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Millennials, built form, and travel insights from a nationwide typology of U.S. neighborhoods

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ABSTRACT

We examine the relationship between the built environment and the travel of Millennials in the United States. We develop a neighborhood typology to characterize the built environment and transportation networks in almost every U.S. census tract, allowing us to identify possible synergistic and/or threshold effects on travel. We measure travel behavior in two ways: (1) using a multi-faceted traveler typology created using latent class analysis, and (2) by measuring the vehicle miles of travel among people in each of these traveler types. This dual approach allows us to distinguish between the built environment changes needed to encourage travel by modes other than driving, and those needed to reduce vehicle miles traveled among drivers. Using a multinomial logistic regression, we find that travel patterns are relatively stable along much of the urban-rural continuum, everything else equal. Driving was substantially lower only in "Old Urban" neighborhoods, where densities, job access, and transit service are dramatically higher than in all other neighborhood types. This finding implies that dramatic changes in the built environment—doubling or even tripling development density or transit service—may do little to get young people out of their cars when initial densities or transit services are low, as they are in most of the U.S. Conversely, reducing vehicle miles traveled among drivers appears to require more modest built form changes, a finding that offers some room for optimism among those concerned with auto dependence.

1. Introduction

Dependence on private vehicles for mobility varies across nations, regions within nations, and households within regions. While private vehicle use confers considerable private benefit to drivers, this benefit comes at great societal economic and environmental cost. Because people tend to drive less in large cities than in outlying areas, analysts and researchers have sought to decipher the transportation-built form connection in hopes of identifying effective strategies to reduce dependence on private vehicles for mobility. These efforts have taken on added importance as climate change joins non-renewable energy consumption, pollution, congestion, and collisions on the list of automobile-related ills.

In transportation-land use research, scholars often, but not always, treat the characteristics of the built environment as independent variables; these have come to be known as the "five D's:" density, diversity, design, destination accessibility, and distance to transit (Cervero and Kockelman, 1997, Ewing and Cervero, 2010). But these characteristics are generally not independent of one another and tend to vary in concert. For example, densely developed places also tend to have shorter distances to transit stops and stations, and greater variety of accessible nearby destinations. As Ewing and Cervero (2010) and others (Bento et al., 2005) have argued, particular built environment characteristics may combine in various ways that result in much larger travel behavior effects than any one element alone. In other words, synergy of built environment effects on travel may be considerably greater than the sum of the parts.

In addition to such *synergistic effects*, *threshold effects* may also be at play. In their meta-analysis of transportation-land use studies, Ewing and Cervero (2010) report that increasing population density by 10% decreases vehicle miles traveled (VMT) by 4%, on average. Armed with this information, planners in small cities and suburban areas may encourage denser development in an effort to decrease driving. But the effects of a 10% increase in development density in an outlying area from 1.0 to 1.1 dwelling units per hectare may be very different from increasing densities from 100 to 110 dwelling units per hectare (Boarnet, 2010). This threshold effect implies that increasing developmental density may not reduce vehicle miles driven much at all in low

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density areas, but may well induce a much larger change in travel at higher initial densities.

To address the unresolved issues of synergy and threshold effects of the built environment on travel behavior, we use a combination of factor and cluster analyses to identify seven distinct neighborhood types based exclusively on characteristics of the built environment and transportation networks in the U.S. This approach allows us to assess the combined influence of density, diversity, transience, stability, and accessibility on travel (synergistic effects). Rather than use multiple continuous measures of the built environment as independent variables, we use neighborhood type as the independent variable of interest in the multivariate modeling. This allows the relationship between the built environment and travel to vary depending on initial built environment conditions (threshold effects).

We measure travel behavior in two ways: (1) using a multi-faceted traveler typology created using latent class analysis, and (2) by measuring the vehicle miles of travel among people in each of these traveler types. This dual approach allows us to distinguish between the built environment changes needed to encourage travel by modes other than driving, and those needed to reduce VMT among drivers.

The present analysis focuses on the Millennial generation, young people ages 16 to 36 in our data (Pew Research Center, 2014). This age range is interesting for a number of reasons. First, Millennials in the U.S. and elsewhere experienced dramatic reductions in automobility (Blumenberg et al., 2012, Mans et al., 2012, Polzin et al., 2014, McDonald, 2015) and licensing in the early 2000s (Williams et al., 2012, Shults and Williams, 2013, Tefft et al., 2013, Schoettle and Sivak, 2014). Similar patterns have also occurred in other countries (Noble, 2005, Kuhnimhof et al., 2011, Delbosc and Currie, 2013, Kuhnimhof et al., 2013, Jorritsma and Berveling, 2014, Le Vine and Polak, 2014). Second, due to their youth and size, the Millennial Generation's decisions about residential location and travel will shape aggregate travel patterns and urban policies for decades to come. Third, many speculate that youth are leading a back-to-the-city movement (Cortright, 2011) that may portend a move away from driving and toward more travel by other modes. Will moving from suburbs to central cities be associated with reductions in driving, or will the new urbanites continue to drive as much as they had in the suburbs? Answering these questions is the aim of this work.

Finally, this article is one piece of a much larger research project on the travel patterns and residential location of young people in the United States. For further information, interested readers are encouraged to consult the full report (http://tinyurl.com/obneh8w) as well as the specific articles highlighted throughout the text.

2. Literature review

2.1. Measuring the built environment

There are many ways to characterize and quantify the built environment of neighborhoods, which have evolved based on data availability, emerging research needs, and advances in computing power (Hamidi et al., 2015). By far the most commonly employed approach is to measure distinct components of the built environment independently (for example, Barrington-Leigh and Millard-Ball (2015) measure street connectivity) and include one or more measures in a multivariate statistical model. As noted above, these variables are often referred to as the five D's: density, diversity, design, destination accessibility, and distance to transit (Cervero and Kockelman, 1997, Ewing and Cervero, 2010). But because the so-called D's tend to vary in tandem, scholars have developed various ways to simultaneously capture multiple facets of the built environment at once. For example, Hamidi et al. (2015) recently updated the “Sprawl Index”, a continuous variable that incorporates four components of sprawl: developmental density, land use mix, degree of centering, and street connectivity. Other scholars have eschewed continuous variables like the Sprawl Index in favor of categorical variables (Salon, 2015). As we discuss below, these categories of built environment types are typically identified using a combination of factor and cluster analyses. The present study employs a typology approach.

