bounded by $[0, 1]$, but whose predicted values fall within that range most of the time, we implement $\boldsymbol{e}$ as a continuous variable with a linear relationship to other variables in the model. To ensure a linear relationship between $\boldsymbol{e}$ and the endogenous travel behavior variables $\boldsymbol{y}$, we transform the capped vehicle ownership rate using the 4th root. More details on this are provided in Supplementary Note 2 as well.

Demographic control variables ($\boldsymbol{C}$)

We include gender, income, age, race, ethnicity, level of education, typical level of physical activity as indicated by the respondent, number of adults and number of children living in the household, employment status and type of the respondent, and whether the traveler works from home. Ordinal variables such as income, age, and the number of adults and number of children living in the household are implemented as dummy variables using ranges (e.g.: Age

<18, Age 18-34, Age 34-64, etc.) to allow for non-linear relationships between these controls and the corresponding endogenous variables.

Further control (*L*)

We control for local climate, local gasoline price, vehicle fuel economy, and day of the week (Monday through Sunday). These factors may affect typical travel behavior and may be correlated with urban form. For example, the gasoline price may be systematically higher in urban areas than rural areas. This means that not accounting for the gasoline price explicitly may falsely attribute some of its effect on travel behavior to urban form, thus over- or underestimating the impact of urban form on travel.

The local gasoline price, vehicle fuel economy (official rating), and day of the week are indicated in the NHTS data. To account for local climate, we obtain weather-station-specific monthly average heat-index temperature, direct solar irradiation, and precipitation from the National Renewable Energy Laboratory Typical Meteorological Year (TMY) dataset [24]. We then assign these values to each household based on the closest weather station to that household and the month of the household's assigned travel day. There are 1,020 weather stations in the database, distributed across the United States. This means that our approach captures the general climate in the area of the traveler, but no micro-climates and other localized effects.

Notably, treating vehicle fuel economy (or efficiency) as exogenous differs from some previous studies (e.g. [34]) that considered vehicle fuel efficiency to be endogenous and affected by urban form or density itself. Our approach is more conservative, as we will not attribute any potential correlation between urban form and vehicle fuel economy to be caused by urban form.

For trips that were not made with a vehicle or were fuel efficiency is missing, fuel efficiency is imputed. First, we try to impute missing fuel efficiency data by using the average fuel efficiency of other trips made by the same person on the same day. If that value is not available either, we try to impute the missing value by using the average fuel efficiency of other trips made by people in the same household. If that value is not available either (likely because the household neither owns any vehicles nor used any vehicles that day), we use the fleet-average fuel efficiency value. Of 149,575 missing fuel efficiency values (16.9% of 882,846 individual trips), 73,333 were imputed using the first option, 54,165 using the second option, and 22,077 using the third option.

Supplementary Information

Supplementary Notes 1–10, Figures 1–12 and Tables 1–8.

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*Author Contributions

M.M. and Z.N. designed the study. M.M. compiled the data, built the model, performed the analysis, and created the figures and tables. M.M. wrote the paper with contributions from Z.N. and R.J. R.J. supervised the work.

Conflict of interest

The authors declare no competing interests.

Availability of data and materials

The unrestricted version of the National Household Travel Survey data, which does not contain the census tract ID of each household and trip, is openly available at https://nhts.ornl.gov/. The processed and filtered NHTS data, without the location of each household, can be made available upon reasonable request. Most measures of urban form at each census block group were obtained from the smart location (SL) database, which is available at https://www.epa.gov/smartgrowth/smart-location-mapping. The data for each census tract that was combined with NHTS, containing geographical information, all processed urban form metrics (those inferred from the SL database and other), and climate variables, is available at [DataDryad link to be inserted upon publication]. This dataset also contains the estimated deviation in daily travel energy use from the baseline due to urban form for each census tract, across the 6 groups of metrics (similar to Figure 4b, but by census tract instead of density and metro area population bracket). The final dataset used to fit our model, which combines the processed and georeferenced NHTS data with the census block group data (aggregated to the census tract level), cannot be made available due to the confidential nature of the former.

Code availability

The code used in this analysis can be made available upon reasonable request.

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