The existing literature on neighborhood typologies informed our research approach in three ways. First, some neighborhood typologies have included both the built environment and the socio-economic characteristics of the people living in the neighborhoods (Lin and Long, 2008), while others have included just the physical characteristics of the neighborhood (Shay and Khattak, 2007, Song and Knaap, 2007). Our goal in the present study was to analyze the relationship between the built environment and travel, independent of socio-economic factors. For this reason, our typology is comprised exclusively of characteristics of the built environment and transportation network. Second, neighborhood studies also vary in their geographic coverage. Some studies categorize neighborhoods in a single metropolitan area (Shay and Khattak, 2007, Song and Knaap, 2007), while others—like ours—cover entire nations (Lin and Long, 2008). Third, despite the subjective nature of neighborhood boundaries, census tracts are frequently used as proxies for neighborhoods in the U.S. (Song and Knaap, 2007). We too use census tracts because the scale of tracts aligns well with the scale of neighborhoods in urban and suburban areas and because the census tract is generally the finest geographic scale at which built environment data are widely available.

2.2. Traveler types

In addition to using typologies to characterize neighborhoods, we also employ a typology approach to characterize travel. Most travel behavior studies focus on a single aspect of travel—vehicle miles of travel or trip-making, for example. But, like neighborhoods, travel is multifaceted as well, and the particular combinations of trip making, automobility, and mode use are of interest for understanding access to opportunities, for reducing emissions and other detrimental effects of driving, and for measuring and encouraging multimodality (Pas, 1988, Buehler and Hamre, 2014). To that end, we use latent class analysis to combine multiple facets of travel—mobility, trip-making, and travel mode over the short- and longer-term—into a single traveler type variable with four distinct types that we describe as: Drivers, Long-distance Trekkers, Multimodals, and Car-less. In some cases scholars do analyze more than one facet of travel in a single study, but often the different travel behavior outcomes are modeled in separate regressions and are only tied together in the discussion of the results. This requires interpreting, synthesizing, and comparing multiple sets of results, which can be difficult. Using a traveler typology can simplify this process. First, it captures the multiple aspects of travel in a single, intuitive typology. Second, the typology can be modeled and interpreted using a single regression. Using typologies to describe travel behavior is relatively uncommon, but the approach has been used successfully to classify people by their latent modal preferences (Vij, 2013) and by their environmental attitudes (Anable, 2005).

2.3. Causality in travel behavior research

For decades, the standard practice among transportation scholars has been to use cross-sectional data and regression analysis to establish correlations between characteristics of the built environment and travel (Boarnet, 2011). But how should such results be interpreted? On one hand, they may reflect a causal relationship. The built environment alters the availability and relative utility of travel by various modes, which likely shapes travel (Crane, 2000, Naess, 2014). Conversely, individuals and households may choose to live in neighborhoods that match their *a priori* travel preferences.

The cross-sectional data used in most travel behavior analyses limit our collective ability to disentangle this self-selection issue (Boarnet, 2011). Most travel diaries do not include information on travel preferences or previous residential locations.

That said, scholars using panel data and statistical methods like structural equation modeling find that self-selection attenuates the strength of the relationship between the built environment and travel (Cao et al., 2009, Ewing and Cervero, 2010), leading most scholars to conclude that the built environment likely shapes travel behavior in a statistically significant, albeit relatively modest manner, even when accounting for self-selection (Committee for the Study on the Relationships Among Development Patterns, 2009, Boarnet, 2010, Ewing and Cervero, 2010).

Those statistical results paired with the well-established causal mechanisms linking travel and the built environment lead some scholars to argue that it is appropriate to use cross-sectional data to approximate the relationship between the built environment and travel so long as the analyst estimates a multivariate regression model that controls statistically for socioeconomic characteristics and other characteristics known to relate to travel behavior (Naess, 2014). This is our approach.

3. Data and methods

3.1. Identifying groups in data

We began by selecting appropriate statistical approaches for identifying groups within multi-dimensional data. For the neighborhoods, we employed a two-step analytical approach combining factor analysis and cluster analysis; for the traveler types we used latent class analysis. Both cluster and latent class analysis are similar in that they identify groupings that are relatively homogenous internally and maximally distinct from one another.

Despite their similarities, the methods differ in important respects. Cluster analysis requires continuous input variables. For this reason, many scholars seeking to classify neighborhoods first use factor analysis to reduce the input variables to a conceptually distinct set of continuous factors (Shay and Khattak, 2007, Song and Knaap, 2007). Moreover, beginning with factor analysis reduces the number of input variables to a manageable number and in addition all inputs are centered at zero and measured on the same scale, which facilitates the subsequent cluster analysis. A different approach was needed for identifying the traveler types because many travel variables are categorical (*e.g.* licensed or not) or measured as counts (*e.g.* number of trips) and cannot therefore be used in cluster analyses. With fewer input and continuous variables, we turned instead to Latent Class (LC) models, which were developed to overcome these and other challenges (Magidson and Vermunt, 2002).

For both cluster analysis and LC models, it is unclear *a priori* how many homogenous groups are present in the data. To determine an appropriate number of clusters or classes, the analyst first estimates a simple model with two groups, then three, then four, and so on. With cluster analysis the analyst uses a number of statistical stopping criteria to determine the optimal number of clusters (Desgraupes, 2014). With latent class analysis the analyst uses the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC)—where lower scores are better—and an entropy score—where higher scores are better—to guide model selection (Lanza et al., 2007). In both approaches, the analyst must also make quasi-subjective decisions about the interpretability of the groups and insure that the groups are large enough to proceed with subsequent analyses (Lanza et al., 2007).

3.2. Identifying neighborhood types

Our neighborhood type data came from two sources: the Environmental Protection Agency's Smart Location Database and the U.S. Census. We identified 20 variables we deemed relevant to describing an area's built form and transportation system characteristics, including housing density, share of housing units that are rented, age of the housing stock, number of jobs within a 45-minute drive, share of metropolitan employment in the tract, jobs-housing balance, road network density (with separate values for car- and pedestrian-oriented roadways), intersection density, and a transit service index. All variables were measured at the tract level and were applied to each of the 73,057 census tracts in the United States.

We used factor analysis to collapse the initial 20 variables into a set of five factors, which we defined as representing the degree to which a neighborhood is 1) dense, 2) diverse, 3) transient, 4) established/stable, and 5) accessible. We then used the five factors as inputs for the cluster analysis, where a seven-cluster solution was optimal according to statistical stopping criteria described above. For more details about the process of identifying the neighborhoods, see Turley Voulgaris et al. (2017).

3.3. Identifying traveler types

The data for the traveler types came from the 2009 National Household Travel Survey (NHTS). In addition to the central component of the survey, the 24-hour travel diary, the NHTS also solicits information on longer term travel patterns as well as detailed personal and household information. The sample includes household data from all 50 U.S. states and is weighted to be nationally representative. After excluding respondents with missing personal or travel information and those who flew or traveled over 400 miles on the survey day, we were left with a sample of 28,980 teens and young adults ages 16 to 36.

We selected seven travel variables from the NHTS to distinguish types of travelers (see column 1 of Table 2). These variables were chosen to account for multiple facets of travel, including mobility, trip-making, extent of automobility, and use of alternative travel modes. Most importantly—because travel patterns vary from day-to-day and such variation is increasingly of interest (Buehler and Hamre, 2014)—we also include travel information reported for an extended period of time (annual miles driven and public transit use in the past two months).

The seven travel variables served as inputs in the latent class model. A four-class model minimized the AIC and BIC, provided a reasonably high entropy score (0.970), and provided interpretable classes that were sufficiently large to permit further analysis. For more details about the process of identifying traveler types, see Ralph (2016).

3.4. Descriptive analysis

With the neighborhood and traveler types in hand, we conducted a descriptive analysis. For each of the seven neighborhood types, we determined the prevalence of the four traveler types in our sample of young adults in the U.S. ages 16 to 36. Because the traveler types encompass multiple facets of travel patterns, the traveler type analysis is inherently general in nature. While we believe this approach to analyzing travel behavior has many benefits, it may also mask substantial heterogeneity in travel patterns across neighborhoods within the traveler types. For example, young travelers characterized as “Drivers” in a suburban neighborhood may drive more miles, on average, than those in urban neighborhoods. To explore this possibility, we also analyzed vehicle miles traveled (VMT) per person in each neighborhood. We chose VMT because it incorporates information on travel mode, trip distance, and number of trips and because of its central relevance to a number of policy issues including traffic congestion, vehicle emissions, and crashes. We report median values for VMT rather than the mean to minimize the influence of respondents who drove unusually far distances on the survey day.

3.5. Multivariate modeling

The descriptive analysis set the stage for the multivariate statistical analysis, which was conducted to account for the well-documented, complex relationships among travel patterns and economic resources, adult roles, demographic characteristics, and built form (Ewing and Cervero, 2010). Failing to simultaneously account for these factors may lead one to overstate the strength of the relationship between travel and the built environment of each neighborhood. Specifically, we estimated models for two dependent variables: traveler type and VMT.

For both models, we drew on the existing literature on transportation and the built environment to identify suitable control variables, which include two measures of economic resources: 1) household income quintile adjusted for the number of people in the household and 2) employment status (employed full-time or part-time *versus* not employed). We include measures of race/ethnicity and gender because they are each associated with travel patterns even after controlling for other socio-economic factors (Giuliano, 2003, Crane, 2007). Because we are specifically interested in the transitional period between adolescence and adulthood, we also include information about the attainment of adult roles (lives independently, marriage status, and has a child). Unlike many scholars, we do not include an education variable because of the difficulty of distinguishing those young people in the midst of study from those who have completed their education, and it is the final levels of educational attainment that are typically used to explain travel outcomes.

While most research has tended to explain how various components of the built environment correlate with various travel outcomes (Ewing and Cervero, 2010), our focus here is on how *particular combinations* of the built environment affect travelers and travel patterns. For this reason, we focus on neighborhood type as our key explanatory variable.

The nature of each dependent variable determined the functional form of the models—a multinomial logistic regression for the nominal traveler types and a quantile regression for the continuous VMT. We chose a quantile regression rather than ordinary least squares because we wanted to minimize the effect of outliers, specifically respondents with very high mileage. We estimated three separate VMT models: one each for three of the four traveler types. The fourth type was omitted from the VMT model because Car-less individuals did not use an automobile on the survey day and therefore VMT was largely invariant among neighborhoods. We estimated the VMT models using negative binomial and poison models as well, to assess the robustness of the results to alternative model specifications. In all cases the results were qualitatively similar. The full model results are presented in Table 4 (traveler type) and Table 5 (VMT). All models were estimated using the NHTS-provided person weights.

Multinomial logistic regression requires a base category, but we wanted to interpret the results for all four traveler types. Fortunately, the "margin" command was developed for Stata, which was designed specifically to ease interpretation of complex models (Mitchell, 2012). The margin command allows us to calculate the average marginal effect, the difference in the predicted probability of being in each traveler type while averaging across the covariates in the sample. This is conceptually similar to determining how travel patterns change when moving from one neighborhood to another. While there are important issues that prevent this analysis from being truly causal, the average marginal effect nevertheless provides a clear and intuitive illustration of the model results. Importantly, even though the regression results include two base categories (Drivers and Rural), the margin command can calculate the expected change in the predicted probability of being a Driver among any combination of neighborhood types. We have chosen to present the average marginal effects relative to (the typically far-flung suburban) "New Developments" because those neighborhoods host the largest share of young people (27%). Finally, we employ this approach for both sets of models and present the results for traveler type and VMT together in Table 6.

4. Results

In the following sections we introduce the seven neighborhood types and the four traveler types. We then present the results of our descriptive and multivariate analyses, which together characterize the relationship between neighborhood types and travel.

4.1. Neighborhood types

The seven neighborhood types can be broadly grouped into three categories: one rural, three suburban, and three urban neighborhoods (see Table 1).

Rural neighborhoods are home to 19% of the U.S. population and are the least dense, have very few jobs nearby, and have very little or no public transit service.

The three types of suburban neighborhoods together are home to 58% of the U.S. population. ***New Developments*** are mostly newly built suburban developments that consist primarily of low-density single-family homes and very few jobs. These neighborhoods are home to more than a quarter (27%) of the entire U.S. population. ***Patchwork*** neighborhoods are mostly mixed-use areas that include relatively low-density housing as well as suburban retail and office developments. These neighborhoods are home to about 18% of people in the U.S. ***Established Suburbs*** are older suburban developments that are home to 13% of U.S. residents. Relative to the other suburban neighborhoods, Established Suburbs tend to have higher densities, greater access to jobs, and better transit service.

The three urban neighborhood types are in combination home to just over one fifth (23%) of the U.S. population. ***Urban Residential*** is a more urban version of Established Suburbs, with correspondingly higher densities, better transit service, and a higher share of rental housing. These neighborhoods are home to about 19% of the U.S. population age 16 to 36. ***Old Urban*** neighborhoods are by far the most densely developed neighborhoods. They are typically very well-served by public transit and have the most jobs available both within the neighborhood itself and within a 45 minute drive. Most of Manhattan in New York City is Old Urban. However, these distinct neighborhoods are home to just 5% of the U.S. population. Finally, ***Mixed-use*** neighborhoods are primarily job centers with some housing. Many cities have a cluster of Mixed-use neighborhoods at the city center, but many areas also have a number of dispersed commercial centers that are classified as Mixed-use. These neighborhoods are also home to about 4% of the U.S. population, but a larger share of jobs.

Table 1
Average built environment characteristics by neighborhood type.

	Homes per acre	Jobs-housing balance	Rental homes (%)	Homes > 40 years old (%)	Transit supply index	Jobs within 45-minute drive	Share of U.S. population
All neighborhoods	3.5	0.4	34%	46%	0.5	118	100%
Rural	0.1	0.3	19%	42%	0.0	14	19%
New Development	1.4	0.2	19%	17%	0.0	68	27%
Patchwork	1.7	0.7	35%	46%	0.1	94	18%
Established Suburbs	4.1	0.3	25%	74%	0.6	186	13%
Urban Residential	5.9	0.3	58%	56%	0.8	147	14%
Old Urban	27.5	0.3	76%	74%	4.2	533	4%
Mixed-use	5.2	0.7	65%	49%	1.1	181	5%

Note: Higher scores on the transit supply index indicate more transit service.

In many metropolitan areas the neighborhood types are arranged spatially in a rough concentric ring pattern that evokes the classical urban geography theories of a century ago by scholars such as Burgess (2008) and Hoyt (1939). Figs. 1 and 2 show the spatial arrangement of neighborhood types in Chicago and New York City.

4.2. Traveler types

We label the four types of travelers identified as Drivers, Long-distance Trekkers, Multimodals, and Car-less. As Table 2 indicates, ***Drivers*** made nearly all of their trips by automobile and as a result enjoyed typically high levels of mobility and trip-making. ***Trekkers*** are similar to Drivers in many respects, but traveled many more miles to complete the same number of trips. ***Multimodals*** were just that: they made half of their trips by walking, biking, or riding transit, and in doing so were able to engage in more activities outside the home than Drivers because they made more daily trips on average. ***Car-less*** young adults traveled exclusively by non-automobile modes and for the most part had very limited mobility and trip-making overall.

Nationally, the vast majority (80%) of young adults were Drivers, while Long-distance Trekkers (4%) and young people who used a variety of modes—the Multimodals (3%)—were both relatively rare. The final group, the Car-less, was the second largest travel type, representing 14% of the aged 16 to 36 population.

4.3. Descriptive results

Table 3 builds on the nationwide analysis described above by illustrating how travel patterns varied across neighborhoods. There is remarkable stability in the prevalence of Drivers in most types of neighborhoods. Drivers were, unsurprisingly, most prevalent in the lowest-density suburban neighborhoods (New Developments) and in Rural areas. Yet moving along the Rural to Urban continuum was associated with only modest declines in the share of Drivers. It was only in Old Urban neighborhoods that the share of Drivers fell sharply and those neighborhoods, as noted above, are both comparatively rare and have very unique built environments.

The variation in the distribution of Drivers was almost entirely offset by the share of Car-less young people. While only 14% of young people were Car-less nationwide, the proportion increased to one in five in Urban Residential and Mixed-use neighborhoods and soared to more than half in Old Urban neighborhoods.

Among Drivers, variations in the built environment across neighborhoods were associated with changes in VMT per day. While the typical Driver in New Developments drove 26 miles a day, those in slightly denser suburban and urban neighborhoods drove roughly 15% less. The reduction in VMT was greater still in Old Urban neighborhoods, where the typical driver drove just 16 miles a day, ten fewer than their counterparts in New Developments.

Long-distance Trekkers were (unsurprisingly) much more common in Rural neighborhoods where destinations tend to be highly dispersed. Just as importantly, the typical Trekker in a Rural area also drove many more miles each day than Trekkers in suburban and urban neighborhoods.

To round out the traveler types, we find (also unsurprisingly) that Multimodals were very uncommon in Rural and most suburban neighborhoods. While Multimodals were much more prevalent in more urban neighborhoods, they nevertheless remained rare; no >6% of young people were Multimodal in any type of neighborhood in 2009. Recall that Multimodals travel by means other than private vehicle for roughly half of their trips. Nationally, Multimodals typically traveled seven miles by automobile each day. Rural Multimodals traveled much further by automobile—15 miles a day—while still making half of their trips by non-automobile modes.

As noted above, the observed variation in neighborhood level travel patterns may stem not only from differences in the built environment, but also from differences in economic resources, adult roles, and race/ethnicity, which varied considerably and systematically by neighborhood type. In particular, young people in Old Urban neighborhoods tend to have lower incomes, are less likely to be employed, and are more likely to be racial/ethnic minorities than young people in other neighborhoods and these characteristics may make them less likely to be Drivers, regardless of the built environment. To untangle these effects, we control statistically for these differences in the multivariate regression models, to which we now turn.

4.4. Multivariate results: traveler type

Table 4 presents the results of the multinomial logistic regression of traveler types. In terms of personal and household characteristics,

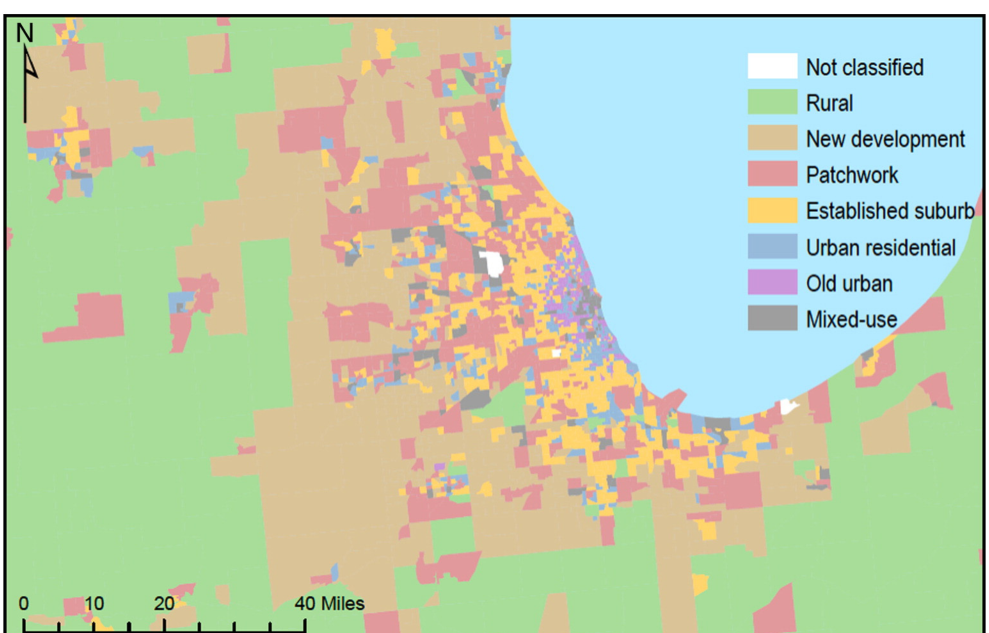

Fig. 1. Spatial arrangement of neighborhood types in Chicago.

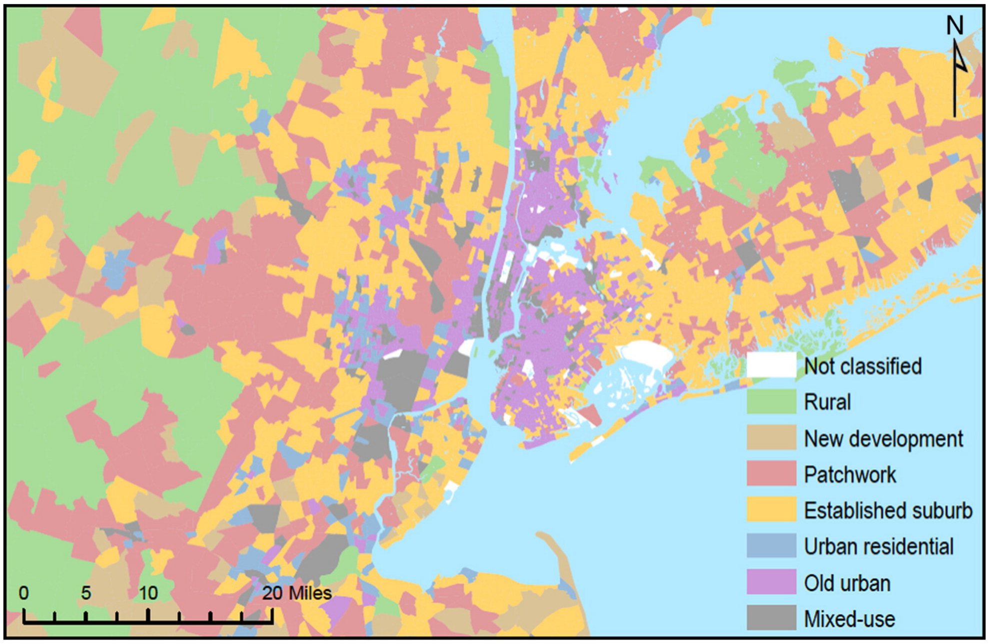

Fig. 2. Spatial arrangement of neighborhood types in New York City.

young people were less likely to be Drivers and more likely to be Car-less if they had relatively low household incomes or were a racial/ethnic minority (other than non-Hispanic Asian). By contrast, young people were more likely to be Drivers and less likely to be Car-less if they were employed, married, had a child, and/or were no longer a teenager. Relative to men, women were more likely to be Drivers and less likely to be Car-less, everything else equal.

Table 6 provides greater detail about the model results by presenting the average marginal effect of moving from a New Development to a different type of neighborhood. Even when controlling statistically for individual characteristics, the independent association between traveler type and neighborhood types remained strong. Most strikingly, young people in Old Urban neighborhoods were still much less likely to be Drivers and much more likely to be Car-less than their otherwise similar peers in New Developments, *ceteris paribus*. The built environment in Old Urban neighborhoods is dramatically different than the typical neighborhood in the United States. Specifically, relative to New Developments, Old Urban neighborhoods have 20 times as many homes per acre, 7.8 times as many jobs available within a 45-minute drive, and vastly superior public transit service. Notably, these neighborhoods are few and far between in the U.S.: just 4% of the population resides in Old Urban neighborhoods.

Beyond the Old Urban neighborhoods, the association between neighborhood and traveler type was more modest. Compare, for instance, New Developments and Established Suburbs, which are physically very different from one another; Established Suburbs have three times as many homes per acre, 2.7 times as many jobs available within a 45-minute drive, and much better (albeit still relatively limited) public transit service. Yet, those dramatic differences in the built environment were associated with just a 9.2 percentage point reduction in the share

Table 2
Travel patterns of young adults (age 16 to 36) in the United States by traveler type in 2009.
Source: 2009 NHTS, weighted values.

	(1) All young people	(2) Drivers	(3) Long-distance trekkers	(4) Multimodals	(5) Car-less
Share of young people (point estimate)[a]	100%	80% [78.9 to 80.6]	4% [3.6 to 4.4]	3% [3.0 to 3.7]	13% [12.1 to 13.5]
Traveler types were identified with a latent class analysis of seven travel variables:					
(A) Miles of survey-day travel[c]	21 [8 to 44]	24 [12 to 48]	48 [21 to 107]	12 [5 to 29]	2 [0.2 to 12]
(B) Trips on the survey day[c]	4 [2 to 6]	4 [2 to 6]	4 [3 to 7]	5 [4 to 6]	2 [2 to 4]
(C) Auto share of survey-day miles[b]	100%	100%	100%	52%	0%
(D) Annual miles driven[c]	8000 [500 to 15,000]	9000 [2000 to 15,000]	50,000 [45,000 to 70,000]	300 [0 to 8000]	0 [0 to 2000]
(E) Share licensed to drive	85%	91%	100%	66%	46%
(F) Share using public transit					
Never	78%	84%	90%	53%	41%
Sometimes	11%	10%	7%	14%	15%
Weekly or more	11%	6%	4%	32%	43%
	100%	100%	100%	100%	100%
(G) Automobiles per adult in the household					
None (%)	5%	1%	0%	8%	29%
Less than one	23%	21%	13%	33%	40%
One or more	72%	78%	87%	59%	31%
	100%	100%	100%	100%	100%

Notes: The seven travel variables (A–G) were used to identify the traveler types. The Drivers category includes young people who are driven by others.
[a] 95% c.i.
[b] median.
[c] median, 25/75th percentile.

Table 3
The traveler type of young adults by neighborhood in the United States in 2009.
Source: 2009 NHTS, weighted values.

	Drivers		Long-distance trekkers		Multimodals		Car-less		All traveler types	
	Pop share (%)	VMT/srvy day	Pop share (%)	VMT/srvy day	Pop share (%)	VMT/srvy day	Pop share (%)	VMT/srvy day	Pop share (%)	VMT/srvy day
Rural area	83	33	6	71	3	15	8	0	100	30
New Development	87	26	3	42	3	7	7	0	100	24
Patchwork Suburb	84	20	2	36	2	3	11	0	100	18
Established Suburbs	77	22	2	57	5	7	16	0	100	16
Urban Residential	72	22	2	33	5	4	20	0	100	15
Old Urban	39	16	1	36	4	8	56	0	100	0
Mixed-use	71	18	3	43	6	4	19	0	100	12
Nationwide	79	24	3	48	4	7	14	0	100	20

Note: Descriptive results. VMT figures are median values.

of Drivers. The lower share of Drivers in Established Suburbs was almost entirely offset by higher levels of Car-less travelers in those areas, which increased by 8.5 percentage points.

For Drivers and Car-less young people, the association between neighborhood type and traveler type was generally as strong as or stronger than the association with individual characteristics. For example, living in a Mixed-use or Urban Residential neighborhood reduced the propensity to be a Driver by roughly the same amount as having a low income (Q1 v. Q3), though the relationship was four times stronger for Old Urban neighborhoods.

4.4.1. Long-distance trekkers

Relative to those in Rural areas, young people in all other neighborhoods were less likely to be Trekkers. Beyond this distinction, there was little variation in the propensity to be someone who drives very long distances over the course of a year among the suburban or urban neighborhood types when controlling for individual and household characteristics.

Of the other explanatory variables, gender and age had by far the strongest relationship with the likelihood of being a Trekker[1]; women and teens were less likely to be Trekkers than men or young adults respectively. Young people were also more likely to be Trekkers if they were employed or lived independently. Young people at extreme high and low ends of the income spectrum were less likely than middle-income young people to be Trekkers, although the relationship was only statistically significant for young people in the highest income quintile.

Table 4
Multinomial logistic regression results: Predicting the traveler type of young people (ages 16 to 36) by neighborhood type, United States (2009) ($N = 27{,}384$).
Source: 2009 NHTS, weighted values.

	Long-distance trekker	Multimodal	Car-less
Neighborhood type (base: Rural)			
New Development	−0.818***	0.135	−0.097
Urban Residential	−1.134***	−0.034	0.312
Established Suburbs	−1.202***	0.783**	0.781***
Urban Residential	−0.985**	1.048***	0.895***
Old Urban	−0.993*	1.285***	2.533***
Mixed-use	−0.669*	1.169**	0.940***
Household income quintile (base: Q1)			
Q2	0.402	−0.708**	−0.480**
Q3	0.181	−0.072	−0.945***
Q4	0.092	−0.061	−0.866***
Q5	−0.251	−0.052	−0.860***
Adult roles (base: Not attained role)			
Employed	0.852***	−0.215	−0.917***
Live independently	0.611**	0.344	0.238
Married	−0.375	−0.549*	−0.432**
Has a child	0.258	−0.076	−0.145
Race/ethnicity (base: NH White)			
NH black	0.357	0.197	0.359*
NH Asian	−0.750*	0.095	0.175
Hispanic	−0.067	−0.075	0.420**
NH other	0.277	0.591	0.197
Gender (base: Male)			
Female	−1.201***	−0.351*	−0.254*
Age (base: 16 to 19)			
Age 20 to 25	0.895*	−1.039***	−0.408**
Age 26 to 36	1.128**	−0.982***	−0.373*
Constant	−4.160***	−2.480***	−1.008***

Note: Pseudo $R^2 = 0.10$, log likelihood $= -15{,}329.42$, likelihood ratio $\chi^2 = 3413.72$, df $= 63$, $p < 0.000$.

4.4.2. Multimodals

Neighborhood type was an important predictor of being a Multimodal, even when controlling for other factors. Young people in three—generally outlying—neighborhood types were the least likely to be Multimodals: Rural, New Development, and Patchwork. Young people were more likely to be Multimodal in the remaining four neighborhood types—Established Suburbs, Urban Residential, Old Urban, and Mixed-use.

Teens were much more likely to be Multimodals than young adults in their twenties or thirties. This finding could indicate that multimodality is a phase that most young people grow out of, but given the limits of our cross-sectional data this conclusion remains speculative. The remaining explanatory variables were generally insignificant or relatively small in magnitude.

4.5. Multivariate results: VMT

Table 5 includes the full model results for the quantile regression of VMT. Table 6 further elucidates the results by providing the average marginal effect of each type of neighborhood relative to New Developments. The results indicate that within each traveler type, VMT varies systematically across neighborhoods. At one extreme, Rural Drivers traveled 9.1 more miles per day than their otherwise similar counterparts in New Developments. At the other extreme, Drivers in Old urban neighborhoods drove 11.2 fewer miles each day than those in New Developments, everything else equal.

Moving from a New Development to a Patchwork Suburb, a neighborhood with slightly higher population and employment densities and greater job access appears to reduce VMT by 5.7 miles per day. This finding suggests that slight changes in the built environment can meaningfully reduce travel. Frustratingly, further incremental changes to the built environment were associated with diminishing returns. Moving from a Patchwork Suburb to an Established Suburb or an Urban Residential neighborhood was not associated with any further decreases in VMT among Drivers. In other words, Drivers in Patchwork Suburbs and Urban Residential neighborhoods both drove

[1] Not to be confused with being a Trekkie, which is something altogether different.

Table 5
Quantile regression results: Predicting VMT of young people in each traveler type by neighborhood type, United States (2009).
Source: 2009 NHTS, weighted values.

	Driver	Long-distance trekker	Multimodal
Neighborhood type (base: Rural)			
New Development	−9.111***	−31.667**	−9.278**
Patchwork Suburbs	−14.778***	−20.556	−10.889***
Established Suburbs	−14.889***	1.556	−7.556*
Urban Residential	−13.111***	−14.444	−9.167*
Old Urban	−20.333***	−35.815	−8.222
Mixed-use	−17.333***	−35.296**	−11.722*
Household income quintile (base: Q1)			
Q2	4.778**	16.000	1.944
Q3	6.556***	5.000	1.389
Q4	7.667***	54.593**	0.389
Q5	9.111***	15.259	0.444
Adult roles (base: Not attained role)			
Employed	3.667***	−12.741*	1.833
Live independently	1.222	−32.370***	2.056
Married	−1.667	29.741**	2.667
Has a child	1.667	−16.37	4.611
Race/ethnicity (base: NH White)			
NH black	−0.222	30.148***	3.111
NH Asian	1.000	−10.296	−2.056
Hispanic	0.778	−14.000	−1.111
NH other	−2.111	38.741	14.5
Gender (base: Male)			
Female	−1.000	−2.630	0.667
Age (base: 16 to 19)			
Age 20 to 25	5.889***	44.148**	0.778
Age 26 to 36	6.000***	59.630***	−4.333
Constant	22.667***	30.407*	12.944***
n	22,847	951	966
R^2	0.028	0.117	0.069

Note: Results of three separate quantile regressions.

approximately 21 miles per day, even though the latter neighborhood type has three times the residential density.

5. Conclusion

Planners seeking to reduce driving often turn to the built environment to achieve their aims. Careful research on the effects of land use and built form on travel yield consistent, yet modest effects (Committee for the Study on the Relationships Among Development Patterns, 2009, Boarnet, 2010). In response, many scholars have speculated that a variety of built environment factors may combine to synergistically influence travel to a greater degree than is frequently found using independent measures such as the 5 D's (Bento et al., 2005, Ewing and Cervero, 2010). There may be, in other words, substantial synergistic effects of the built environment on travel behavior. We examine this question among teens and young adults in the U.S., who have been widely presented as both more urban and less auto-dependent than older generations (Cortright, 2011, Blumenberg et al., 2012, Tefft et al., 2013, McDonald, 2015).

First and foremost, we find that particular constellations of built environment factors can indeed significantly influence travel, particularly in the densest, most transit-oriented neighborhoods in the U.S. Specifically, while Drivers make up the majority in most U.S. neighborhoods, they do not in Old Urban neighborhoods, where high densities, excellent transit service, and superior job access facilitate travel by non-automobile modes.

That said, we also find that travel patterns are relatively, and even remarkably, stable along much of the urban-rural continuum, where most young adults live. For policymakers, this stability implies that relatively modest changes in the built environment, such as we see between sprawling new development and inner-ring Established Suburban neighborhoods, is likely to have little effect on travel behavior. Established Suburbs have residential and employment densities that are nearly triple those in New Developments, on average; proposals to double or triple densities in New Developments would be an almost impossible lift politically, yet our findings suggest that even such a radical transformation of the most common American suburban form would likely do little to reduce the share of Drivers. While we do see dramatically lower levels of driving in Old Urban neighborhoods characterized by extremely high building densities and extensive public transit service, *ceteris paribus*, the characteristics of Old Urban neighborhoods are so unique that it would take a heretofore unprecedented effort to transform any of the other neighborhood types into Old Urban neighborhoods.

While the effect of the built environment on the share of Drivers is quite modest, the effect of built form on VMT among Drivers offers more room for optimism among those concerned with auto dependence. We find in this analysis, for example, that the comparatively modest built environment difference between New Developments and Patchwork Suburbs were enough to reduce VMT by 5.7 miles per day for the typical Driver. These results suggest an important distinction between getting young people out of their cars—which requires dramatic changes to the built environment—and reducing vehicle miles traveled among Drivers—which appears to require more modest built form changes.

Table 6
Average marginal effect of changing neighborhood type on traveler type and VMT per day for young adults in the United States in 2009 (base: New Developments).
Source: 2009 NHTS, weighted values.

	Drivers		Long-distance trekkers		Multimodals		Car-less	
	Pop share (%)	VMT/srvy day	Pop share (%)	VMT/srvy day	Pop share (%)	VMT/srvy day	Pop share (%)	VMT/srvy day
Travel in New Developments	85.6	26.2	2.9	42.8	2.9	7.1	8.5	0.0
Change relative to New Developments								
Rural Area	−3.4 [−0.1 to −6.6]	9.1 [5.4 to 12.8]	3.3 [1.1 to 5.5]	31.7 [7.8 to 55.6]	−0.5 [0.7 to −1.6]	9.3 [3.0 to 15.6]	0.5 [−1.9 to 3.0]	–
Patchwork Suburb	−2.2 [0.9 to −5.4]	−5.7 [−3.4 to −7.9]	−0.8 [0.3 to −1.9]	11.1 [−4.5 to 26.7]	−0.5 [0.7 to −1.8]	−1.6 [−2.1 to 5.3]	3.6 [0.8 to 6.4]	–
Established Suburbs	−9.2 [−4.9 to −13.5]	−5.8 [−3.1 to −8.5]	−1.1 [0.1 to −2.3]	33.2 [−32.3 to 98.8]	1.9 [0.2 to 3.6]	1.7 [−3.0 to 6.5]	8.5 [4.6 to 12.3]	–
Urban Residential	−11.9 [−7.7 to −16.2]	−4.0 [−1.2 to −6.8]	−0.7 [0.7 to −2.2]	17.2 [−23.9 to 58.3]	3.0 [0.3 to 5.8]	0.1 [−7.6 to 7.8]	9.6 [6.2 to 12.3]	–
Old Urban	−39.6 [−31.9 to −47.3]	−11.2 [−5.1 to −17.3]	−1.5 [−0.2 to −2.8]	−4.1 [−43.5 to 35.2]	1.4 [−1.1 to 4.0]	1.1 [−8.8 to 10.9]	39.7 [32.1 to 47.3]	–
Mixed-use	−13.6 [−6.9 to −20.2]	−8.2 [−5.0 to −11.5]	0.0 [−1.6 to 1.6]	−3.6 [−19.1 to 11.8]	3.6 [−0.5 to 7.7]	−2.4 [−10.2 to 5.3]	10.0 [4.6 to 15.3]	–

Note: Change relative to New Developments for population share is the percentage point change in the predicted probability of being in each traveler type. For VMT, the change is in miles per day. Figures are based on the results of a multinomial logistic regression model (for traveler type) and a quantile regression (for VMT), both of which control statistically for household income quintile, adult roles, race/ethnicity, gender, and age category. Values in brackets reflect the 95% confidence interval.

Of course, the relationship between neighborhood and traveler type may not be causal; specific types of travelers may seek out neighborhoods that facilitate their preferred travel patterns. Those young people who prefer to live less auto-dependent lifestyles, for instance, may choose to locate in Old Urban neighborhoods because the superior transit service and greater densities in those areas make it possible to live a fulfilling life without a car (Glaeser et al., 2000).

While considerable ink has been spilt debating the complex causality among land use and travel behavior, for the purposes of public policy the direction of the causal arrows may be of minor importance, regardless of whether self-selection or the built environment is the primary causal force at play. In most U.S. neighborhoods, non-automobile travel offers substantially less access than travel by automobile (Wachs and Kumagai, 1973, Grengs, 2010). Young people who would prefer high levels of accessibility while living a Car-less or Multimodal traveler lifestyle have a very limited number of residential neighborhoods from which to choose, as such neighborhoods are in decidedly short supply (Levine 2005). As noted above, Old Urban neighborhoods, which are by far the most hospitable to travel by non-automobile modes, comprise just 5% of all U.S. Census tracts and are confined to the nation's oldest, largest metropolitan areas – half of all Old Urban neighborhoods are in New York City[2]. Outside of those neighborhoods, the built environment limits the quality of non-automobile options and nearly everyone with the financial resources to do so travels by automobile. Equally, in those neighborhoods, many of those who walk, bike, or ride public transit do so not out of choice but because they have no other option. In effect, the built environment sets an upper limit on the number of people in particular neighborhoods who voluntarily choose to walk, bike, or use public transit rather than drive.

Regardless of the causal forces at work, if for environmental or equity reasons our policy aim is to reduce the number of Drivers and Long-distance Trekkers and increase the number of Multimodals and Car-less young people, then we need more of, what might be termed, “radically urban” neighborhoods that are both a challenge to drive in (due to limited road capacity and parking) and hospitable to travel by other means. Such neighborhoods will not be created by doubling densities or adding transit service to the suburbs where most (58%) young American adults live, but will require dramatic increases in the development densities and transit service in already built-up neighborhoods where traffic congestion is endemic and where local resistance to such changes is likely to be fierce.

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[2] Notably we cannot determine whether demand for Old Urban neighborhoods outstrips supply.

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